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Adaptive Vibration Control of Structure-AMD Coupled System Using Multi-layer Neural Networks

階層型ニューラルネットワークによる構造―ＡＭＤ連成システムの振動制御に関する研究

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Multi-layer neural network has been regarded as a useful algorithm in identification and dynamic control of structures. As one of the existing researches, the active vibration control for structure-actuator coupled system consisted of a tendon system controlled by a signal hydraulic actuator using multi-layer neural networks has been studied. Active Mass Driver (AMD), as another kind of control device, has been studied on the concept of conventional control methods and control design. In this paper, a coupled system consisting of a four-story frame structure and an AMD driven by a electrohydraulic actuator was investigated. Firstly, considering the dynamics of electrohydraulic actuator, the dynamic equation of a structure-AMD coupled system was formulated. Secondly, an emulator neural network with suitably chosen input variables corresponding to the structure-AMD coupled system was established and trained for the purpose of non-parametric identification. Lastly, a neurocontroller was set up and trained with the aid of the trained emulator neural network to control the dynamic response of the structure-AMD coupled system subjected to earthquake loading. Because accelerometers can readily provide reliable and inexpensive measurement of absolute structural acceleration at strategic points on a structure, development of identification method based on acceleration feedback is presented. The effectiveness of the identification and control is evaluated through numerical simulations.

Key Words: *artificial neural networks, active mass driver(AMD), coupled system, actuator dynamics, electrohydraulic actuator, structural control, acceleration feedback*

1. Introduction

With increasing research activities in the field of structural control over the last two decades, significant progress has been achieved toward making active structural control as a viable technology for enhancing structural functionality and safety against natural hazards such as strong earthquakes and high winds. Since the initial conceptual study by Yao[1], a number of structural control methods and devices have been proposed. Some of the widely used structural control methods are explained by Abdel-Rohman[2] and Soong[3]. Most of these control algorithms require the analysis and identification of the system in an explicit mathematical form. The effectiveness, robustness and stability of controllers depend on the accuracy of the dynamic system models. These contemporary control techniques often rely on the assumption of a good dynamic mathematical model containing identified system parameters such as mass, stiffness and damping. The conventional control methods and control design are highly dependent on the parametric construction of the dynamic system models. However, there are many factors such as structural uncertainties, non-linearities, and measurement noises which are so difficult to be identified and incorporated in control loop as to result in poor mathematical models and less-effective control algorithms.

Structural identification is the basement of structural control and is a deliberate and challenging task. The ability of artificial neural networks to approximate arbitrary continuous function provides an efficient mechanism for identification and control of structures. Modeling a dynamic system by using neural networks has been increasingly recognized as one of the system identification paradigms. The structural dynamics can be identified by neural networks in an implicit form, in other words, in a non-parametric form, where modeling of structural parameters such as stiffness, damping and mass are not necessary. The knowledge acquired by a neural network is stored in its connection weights, which are adaptive and can change in response to outside stimuli. At present, several neural networks with different structures have been proposed to solve the above problems.[4-5] The most widely used neural network is the feed forward multi-layer neural network, which is trained by a back-propagation algorithm. Neural networks are being recognized as effective tools in control problems.

Numerous engineering applications of neural networks have been reported in the literature of recent years. A number of civil engineering applications of neural networks were reviewed by Ghaboussi et al.[4], Chen et al.[5] and Xu et al.[6-8]. An experimental study on the vibration control of a three-layer frame structure by a control system consisted of a tendon system controlled by a signal hydraulic actuator has been carried out on the shake table at the university of Illinois at Urban-Champaign. The structure-actuator interaction was considered. The effectiveness of neurocontroller has been demonstrated by the experimental results. The robustness and the relative stability were presented and discussed[9-10]. In case of large-scale structure-actuator coupled systems, a localized identification and control schematic by multi-layer neural networks have been studied by Xu et al[6].

