

Adaptive Fuzzy-Neural Network Control for Magneto-Rheological Suspension

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Abstract

Since Magneto-rheological (MR) suspension has nonlinearity and time-delay, the application of linear feedback strategy has been limited. This paper addresses the problem of control of MR suspension with time-delay when transient dynamics are present. An adaptive fuzzy-neural network control (FNNC) scheme for the transient course is proposed using fuzzy logic control and artificial neural network methodologies. To attenuate the adverse effects of time-delay on control performance, a prediction neural network (PNN) is established. Then, through a numerical example of a quarter car model and a real road test with a bump input, the comparison is made between passive suspension and semi-active suspension. The results show that the MR vehicle with FNNC strategy can depress the peak acceleration and shorten the setting time, and the effect of time-delay can be attenuated. The results of road test with the similarity of numerical study verify the feasibility of the control strategy.

1 Introduction

Recently, semi-active vehicle suspension with MR dampers has attracted more attention for its ability to improve the ride comfort of a ground vehicle [1]. However, MR suspension system always exhibits nonlinearity and time-delay like other semi-active suspension [2]. The MR damper's control forces are calculated according to the last response of vehicle in the traditional time-history analysis method, an inherent time-delay problem lies in the traditional method. Some studies have already shown the importance of solving the time-delay in control systems [3]. When MR vehicle runs across a bump, one may feel violent jerk. The time span of vehicle running across the bump is so short that it is necessary to consider the adverse effect of time-delay on control performance. Therefore, a prediction neural network (PNN) is adopted in this paper to solve the problem. Due to the nonlinearity and uncertainty of MR suspension, some intelligent control strategies have been used to control the semi-active system [4].

Among them, the adaptive fuzzy-neural network control (FNNC) strategy has attracted increasing attention essentially because it can provide a powerful learning technique for complex unknown plants to perform complex tasks in highly nonlinear dynamical environment, and can also have available quantitative knowledge from repetitive adjustment of the system with better performance than those of fuzzy control with constant rules bases [5], [6]. Hence, the FNNC strategy is also proposed to control MR suspension system. The organization of this paper is as follows: first, a quarter car nonlinear model with time-delay was constructed; next, adaptive FNNC for MR suspension system with time-delay is designed and a time-delay compensator which is realized by PNN model is designed for overcoming the effects of time-delay in the closed-loop system; then the simulation is performed based on it; finally, the real road test is carried out to verify the actual control effectiveness.

2 A Quarter Car Nonlinear Model with Time-delay

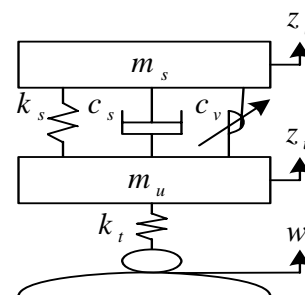


Fig. 1. Quarter car model

In studying dynamic systems, the terminology sprung and unsprung bodies are often used in dynamics literature to the two bodies of a quarter car model. Fig.1 shows an automobile nonlinear model using MR suspension system with time-delay. Where, the sprung body represented by

m_s , and unsprung body denoted by m_u , are connected together by a linear spring and nonlinear MR damper with time-delay. The unsprung body is connected to a movable base. Then the dynamic equations can be written:

$$m_s \ddot{z}_s + k_s(z_s - z_u) + (C_s + C_v)(\dot{z}_s - \dot{z}_u) = 0 \quad (1)$$

$$m_u \ddot{z}_u - (C_s + C_v)(\dot{z}_s - \dot{z}_u) + k_t(z_u - w) = 0 \quad (2)$$

If new state variables are defined as:

$$x = [x_1 \ x_2 \ x_3 \ x_4]^T = [z_s - z_u \ \dot{z}_s \ z_u - w \ \dot{z}_u]^T$$

where x_1 is the displacement of suspension, x_2 is the absolute velocity of sprung mass, x_3 the tire deflection and x_4 is the absolute velocity of unprung mass.

Then Equations (1)-(2) is formulated in a standard state space form without time-delay as:

$$\dot{x} = Ax + Bu + L\dot{w} \quad (3)$$

Where u is the control damping force of MR damper, which is composed of velocity damping force and Coulomb friction [7].

$$u = -C_e V + F_{MR} \quad (4)$$

Where C_e is damping coefficient, F_{MR} is controllable damping force and V is velocity of piston.

