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Artificial Neural Networks for Structural Vibration Control

Ju-Tae Kim[1)], Ju-Won Oh[2)] and In-Won Lee[3)]

1), 3) Department of Civil Eng., KAIST, Taejon, 305-701, Korea
2) Department of Civil & Environmental Eng., Hannam University, Taejon, 300-791, Korea

ABSTRACT

An optimal control algorithm using neural networks is proposed. Controller neural network is trained by a training rule developed to minimize cost function. Not only linear structure but nonlinear structure can be controlled by proposed neuro-controller. Bilinear hysteretic model was used to simulate nonlinear structural behavior. Two main advantages of neuro-controller can be summarized as follows. First, it can control structure with unknown dynamics. Second, it can be easily applied to nonlinear structural control. Examples showed that structural response can be reduced to desirable level.

INTRODUCTION

Artificial neural networks have been widely used in structural engineering fields. Especially, vibration control using neural networks has been a new research topic for structural control engineers for last five years. Some characteristics of neural networks appealing to control engineers are non-linearity, parallelism, and learning capability. Although modern control theories have been well established in electrical engineering, they cannot be directly applied to civil engineering structures due to some problems such as non-linearity, uncertainty and time-varying properties of them. These problems necessarily made neural networks a promising tool for the control of civil structures.

Pioneering studies by H. M. Chen et al. and K. Bani-Hani et al. showed that neural networks can be applied to the control of large civil structures successfully. The vibration of nonlinear structures showing hysteretic behavior was also controlled via nonlinearly trained neural networks.

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1) Graduate Assistant
2) , 3) Professors

In this study, the earthquake-induced vibrations of both a linear and a nonlinear structure are to be controlled by neural networks trained to minimize pre-defined cost function. Results show that conventional optimal control can be easily extended to nonlinear structural control with the help of neural networks.

NEURAL NETWORKS FOR VIBARTION CONTROL

Block diagram for the control of structural vibration is described in Fig. 1. Emulator neural network is first trained to imitate the structural response for the same input signal as applied to the structure. Then it is used to obtain sensitivity information of the structural responses. Controller neural network is then trained to suppress undesired vibration caused by external disturbances such as wind and earthquakes. The training rule updates the weights of the controller with the help of the information on the sensitivity of the structural responses to control force and control force itself. Weight updating criterion is to reduce the cost function defined by Eq. (1).

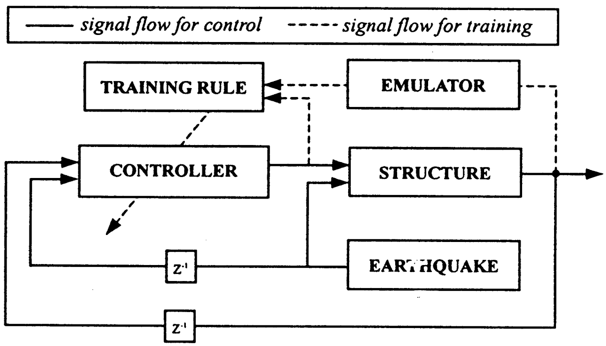

Fig. 1. Block diagram for structural control using neural network

$$J = \frac{1}{2}\int_0^{\infty}\left(\bar{x}^T Q\bar{x} + \bar{u}^T R\bar{u}\right)dt \qquad (1)$$

where $\bar{x} = \{x, \dot{x}\}^T$, $\bar{u} = \{u_1, u_2, \cdots, u_m\}^T$ and Q, R are weighting matrices. The discrete form of Eq. (1) can be written as Eq. (2), where Δt is time increment for analysis and control and N is the total time step considered.

$$\hat{J} = \sum_{n=0}^{N} \hat{J}_n = \sum_{n=0}^{N} \frac{1}{2}\left\{\bar{x}(n)^T Q\bar{x}(n) + \bar{u}(n)^T R\bar{u}(n)\right\}\Delta t \qquad (2)$$

Because the state, $\bar{x}$, and control force, $\bar{u}$, are the implicit and the explicit function of the weight of the controller neural network, $\hat{J}$ can be minimized through the appropriate weight modification. There are two types of learning mode. One is pattern learning and the other is batch learning. Weights are updated at each time step in pattern learning mode, therefore this scheme is related to instantaneous optimal control method, whereas weights are updated once for all time steps in batch learning. The latter scheme is related to optimal control method. In this paper, pattern learning mode is used for weight updates. Pattern learning mode can also minimize global cost function. This is shown in numerical example.

Weight updates equation between input and hidden layer can be expressed as Eq. (3) by steepest descent rule.

$$\begin{aligned}\Delta W_{kj} &= -\eta \frac{\partial \hat{J}_n}{\partial W_{kj}} \\ &= -\eta \left(\left\{ \frac{\partial \hat{J}_n}{\partial \overline{x}} \right\} \left[\frac{\partial \overline{x}}{\partial \overline{u}} \right] \left\{ \frac{\partial \overline{u}}{\partial W_{kj}} \right\} + \left\{ \frac{\partial \hat{J}_n}{\partial \overline{u}} \right\} \left\{ \frac{\partial \overline{u}}{\partial W_{kj}} \right\} \right) \\ &= -\eta \Delta t \left(\overline{x}^T Q \left[\frac{\partial \overline{x}}{\partial \overline{u}} \right] + \overline{u}^T R \right) \left\{ \frac{\partial \overline{u}}{\partial W_{kj}} \right\}\end{aligned} \tag{3}$$

where η is learning rate.

