SEMIACTIVE NEURO-CONTROL FOR SEISMICALLY EXCITED STRUCTURE USING MR DAMPER

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ABSTRACT : A new semiactive control strategy for seismic response reduction using a neuro-controller and a magnetorheological (MR) fluid damper is proposed. The proposed control system adopts a clipped algorithm which induces the MR damper to generate approximately the desired control force. 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 by using the clipped algorithm the appropriate command voltage is selected in order to cause the MR damper to generate the desired control force. In mumerical simulation, a three-story building structure is semiactively controlled by the trained neural network under the historical earthquake records. The simulation results show that the proposed semiactive neuro-control algorithm is quite effective to reduce seismic responses. In addition, the semiactive 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 semiactive neuro-control strategy using MR fluid dampers could be effectively used for control of seismically excited structures.

KEYWORDS: semiactive control, neural network, MR damper, clipped algorithm, sensitivity evaluation algorithm.

1. INTRODUCTION

Vibration control strategy of seismically excited structural systems using artificial neural networks was proposed by Ghaboussi *et al.*(Ghaboussi 1995) and Chen *et al.*(Chen 1995). They showed that neural network could 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.* (Kim 2000), however, proposed a new training algorithm that 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 that expects sensitivity of structural response. Kim *et al.* (Kim 2001) also proposed a sensitivity evaluation algorithm to make the neuro-control system compact and to reduce the total training time without the emulator.

Semiactive 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.

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

2. ACTIVE CONTROL SYSTEM USING NEURAL NETWORK

Figure 1 shows the block diagram of the neuro-control method proposed by Kim *et al*. (Kim 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.

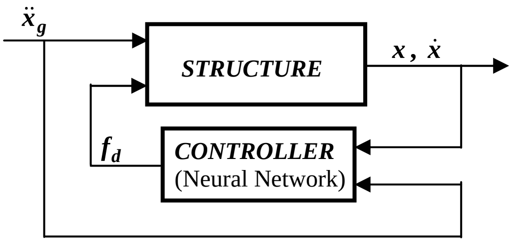

Figure 1. Active neurocontrol system (Kim et al. 2001)

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

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

where $\mathrm{z}(n\times 1)$ and $\mathrm{u}(m\times 1)$ are the state and the control signal; $\mathrm{Q}(n\times n)$ and $\mathrm{R}(m\times m)$ 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 this rate, the convergence of training can be improved. Using the chain rule, finally, the weight update can be simply expressed as

$$\Delta W_{ji}^2 = \eta - \left(\mathrm{z}_{k+1}^T\mathrm{Q}\left\{\frac{\partial \mathrm{z}_{k+1}}{\partial u_{k,j}}\right\} + \mathrm{u}_k^T\mathrm{r}_j\right)G_j\left(f^2\right)'\Big|_{net_j^2} o_i^1 \tag{3}$$

In Eq. (3), G_j is the gain factor, and r_j is the j-th column vector of R. The bias is also updated by

$$\Delta b_j^2 = \eta\delta_j^2 \tag{4}$$

In Eq. (3) 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 and bias can be obtained as

$$\Delta W_{ih}^1 = \eta\sum_{j=1}^{n3}\delta_j^2 W_{ji}^2\left(f^1\right)'\Big|_{net_i^1} I_h, \qquad \Delta b_i^1 = \eta\delta_i^1 \tag{5}$$