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NEURO-CONTROL FOR SEISMIC RESPONSE REDUCTION USING A SEMI-ACTIVE MR FLUID DAMPER

Heon Jae Lee*, Sang Won Cho, Hyung Jo Jung, Ju Won Oh[1] and In Won Lee
Korea Advanced Institute of Science and Technology, Korea
[1]Hannam University, Korea

Abstract

A new semi-active control strategy for seismic response reduction using a neuro-controller and a magnetorheological (MR) fluid damper is proposed. The proposed control system consists of the improved neuro-controller and the bang-bang-type controller. The improved neuro-controller, which was developed by employing the training algorithm based on a cost function and the sensitivity evaluation algorithm replacing an emulator neural network, produces the desired active control force, and then the bang-bang-type controller causes the MR fluid damper to generate the desired control force, so long as this force is dissipative. In numerical simulation, a three-story building structure is semi-actively controlled by the trained neural network under the historical earthquake records. The simulation results show that the proposed semi-active neuro-control algorithm is quite effective to reduce seismic responses. In addition, the semi-active control system using MR fluid dampers has many attractive features, such as the bounded-input, bounded-output stability and small energy requirements. The results of this investigation, therefore, indicate that the proposed semi-active neuro-control strategy using MR fluid dampers could be effectively used for control of seismically excited structures.

Introduction

Vibration control of seismically excited structural systems using artificial neural networks was proposed by Ghaboussi et al. (1995) and Chen et al. (1995). They showed that neural network can successfully control structural vibration system. But there are some problems with training neural network. One of the most important problems is that one should predetermine the desired structural response for the training of a neural controller. Kim et al. (2000), however, proposed a new training algorithm which does not require desired responses. They used cost function as a training criterion and showed that structures under ground motion could be successfully controlled by the neuro-controller trained by minimizing the cost function. Another problem is the need of emulator neural network which expects sensitivity of structural response. Kim et al. (2001) also proposed a sensitivity evaluation algorithm to make the neuro-control system compact and to reduce the total training time without the emulator.

Semi-active control systems do not have the potential to destabilize the structural system and require only a small amount of power, because those systems not only offer the reliability of passive control systems but also maintain the versatility and adaptability of fully active control systems.

The objective of this paper is to propose a new semi-active control method for seismic protection of building structures. Herein, an MR fluid damper, used in conjunction with a neural network-based control algorithm, is proposed as part of a seismic hazard mitigation strategy.

Address : Department of Civil and Environment Engineering, KAIST, Gu-seong Dong, Daejeon, Korea 305-701
Fax No. : +82-42-864-3658, E-mail : wildhawk7@hanmail.net

Active control system using neural network

Fig. 1 shows the block diagram of the neuro-control method proposed by Kim et al. (2001). In this method, the sensitivity of the structural response to input load is calculated not by emulator neural network but by the sensitivity evaluation algorithm. In addition, a cost function is used to train the neuro-controller. Therefore one does not have to determine the desired output to train the controller.

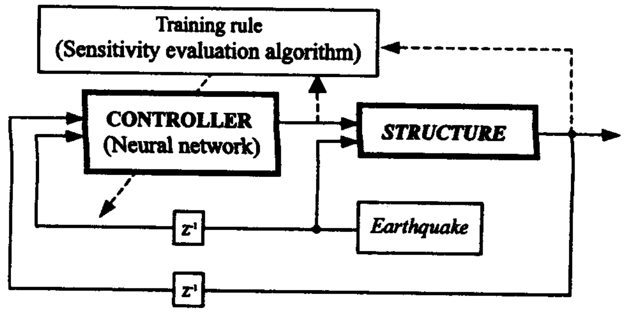


Fig. 1. Control diagram for active neuro-control (Kim et al., 2001)

To derive training rule, the cost function comprised of the structural response and the control signal in the discrete-time domain is defined as

$$\hat{J} = \frac{1}{2}\sum_{k=0}^{N_f-1}\left\{\mathbf{z}_{k+1}^T\mathbf{Q}\mathbf{z}_{k+1} + \mathbf{u}_k^T\mathbf{R}\mathbf{u}_k\right\} = \frac{1}{2}\sum_{k=0}^{N_f-1}\hat{J}_k \tag{1}$$

where $\mathbf{z}(n\times 1)$ and $\mathbf{u}(m\times 1)$ are the state and the control signal; $\mathbf{Q}(n\times n)$ and $\mathbf{R}(m\times m)$ are the weighting matrices; k and N_f are the sampling number and the total number of sampling time. The first term in braces of Eq. (1) means the vibration energy and the second term means the control energy. If the neuro-controller is trained by minimizing the cost function, there is no need to predetermine the desired response and both the response and the control signal are available at every instant.