Two kinds of widely used control devices, such as active tendon system and active mass driver, have been studied based on the concept of conventional control methods and control design[12-13]. Ghaboussi et al. has verified the effectiveness of multi-layer neural networks for the control of linear and nonlinear system by active tendon[9-11]. An open-close loop control algorithm of the seismic response of structures with active mass driver system was presented by Sato et al.[14], in which an AMD driven by a AC motor was employed, and the dynamic performance of the motor was considered. In order to develop the multi-layer neural networks for structural control problems, the possibility and effectiveness of multi-layer neural network for AMD system was studied. An active mass damper for the control of an elastic arm, which is a single degree-of-freedom structure, by using neural networks was studied by Kumagai et al.[15], in which an idealistic actuator was employed. On the other hand, an active structural response control method with self-learning mechanism was developed by Sato et al. [16], but the dynamic performance of the active tendon system was not included in the system formulation. Moreover, the predictive control of structural seismic response with time delay by using Kalman filtering technique and identification for nonlinear system by neural network was proposed by Sato et al.[17-18]

In this paper, a four-story frame structure and an electrohydraulic actuator driven AMD coupled system is studied. The dynamic performance of electrohydraulic actuator is considered. Firstly, considering the dynamics of electrohydraulic actuator, the dynamic equation of the structure-AMD coupled system was formulated. Secondly, an emulator neural network with suitably chosen input variables was constructed and trained for the purpose of non-parametric identification by a generalized delta rule training algorithms for the purpose of learning the mapping between the actuator signal and the response of the structure. Lastly, a three-layer neurocontroller was set up and trained with the aid of the trained emulator neural network to control the dynamic response of the structure-AMD coupled system. The trained controller can then operate independently in controlling the structure. Numerical simulation is carried out to show the performance of presented control algorithm, the numerical integration accounts for the actuator dynamics, and a time delay is included in our numerical simulation. As accelerometers can readily provide reliable and inexpensive measurement of absolute structural acceleration at strategic points on a structure, development of a non-parametric identification method based on acceleration feedback is presented. The effectiveness of the identification and control is evaluated through the numerical simulations.

2. Equations of Motion of Coupled System of Structure- AMD Actuators

2.1 Equations of Motion of Structure and AMDs

The motion of a structure and AMD systems can be characterized by the following equations.

$$\begin{aligned}&[M_1]\{\ddot{x}_1\}+\left([C_1]+[I_u][C_2][I_u]^T\right)\{\dot{x}_1\}-[I_u][C_2]\{\dot{x}_2\}\\&+\left([K_1]+[I_u][K_2][I_u]^T\right)\{x_1\}-[I_u][K_2]\{x_2\}\\&=-[I_u]\{f\}-[M_1]\{I_1\}\ddot{x}_g\end{aligned}\tag{1}$$

$$\begin{aligned}&[M_2]\{\ddot{x}_2\}+[C_2]\{\dot{x}_2\}-[C_2][I_u]^T\{\dot{x}_1\}+[K_2]\{x_2\}\\&-[K_2][I_u]^T\{x_1\}=[I_3]\{f\}-[M_2][I_2]\ddot{x}_g\end{aligned}\tag{2}$$

where $[M_1]$, $[D_1]$ and $[K_1]$ are $n\times n$ mass, damping, and stiffness matrices of structure; $\{\ddot{x}_1\}$, $\{\dot{x}_1\}$ and $\{x_1\}$ are $n \times 1$ acceleration, velocity, and displacement vectors of structure; $\ddot{x}_g$ is earthquake base acceleration; $\{f\}$ is a $m \times 1$ vector representing the coupled force between structure and AMDs ; $\{f\} = \{f_1 \quad f_2 \quad \cdots \quad f_m\}^T$, $f_i, (i = 1,m)$, is the control force between the ith controller and structure. Moreover, $[I_u]$ is a $n \times m$ matrix. The element I_{kl} of matrix $[I_u]$ equals 1 when the degrees-of freedom k attach to the lth actuator, equals 0 when the degrees-of freedom k does not attach to the lth actuator; and $[I_1]$ is a $n \times 1$ identity vector.

$$[M_2] = \begin{bmatrix} m_1 & 0 & 0 & 0 \\ 0 & m_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & m_m \end{bmatrix}; \quad [C_2] = \begin{bmatrix} c_1 & 0 & 0 & 0 \\ 0 & c_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & c_m \end{bmatrix};$$

$$[K_2] = \begin{bmatrix} k_1 & 0 & 0 & 0 \\ 0 & k_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & k_m \end{bmatrix} \qquad (3)(4)(5)$$

m_i, c_i, k_i, ($i = 1,m$) are the mass , damping and stiffness of ith AMD system; $\{\ddot{x}_2\}$, $\{\dot{x}_2\}$ and $[x_2]$ are $m \times 1$ acceleration, velocity, and displacement vectors which represent the acceleration, velocity, and displacement of the AMD systems; $[I_2]$ is a $m \times 1$ identity vector; $[I_3]$ is a $m \times m$ identity matrix.