Weight update equation between hidden and output layer can be written by Eq. (4).

$$\begin{aligned}\Delta W_{ji} &= -\eta \frac{\partial \hat{J}_n}{\partial W_{ji}} \\ &= -\eta \left(\left\{ \frac{\partial \hat{J}_n}{\partial \overline{x}} \right\} \left[\frac{\partial \overline{x}}{\partial \overline{u}} \right] \left\{ \frac{\partial \overline{u}}{\partial W_{ji}} \right\} + \left\{ \frac{\partial \hat{J}_n}{\partial \overline{u}} \right\} \left\{ \frac{\partial \overline{u}}{\partial W_{ji}} \right\} \right) \\ &= -\eta \Delta t \left(\overline{x}^T Q \left[\frac{\partial \overline{x}}{\partial \overline{u}} \right] + \overline{u}^T R \right) \left\{ \frac{\partial \overline{u}}{\partial W_{ji}} \right\}\end{aligned} \tag{4}$$

NONLINEAR STRUCTURAL MODEL

To simulate control effect on nonlinear structure, nonlinear equation of motion is considered.

$$m\ddot{x} + c\dot{x} + k(x) = -m\ddot{x}_g \tag{5}$$

where m and c are mass and stiffness respectively. The nonlinear stiffness function, $k(x)$, is defined by

$$k(x) = \alpha kx + (1-\alpha)kdw \tag{6}$$

where α, k and d are positive numbers. The variable w is governed by the differential equation.

$$\dot{w} = \frac{1}{d}(a\dot{x} - \beta|\dot{x}||w|^{n-1}w - \gamma\dot{x}|w|^n) \tag{7}$$

where a, β, γ, d are positive number and n is an odd number. This model can simulate nonlinear hysteretic behavior. Detailed description of this model can be seen in the reference (H. Irschik et al.)

NUMERICAL EXAMPLES

Control of Linear Structure

The linear single degree of freedom structure is composed of mass(1 kg), damping(1.25 N/m/sec) and stiffness(39 N/m). El Centro earthquake(1940) is used for the training of controller. Then, two more ground motion, California earthquake(1952) and Northridge earthquake(1994), are used for test. The Inputs to the controller neural network are delayed signals of structural displacement, velocity and ground acceleration, namely $x_{k-1}, \dot{x}_{k-1}, \ddot{x}_{g,k-1}$. The number of nodes of hidden layer is four. The output is control force. Fig. 2 shows learning history of the cost function. Although the controller is trained in pattern learning mode, which implies instantaneous optimal control method, the global cost function $\hat{J}$ is minimized.

Controlled and uncontrolled responses are shown in Fig. 3. Neuro-controller trained by El Centro earthquake can also reduce vibrations induced by other earthquakes which were not trained. It explains the generalization characteristics of neural networks

Control of Nonlinear Structure

The nonlinear model of Eq. (5) is used for nonlinear structural control example. The parameters used in the simulation are $\alpha(0.6)$, $\beta(0.5)$, $\gamma(0.5)$, $a(1.0)$, $d(0.04)$, $n(5)$, $k(39)$, and mass, damping are the same as the linear model.

Fig. 4 shows that neuro-controller can also learn to control the responses of nonlinear structure. The mathematical approach of optimal control is restricted to linear structural control, but neural network approach can be simply applied to nonlinear structural control. Fig. 5 shows the relationship between restoring force and displacement. Uncontrolled responses show bilinear hysteretic behavior while controlled responses show linear behavior with amplitudes being reduced.

CONCLUSIONS

Optimal control algorithm of linear and nonlinear structure using neural network was developed. Learning rule is to minimize instantaneous cost function, but it can reduce global cost function. Two main advantages of structural control using neural network can be summarized as follows. First, we can control the structure of unknown dynamics through the learning of responses itself. Second, we can also control highly nonlinear structure due to the nonlinear characteristics of neural networks. The response of nonlinear structure with bilinear hysteretic behavior was controlled in numerical example.

Mathematical approach of optimal control cannot consider the ground motion, however it is considered in the proposed control method. Therefore, controller trained by some earthquake can also suppress the vibration induced by other earthquakes.