If considering the time-delay of MR suspension system, the control force is $u' = u(t - t_d)$, t_d is time-delay. Then Equation (3) can be written:

$$\dot{x} = Ax + Bu(t - t_d) + L\dot{w} \quad (5)$$

3 Adaptive Fuzzy-neural Network Controller Design Considering the Time-delay of MR Suspension System

A schematic of the adaptive fuzzy-neural control system with time-delay compensation is shown in Fig.2. The controller consists of two parts. One is the FNNC, which calculates the control force according to error and the change of the error, the other is the PNN, which is the neural network model of the predictor for the MR suspension without time-delay. The MR suspension with time-delay is expressed as $G(s)e^{-\tau}$. $G(s)$ is a transfer

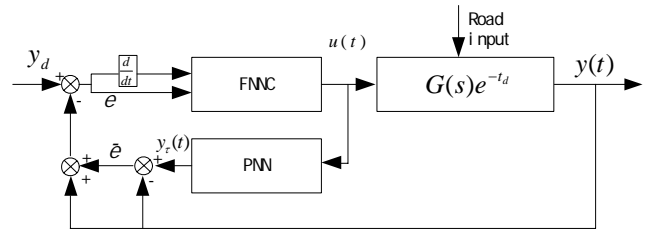


Fig.2 Fuzzy-neural network control system with time-delay compensator function which can be transformed through Equation (3), and the input is control damping force of MR damper, the output is vertical vibration acceleration of car body, the disturbance is road input.

3.1 FNNC Design

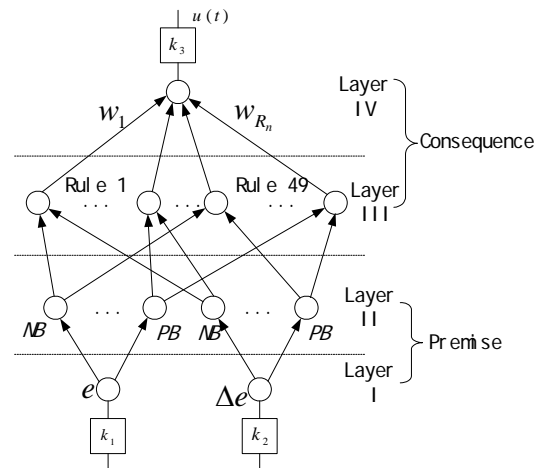


Fig.3. Neural network model of FNNC

As shown in Fig.3, the FNNC system is characterized by premise and consequence. The premise consists of two layers, the first layer is the fuzzy input linguistic vector $(e, \Delta e)^T$ and the second is to fuzz the input linguistic vector, which contains 14 neurons corresponding to 14 fuzzy sets of two linguistic variables. Seven fuzzy sets of one input linguistic variable are $\{NB, NM, NS, ZE, PS, PM, PB\}$. The Gaussian membership functions with equal width intervals of the means are thus proposed to eliminate the sharp boundary and are defined:

$$A_{ij}(z) = \exp\left(-\frac{z_k - \bar{z}_k}{2\sigma_k}\right), k = 1, 2, \dots, 2l \quad (6)$$

In which, $l = 7$, \bar{z}_k and σ_k are the mean and variance of the K th Gaussian membership function $\mu_k(z)$, respectively.

The third layer contains 49 neurons to realize fuzzy reasoning. The output from the FNNC system in the last layer can be expressed as:

$$u = \sum_{i=1}^{R_n} \mu_i w_i / \sum_{i=1}^{R_n} \mu_i = \sum \bar{\mu}_i w_i \quad (7)$$

Where $R_n = 49$ and $\mu_i = \prod A_{i1}(e) * A_{i2}(\Delta e)$

Weights of the last layer are tuned by back propagation algorithm. The error between expected output $y_d(t)$ and actual output $y(t)$ with time-delay is:

$$e = \frac{1}{2} \sum (y(t) - y_d(t))^2 \quad (8)$$

Then weights modified as:

$$w_i(t+1) = w_i(t) - \eta \frac{\partial e}{\partial w_i(t)} + \xi \Delta w_i(t) \quad (9)$$

In which η and ξ are learning factor and momentum factor and

$$\frac{\partial e}{\partial w_i(t)} = \frac{\partial e}{\partial y(t)} \frac{\partial y(t)}{\partial \lambda(t)} \frac{\partial \lambda(t)}{\partial w_i(t)} = -(y_d(t) - y(t)) \frac{\mu_j}{\sum_{j=1}^{R_n} \mu_j} \frac{\partial y(t)}{\partial \lambda(t)}$$

$$\frac{\partial y(t)}{\partial u(t)} = \frac{y(t) - y(t-1)}{u(t) - u(t-1)},$$

$$\Delta w_i(t) = w_i(t) - w_i(t-1)$$

To achieve good control performance, a simulink model is formulated based on the equation (5) with a bump input, which is acquired by measuring the real bump road signal, and used in the teaching signal generation. The genetic algorithm is adopted to search out the best control force for the MR damper that minimizes the fitness function (10). The control rules and the shape of each input/output membership function are tuned by learning from the teaching signal generated by the genetic algorithm. A trade-off is assumed between ride comfort and stability of the car body to choose an ideal control force. A reasonable fitness function is selected as follows:

$$Fit = a \sqrt{\frac{1}{T} \int_0^T \ddot{x}_s^2 dt} + (1-a) \sqrt{\frac{1}{T} \int_0^T \ddot{x}_u^2 dt} \quad (10)$$

Where a represents the weighting factor, T is simulation time.