2.2 Equation of Hydraulic Actuator[4)]

Hydraulic actuator is employed as the active control device. Suppose there are m actuators used.[20)]

(1) Valve Equation

A first-order linear differential equation is used to describe the relation between control signal e_i to the valve flow rate q_i of ith actuator.

$$e_i = a_{i1}\dot{q}_i + a_{i2}q_i \qquad (i = 1,m) \qquad (6)$$

The parameters in this equation a_{i1} and a_{i2} are related to the constant gains k_{i1} and k_{i2} and the valve's time constant τ_i.

$$a_{i1} = \frac{\tau_i}{k_{i1}k_{i2}}\ ; \ a_{i2} = \frac{1}{k_{i1}k_{i2}} \qquad (i = 1,m) \qquad (7)$$

The electrical signal e_i to the actuator is in the form of a series of step functions. Let actuator signal e_i keep constant during a sampling period, the valve flow rate q_i can be determined as follow,

$$q_i = k_{i1}k_{i2}\left[1 - \exp\left(\frac{-t}{\tau_i}\right)\right]e_i + q_{i0}\exp\left(\frac{-t}{\tau_i}\right) \qquad (i = 1,m) \qquad (8)$$

The actuator signal e_i is issued at the beginning of each sampling period, which is considered as the origin of time t in equation (8), and the valve flow at the beginning of the sampling period is q_{i0}.

(2) Ram Equation

The relationship among the actuator force f_i, the ram displacement x_{ir}, and the valve flow rate q_i of ith actuator can be described as the following differential equation.

$$q_i = a_i\dot{x}_{ir} + p_i f_i + d_i\dot{f}_i \qquad (i = 1,m) \qquad (9)$$

$$d_i = \frac{v_i}{\beta_i a_i}, \quad p_i = \frac{c_i}{a_i} \qquad (10,11)$$

where a_i is the area of ram, c_i is the coefficient of leakage, v_i is volume of piston, β_i is compressibility of i-th actuation system.

Equation (9) can be rewritten in matrix form as follow

$$[D_3]\{\dot{f}\} + [A_3][I_u]^T\{\dot{x}_1\} - [A_3]\{\dot{x}_2\} + [K_3]\{f\} = \{q\} \qquad (12)$$

where $[D_3] = \begin{bmatrix} d_1 & 0 & 0 & 0 \\ 0 & d_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & d_m \end{bmatrix}; [A_3] = \begin{bmatrix} a_1 & 0 & 0 & 0 \\ 0 & a_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & a_m \end{bmatrix};$

$$[K_3] = \begin{bmatrix} p_1 & 0 & 0 & 0 \\ 0 & p_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & p_m \end{bmatrix}; \ \{q\} = \{q_1 \quad q_2 \quad \cdots \quad q_m\}^T$$

(13,14,15,16)

2.3 Motion Equation of Coupled System

The equation of actuator dynamics and the structure's equations of motion are coupled through the displacements and the actuator forces. Displacements in some of the structural degree of freedom are tired to the ram displacements, while the generation of the actuator force is influenced by the motion in those structural degrees of freedom.

The coupled equations for the system of the structure and AMD can be written as follow,

$$
\begin{aligned}
&\begin{bmatrix} [M_1] & 0 & 0 \\ 0 & [M_2] & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{Bmatrix} \{\ddot{x}_1\} \\ \{\ddot{x}_2\} \\ \{\ddot{f}\} \end{Bmatrix} \\
&+ \begin{bmatrix} [C_1]+[I_4][C_2][I_4]^T & -[I_4][C_2] & 0 \\ -[C_2][I_4]^T & [C_2] & 0 \\ [A_3][I_4]^T & -[A_3] & [D_3] \end{bmatrix} \begin{Bmatrix} \{\dot{x}_1\} \\ \{\dot{x}_2\} \\ \{\dot{f}\} \end{Bmatrix} \qquad (17) \\
&+ \begin{bmatrix} [K_1]+[I_4][K_2][I_4]^T & -[I_4][K_2] & [I_4] \\ -[K_2][I_4]^T & [K_2] & -[I_3] \\ 0 & 0 & [K_3] \end{bmatrix} \begin{Bmatrix} \{x_1\} \\ \{x_2\} \\ \{f\} \end{Bmatrix} \\
&= \begin{Bmatrix} -[M_1][I_1]\ddot{x}_g \\ -[M_2][I_2]\ddot{x}_g \\ \{q\} \end{Bmatrix}
\end{aligned}
$$