By applying the gradient decent rule to the cost at the k-th step, the update for the weight, W_{ji}^2, at the k-th step can be expressed as

$$\Delta W_{ji}^2 = -\eta\frac{\partial\hat{J}_k}{\partial W_{ji}^2} \tag{2}$$

where η is the rate of training. By varying the rate, the convergence of training can be improved. Using the chain rule, the partial derivative of Eq. (2) can be rewritten as

$$\frac{\partial\hat{J}_k}{\partial W_{ji}^2} = \frac{\partial\hat{J}_k}{\partial net_j^2}\frac{\partial net_j^2}{\partial W_{ji}^2} \tag{3}$$

Then, let's define the generalized error as

$$\delta_j^2 = -\frac{\partial \hat{J}_k}{\partial net_j^2} = -\frac{\partial \hat{J}_k}{\partial o_j^2}\frac{\partial o_j^2}{\partial net_j^2} \tag{4}$$

Finally, the weight update can be simply expressed as

$$\Delta W_{ji}^2 = \eta \delta_j^2 o_i^1 \tag{5}$$

where

$$\delta_j^2 = -\left(\mathbf{z}_{k+1}^T \mathbf{Q}\left\{\frac{\partial \mathbf{z}_{k+1}}{\partial u_{k,j}}\right\} + \mathbf{u}_k^T \mathbf{r}_j\right) G_j \left(f^2\right)'\Big|_{net_j^2} \tag{6}$$

In Eq. (6), the gain factor, G_j, satisfies

$$u_j = G_j o_j^2 \tag{7}$$

and $\mathbf{r}_j$ is the j-th column vector of $\mathbf{R}$. The bias is also updated by

$$\Delta b_j^2 = \eta \delta_j^2 \tag{8}$$

In Eq. (6) all the terms except the sensitivity of the state to the control signal are available at the k-th step. And the sensitivity can be calculated through the sensitivity evaluation algorithm.
In the same manner, updates for the weight, ΔW_{ih}^1, can be obtained as

$$\Delta W_{ih}^1 = \eta \delta_i^1 I_h \tag{9}$$

where

$$\delta_i^1 = -\frac{\partial \hat{J}_k}{\partial net_i^1} = -\sum_{j=1}^{n3} \frac{\partial \hat{J}_k}{\partial net_j^2}\frac{\partial net_j^2}{\partial o_i^1}\frac{\partial o_i^1}{\partial net_i^1} = \sum_{j=1}^{n3} \delta_j^2 W_{ji}^2 \left(f^1\right)'\Big|_{net_i^1} \tag{10}$$

And the bias of the hidden layer is updated by

$$\Delta b_i^1 = \eta \delta_i^1 \tag{11}$$

Semi-active neuro-control system using MR fluid damper

The strategy of the proposed semi-active control algorithm for seismic protection using MR fluid dampers, which is assumed to be ideal; i.e. it can generate the desired dissipative forces without considering delay and dynamics of the device, is comprised of two controllers. The *first* (or *primary*) controller produces the desired active control force, and then a *secondary* controller clips the bang-bang-type controller causes the smart damper to generate the desired active control force, so long as this force is dissipative.

In this study, a neural network-based algorithm that is already described in the previous section is adopted as the *primary* controller, and the *secondary* control strategy is given by

$$f_{\mathrm{sa}} = \begin{cases} f_{\mathrm{a}}, & f_{\mathrm{a}} \cdot \dot{x}_{\mathrm{dev}} < 0 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where f_{sa} is the control force of the smart damper, f_a is the "desired" control force of the device, and $\dot{x}_{\mathrm{dev}}$ is the velocity across the damper. Because the MR fluid damper is an energy-dissipation device that cannot add mechanical energy to the structural system, special care must be taken in the design of the primary controller so that the "desired" control force f_a is dissipative during the majority of the seismic event. The MR fluid damper control design is depicted in Fig. 2.