3.2 Time-delay Compensation

The principle of the compensator PNN in Fig.4 is based on the smith predictor [8]. PNN can be realized using a back propagation network with four layers and nodes N1-N2-N3-N4 (In this paper, N1=4, N2=8, N3=8, N4=1). The mapping relationship of the model is described as:

$$y_M(t+1) = f_M(u(t-t_d), u(t-t_d-1), \dots, u(t-t_d-m), y(t), \dots, y(t-n)) \quad (11)$$

Where m and n denote the orders of MR suspension system, and defining:

$$s^T = (s_1, \dots, s_{N1})^T = (u(t-t_d), u(t-t_d-1), \dots, u(t-t_d-m), y(t), \dots, y(t-n))^T$$

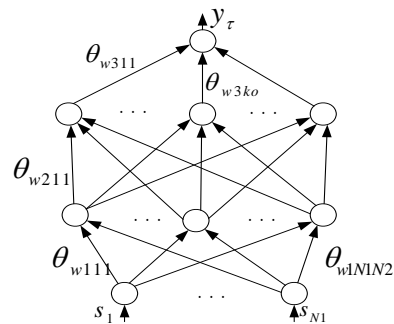


Fig.4. Neural network model of PNN

The activation functions in the last three layers of the PNN are respectively:

$$f_{1j} = 1 / \{1 + \exp[-(\sum_{j=1}^{N1} w_{1ij} x_i + q_{1j})]\}, \quad j = 1, \dots, N_2 \quad (12)$$

$$f_{2k} = 1 / \{1 + \exp[-(\sum_{j=1}^{N3} w_{2jk} f_{1j} + q_{2k})]\}, \quad k = 1, \dots, N_3 \quad (13)$$

$$y_M(t+1) = 1 / \{1 + \exp[-\sum_{k=1}^{N_3} w_{3ki} f_{2k} + q_{3i}]\} = f_M(f_{2k}(f_{1j})) \quad (14)$$

The output of conventional control system with the time-delay t_d is

$$y(t+1) = L^{-1}\{G(s)e^{-t_d s}\} = f(u(t-t_d), u(t-t_d-1), \dots, u(t-t_d-m), y(t), \dots, y(t-n)) \quad (15)$$

The output without time-delay is:

$$y_\tau(t+1) = L^{-1}\{G(s)\} = f_\tau(u(t), \dots, u(t-m), y_\tau(t), \dots, y_\tau(t-n)) \quad (16)$$

Where $L^{-1}\{\bullet\}$ is the inverse Laplace transform.

The predicted value of the output of the MR suspension system without time-delay is given by the neural network model PNN and used to realize a compensating control. The PNN network is trained by the sequence of the input-output samples. Using the same mapping network as (7), we can obtain the predicted value of the output without time-delay as follows:

$$y_\tau(t+1) = f_{M\tau}(u(t), u(t-1), \dots, u(t-m), y_\tau(t), \dots, y_\tau(t-n)) \quad (17)$$

The compensating error is

$$\bar{e} = y_\tau(t+1) - y(t+1) \quad (18)$$

Off-line and on-line learning algorithms can be used to modify the weights of PNN network. The off-line learning results of the PNN can be used as a reference model of MR suspension system. The weights of PNN are modified by the index (18) using the principle of error gradient descent. The learning algorithms for the PNN are described in the following:

If defining

$$\theta_3(t) = (y(t) - y_M(t))(1 - y_M(t))y_M(t) \quad (19)$$

$$\theta_{2k}(t) = f_{2k}(t)(1 - f_{2k}(t))\theta_{w_{3ko}}(t)\theta_3(t), \quad k = 1, \dots, N_3 \quad (20)$$

$$\theta_{1j}(t) = f_{1j}(t)(1 - f_{1j}(t))\sum_{k=1}^{N_3} \theta_{w_{2jk}}(t)\theta_{2k}(t), \quad j = 1, \dots, N_2 \quad (21)$$