The equation of structure-actuator coupled system is numerically integrated by Newmark- β method to obtain the solution of dynamic response of structure and the coupled forces between structure and actuators under earthquake excitations and control signals. The integration time step used in the numerical analysis is chosen to be a small fraction(one-tenth) of the sampling period. This will allow for a realistic representation of the generation of actuator forces during the sampling period as a result of the actuator's dynamics, and the interaction between the structure and the actuators.

3. Structure-AMD Coupled System

The structure under study, shown in **Fig.** 1, is a four-story frame. The model of a shear-resisting structure is considered with only four degrees of freedom for the four floors. For control purposes, a simple implementation of an AMD was placed on the fourth floor of the structure. The AMD consists of a single hydraulic actuator with steel masses attached to the end of the piston rod. When AMD is used as controller, the structure-AMD coupled system has five degrees of freedom. The mass of each floor is 4500kg, and stiffness of the each floor is 4.1e6kg/cm. The moving mass for the AMD was 400kg, and consisted of the piston, piston rod, and the steel disks bolted to the end of the piston rod. Thus, the moving mass of the AMD was 2.2 percent of the total mass of the structure. Because the hydraulic actuators are inherently open-loop unstable, position feedback was employed to stabilize the control actuator. The displacement of AMD relative to the control point is measured using a LVDT (linear variable differential transformer), rigidly mounted between the end of the piston rod and the point of control.

The following parameters of electrohydraulic actuator are used for composing the equations of the actuator dynamics.

The area of ram is 50cm^2, the volume of chamber is 40000cm^3, the coefficient of leakage is 10.0cm^5/(kgf.s), the compressibility of actuator system is 2.1e^{5}kgf/cm^2, the time constant is 0.20s, the maximum absolute value of actuator force is 60T, the actuator gain, k_1, is 100.0, k_2 is 100.0cm^3/s, and actuator transducer gain, k_3, is 10.0 1/kgf.

The actuator signals are issued at the beginning of each sampling period and are kept constant within each sampling period. This will allow for the analysis to properly account for the effects of actuator dynamics in generating actuator forces.

4. Acceleration Feedback Identification for Coupled Systems by Multi-layer Neural Networks

4.1 Emulator neural network for Identification of Structure-AMD Coupled System

Modeling the dynamical systems by neural networks has been increasingly recognized as one of the system identification paradigms. The application of neural networks in system identification is due to their generalization ability and their capability to describe the system accurately. The neural network modeling problem in system identification is to develop a neural network model that is capable of learning and predicting the functional mapping between the inputs and the outputs of an unknown linear or nonlinear multivariable dynamic system. We call this kind of neural network as emulator neural. However, neural network presentation is not exactly the same as the function they learn. A typical three-layer back-propagation neural network is designed for the purpose of identification. The two kinds of operations called as "feed forward" and "error back-propagation" have been described in references.[4—11,15,16,18)]

A typical three-layer back-propagation neural network with l nodes in the input layer, m neurons in the hidden layer and n neurons in the output layer is designed. Weights w_{hi} $(h=1,m;\ i=1,l)$, w_{oh} $(o=1,n;\ h=1,m)$ are used to represent the strength of connections of the neurons between the input layer and the hidden layer, the hidden layer and output layer respectively.

The first type of operation of three-layer neural network is called as "feed forward". In this operation, the output of a neuron i of hidden layer and output layer N can be shown as,

$$x_i = f\left(\overline{x}_i^{\,N}\right) \qquad (18)$$

where

$$\bar{x}_i^N = \sum_{j=1}^{n} w_{ij}^{N,N-1} x_j^{N-1} - h_i^N \tag{19}$$

$$f(x) = 1/\{1+\exp(-x)\} \tag{20}$$

where $f(x)$ is an activation function, which is differentiable; x_j^{N-1} is the output of neuron j of layer $N-1$; h_i^N is the bias representing the threshold of the activation function of neuron i of layer N. The output of the neuron of input layer equal to the input value.