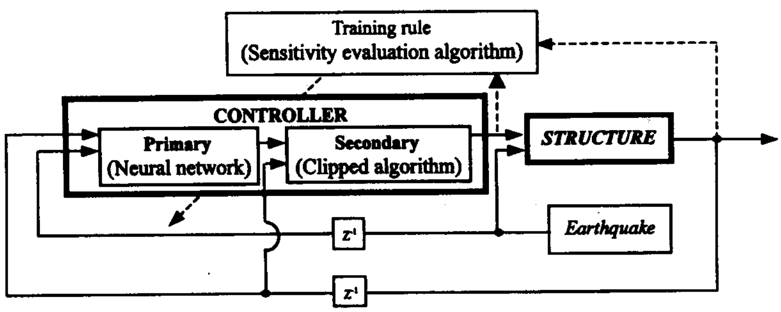


Fig. 2. Smart damper control strategy using clipped algorithm

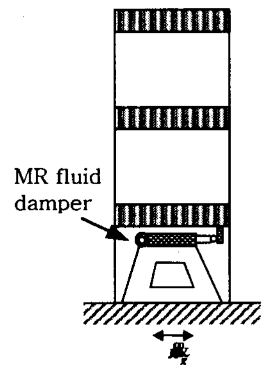


Fig. 3. Three-story building structure employing MR fluid damper

Numerical Simulation Results

To verify the effectiveness of the proposed semi-active control design, simulation results of the proposed semi-active control design are compared to those of an active control design as well as the same number and location of the sensors/actuators employed for the proposed control design.
A model of a three-story building configured with a single smart damper is considered as shown Fig. 3 (Spencer et al., 1997). The neuro-controller has three layers: input layer, hidden layer, and output layer. The input layer has five nodes to which the feedback signals of the displacement, velocity of the first and third floor and the ground acceleration are fed. The hidden layer has five nodes. The output has only one node which produces control signal. The sigmoid function is used as the activation function of the hidden layer and the linear function for the output layer. Weighting matrix $\mathbf{Q}$ and r are as follows.

$$\mathbf{Q} = diag(1,0,1,1,0,1), \quad r = 10^{-10} \tag{10}$$

Total intervals among the dynamic responses under El Centro earthquake (1940), whose peak ground acceleration(PGA) is 0.348g, are used as the training data. Training was repeated until the number of epochs reaches 200.
After the neuro-controller is sufficiently trained, the test structure is controlled by the trained neuro-controller under the three historical earthquake records, such as the El Centro, which is already used to train the network, and the Northridge (PGA:0.334g) and the California (PGA:0.156g) earthquake, which are to test the performance of the trained neuro-controller. Fig. 4 shows the time histories of

the responses such as the displacement and acceleration during the El Centro earthquake. Since the proposed neuro-controller was trained by using El Centro earthquake, all the responses are considerably reduced under control action. Fig. 5 shows the responses of the test structure during the Northridge and the California earthquakes, respectively. As seen from the figures, the neuro-controller using the MR fluid damper still performs very well.

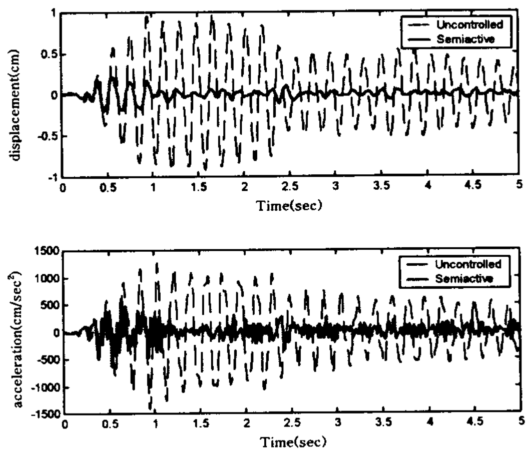
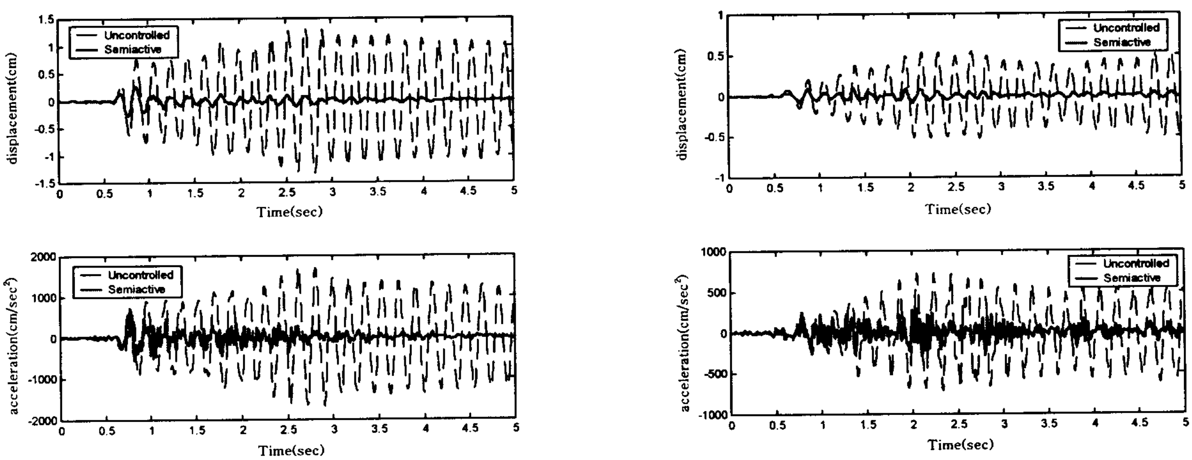