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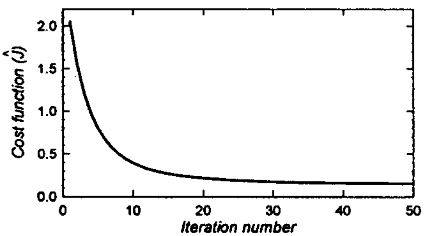

Fig. 2. Learning history

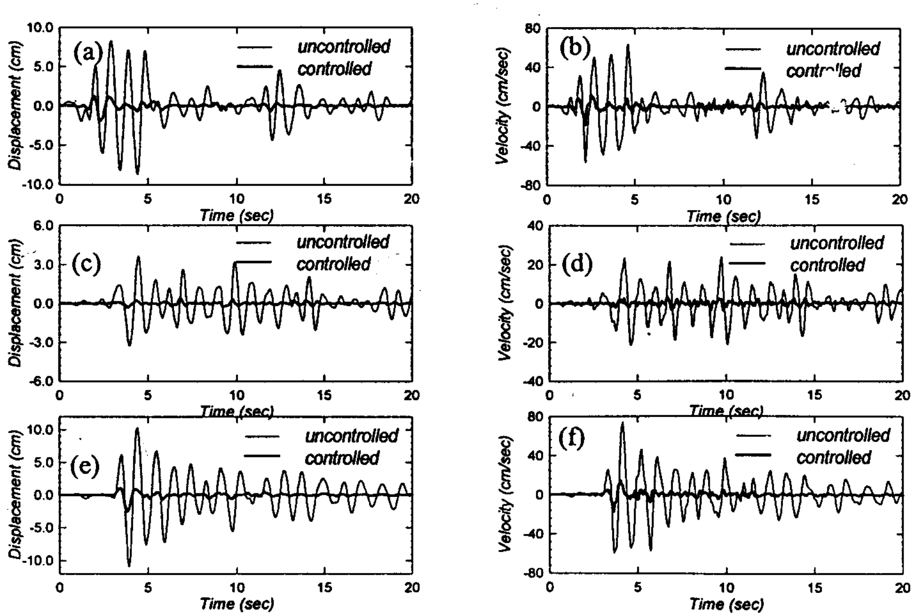

Fig. 3. Uncontrolled and controlled responses of linear structure : (a) and (b) by El Centro, (c) and (d) by California, (e) and (f) by Northridge earthquake

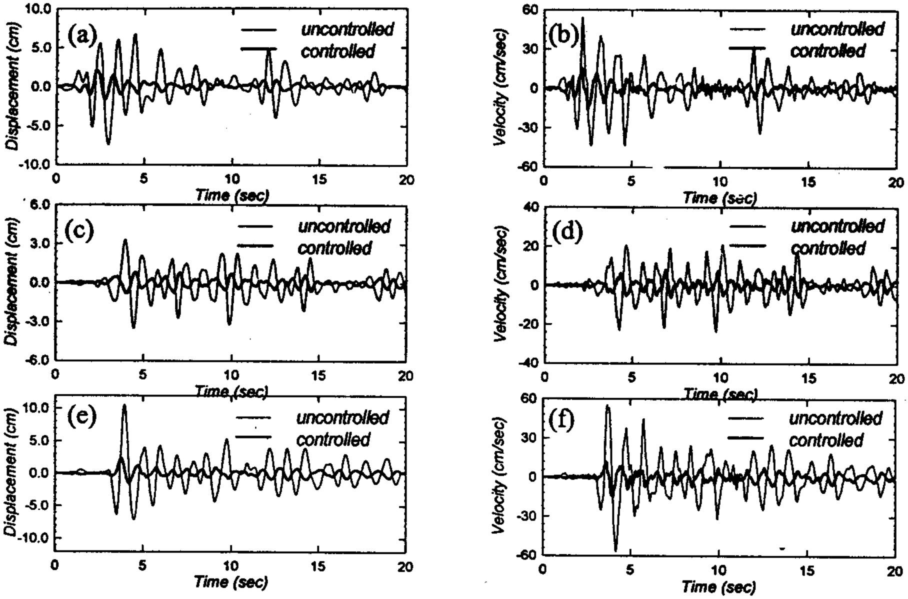

Fig. 4. Uncontrolled and controlled responses of nonlinear structure : (a) and (b) by El Centro, (c) and (d) by California, (e) and (f) by Northridge earthquake

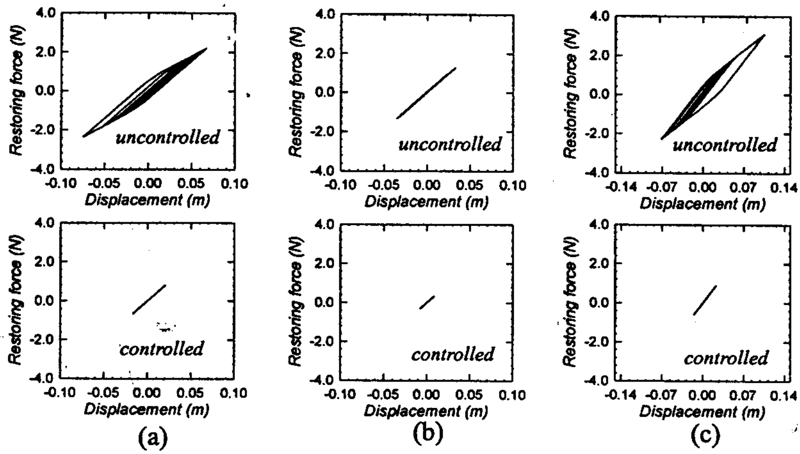

Fig. 5. Restoring force vs. displacement : (a) El Centro, (b) California, (c) Northridge earthquake