Then weights of PNN can be modified as:

$$\Delta\theta_{3ko}(t) = h_3\theta_3(t)f_{2k}(t) + g_3\Delta\theta_{w_{3ko}}(t-1)$$

$$\theta_{w_{3ko}}(t+1) = \theta_{w_{3ko}}(t) + \Delta\theta_{w_{3ko}}(t)$$

$$q_{3o}(t+1) = q_{3o}(t) + h_3\theta_3(t)$$

$$\Delta\theta_{w_{2jk}}(t) = h_2\theta_{2k}(t)f_{1j}(t) + g_2\Delta\theta_{w_{2jk}}(t-1)$$

$$\theta_{w_{2jk}}(t+1) = \theta_{w_{2jk}}(t) + \Delta\theta_{w_{2jk}}(t)$$

$$q_{2k}(t+1) = q_{2k}(t) + h_2\theta_{2k}(t)$$

$$\Delta\theta_{w_{1ij}}(t) = h_1\theta_{1j}(t)s_i + g_1\Delta\theta_{w_{1ij}}(t-1)$$

$$\theta_{w_{1ij}}(t+1) = \theta_{w_{1ij}}(t) + \Delta\theta_{w_{1ij}}(t)$$

$$q_{1j}(t+1) = q_{1j}(t) + h_1\theta_{1j}(t)$$

In which, $h_i, g_i \in (i = 1, 2, 3)$ are learning factors and momentum factors respectively.

4 Simulation

The nominal parameters for these simulations are $k_s=15000N/m$, $k_t=116900N/m$, $m_u=25.9Kg$, $m_s=264.2Kg$, $c_s=1000Ns/m$. These parameters used in the simulation of the genetic algorithm are population size=100, mutation probability=0.2, crossover probability=0.1.

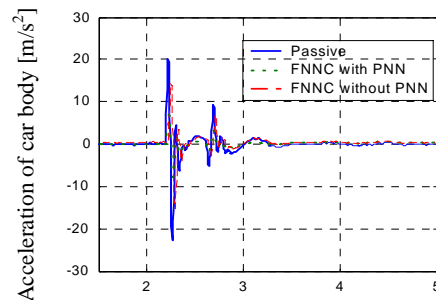


Fig.5. Acceleration time history of car body

The simulation result is shown in Fig.5. It can be seen that MR suspension employing FNNC with PNN or FNNC without PNN reduces the vertical vibration acceleration and adjusting time of car body compared to the passive suspension. The adjusting time of two strategies is almost the same. However, the peak value of FNNC with PNN is smaller than that of FNNC without PNN, which indicates that FNNC with PNN achieves better performance than FNNC without PNN.

5 Road Test

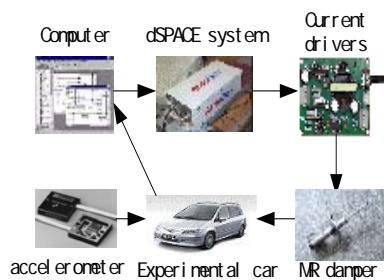


Fig.6. Real time control system

To verify the actual control performance, the control system based on dSPACE, which consists of DS1005 PPC board, DS2002 multi-Channel A/D Board and DS2102 high-resolution D/A Board, is fabricated in Fig.6. Mazda 323 is selected as experimental car. Four MR shock absorbers are used to replace the passive ones. Four accelerometers are placed on carriage's foursquare floor to record the vertical accelerate signal of sprung mass. Other four accelerometers are placed on two axis of vehicle to record the vertical acceleration signal of unsprung mass. Every seat has a passenger to simulate the condition of full load. The test car is driven straight down an arc road with the same dimension of the simulation at speed (20km/h). The experimental result is shown in Fig.7. Some similar conclusions with that of the simulation can be drawn. MR suspension using FNNC with or without PNN can both depress the vibration of car body and reduces the peak acceleration and shorten adjusting time. The FNNC with PNN is more effective than the FNNC without PNN in improving the ride comfort. Due to model error of simplification, it can also be seen that the experimental data is smaller than the simulated, and experimental arc road is superposed on random road.

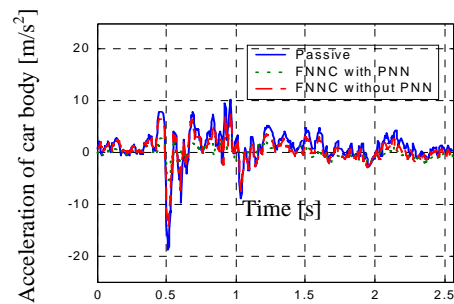


Fig.7. Acceleration time history of car body

6 Conclusion

The MR suspension with time-delay is proposed and studied. For vibration control of the MR suspension system, a FNNC is designed. Time-delay of MR suspension is compensated by PNN. The performances of the suspension system under bump input are evaluated through computer simulation and road test. Both the result of simulation and that of road test show that the MR suspension system using FNNC can substantially reduce vertical peak acceleration of car body, shorten adjusting time and improve ride comfort. The MR suspension system using FNNC with PNN can achieve better control performance than that using FNNC without PNN.

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