Fig. 4. Time histories of the responses on the third floor under the El Centro earthquake



(a) the Northridge earthquake.

(a) the California earthquake.

Fig. 5. Time histories of responses on the third floor under the Northridge and California earthquakes.

The peak responses for the controlled structure are compared to those for the uncontrolled structure as shown in Table 1. The overall performance of the proposed semi-active neuro-control system is much superior to that of the uncontrolled system although the performance of the active neuro-control system is slightly better than that of the proposed system. Note that, in the case of a severe earthquake, a fully active control system such as the neuro-control system may not work for seismic protection due to a power failure, where a semi-active control system such as the proposed system can operate well because semi-active control devices use only a small fraction of the power required to operate the active control system.

Table 1. Peak responses under the earthquakes (ratio)

	El Centro Earthquake			Northridge Earthquake			California Earthquake		
Control Strategy	Uncontrolled	Active neuro-control	Semi-active neuro-control	Uncontrolled	Active neuro-control	Semi-active neuro-control	Uncontrolled	Active neuro-control	Semi-active neuro-control
x_i (cm)	0.549 (1.00)	0.098 (0.18)	0.138 (0.25)	0.683 (1.00)	0.093 (0.14)	0.177 (0.26)	0.316 (1.00)	0.043 (0.14)	0.069 (0.22)
	0.836 (1.00)	0.133 (0.16)	0.198 (0.24)	1.102 (1.00)	0.174 (0.16)	0.254 (0.23)	0.476 (1.00)	0.051 (0.11)	0.084 (0.18)
	0.973 (1.00)	0.215 (0.22)	0.216 (0.22)	1.343 (1.00)	0.210 (0.16)	0.273 (0.20)	0.544 (1.00)	0.081 (0.15)	0.099 (0.18)
d_i (cm)	0.549 (1.00)	0.198 (0.18)	0.138 (0.25)	0.683 (1.00)	0.093 (0.14)	0.177 (0.26)	0.316 (1.00)	0.043 (0.14)	0.069 (0.22)
	0.317 (1.00)	0.124 (0.39)	0.136 (0.43)	0.422 (1.00)	0.108 (0.26)	0.129 (0.39)	0.169 (1.00)	0.046 (0.27)	0.060 (0.36)
	0.203 (1.00)	0.082 (0.40)	0.092 (0.45)	0.248 (1.00)	0.095 (0.38)	0.084 (0.34)	0.104 (1.00)	0.041 (0.39)	0.042 (0.40)
$\ddot{x}_{ai}$ (cm/sec^2)	880 (1.00)	660 (0.75)	777 (0.88)	917 (1.00)	661 (0.72)	693 (0.76)	581 (1.00)	358 (0.62)	429 (0.74)
	1065 (1.00)	569(0.53)	887 (0.83)	1287 (1.00)	593 (0.46)	837 (0.65)	662 (1.00)	270 (0.41)	515 (0.78)
	1414 (1.00)	567 (0.40)	639 (0.45)	1726 (1.00)	659 (0.38)	587 (0.34)	726 (1.00)	286 (0.39)	291 (0.40)
f (N)	-	1000	803	-	1000	790	-	522	537

Conclusoins

A semi-active neuro-contrl method using an MR fluid damper is presented for seismic response reduction. In the neuro-control algorithm considered in this study, the training algorithm based on a cost function and the sensitivity evaluation algorithm are introduced. Moreover, an MR fluid damper is considered as a supplemental damping device. Numerical simulation results show that the proposed semi-active neuro-control algorithm is quite effective to reduce seismic responses. In addition, the semi-active control system has many attractive features, such as the bounded-input, bounded-output stability and small energy requirements. The results of this investigation, therefore, indicate that the proposed semi-active neuro-control strategy using MR fluid dampers could be effectively used for control of seismically excited structures.

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