The second type of operation of the back-propagation neural network is called as "error back-propagation". The error function E is defined as,

$$E = \sum_p \sum_i \frac{(d_i - x_i^F)^2}{2} \tag{21}$$

where d_i, x_i^F are the desired output and the network output of the ith neuron in output layer respectively; i, p are the number of output nodes of output layer and the total number of patterns (examples) contained in the training set.

Usually, the learning algorithm for training neural network called delta rule which is based on the gradient steepest decent method is widely used. In order to increase the rate of learning and yet avoid the danger of instability, a modified algorithm called the generalized delta rule is used in this paper by including a momentum term, which describe the relationship of the correction of weight $w_{ij}^{N,N-1}$ between layer $N-1$ and N at iteration $k+1$ and at iteration k as follows[19],

$$\Delta w_{ij}^{N,N-1}(k+1) = \eta \delta_i^N x_j^{N-1} + \alpha \Delta w_{ij}^{N,N-1}(k) \tag{22}$$

where

$$\delta_i^N = -\frac{dE}{d\bar{x}_i^N} \tag{23}$$

$\Delta w_{ij}^{N,N-1}(k+1)$ and $\Delta w_{ij}^{N,N-1}(k)$ are the correction applied to weight $w_{ij}^{N,N-1}$ at iteration $k+1$ and k; η is a positive constant called the learning-rate parameter, and α is usually a positive value called the momentum constant. In any event, care has to be exercised in the selection of the learning-rate parameter. A small learning-rate parameter lead to a slower rate of learning, on the other hand, if we make the learning-rate parameter too large, the learning procedure may become unstable. In this paper, let η equal to 0.8. Moreover, as described by Hagiwara,[19] the momentum constant must be restricted to the range $0 \leqq |\alpha| < 1$, so we let $\alpha=0.6$ here.

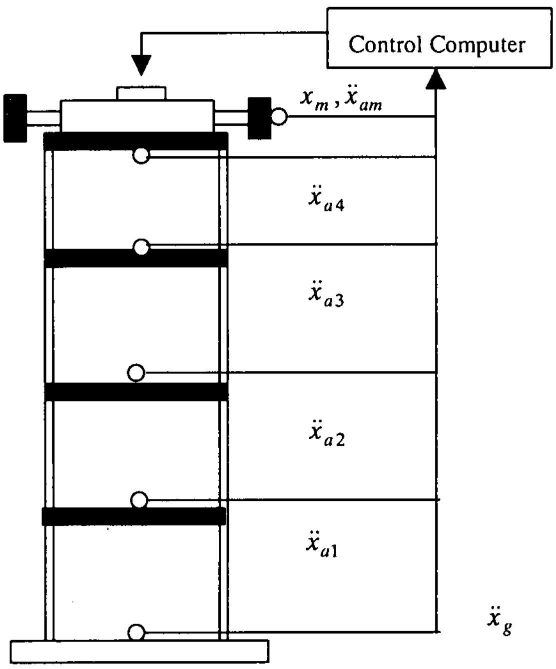


Fig. 1 Schematic Diagram of Experimental Setup

The updated value of weight $w_{ij}^{N,N-1}$ at iteration $k+1$ is computed as follows,

$$w_{ij}^{N,N-1}(k+1) = w_{ij}^{N,N-1}(k) + \Delta w_{ij}^{N,N-1}(k+1) \tag{24}$$

The neural network learning process is to adjust the connection weights by repeatedly training thereby minimizing the error between the network output and the desired target in the training set.

Most of the current modern-state-space based active structural control strategies for earthquake protection have been based either on full-state feedback (i.e. all structural displacements and velocities) or on velocity feedback. However, because displacements and velocities are not absolute, but dependent on the inertial reference frame in which they are taken, their accurate measurement at arbitrary locations on a large-scale structure is difficult to achieve directly. Because accelerometers can readily provide reliable and inexpensive measurement of accelerations at strategic points on the structure, acceleration feedback strategy is used in this paper. In this study, accelerometers were positioned on the ground, on each floor of the structure, and on the AMD, as shown in **Fig. 1**. The absolute accelerations are used as parts of inputs to emulator neural network and neurocontoller. x_m is the relative displacement of the mass, which is equal to the displacement of the ram of hydraulic actuator.

Deciding the input variables to emulator neural network is a critical task especially for the structure-AMD coupled system. In the study of active tendon system by multi-layer neural networks, the nodes in input layer represent the absolute acceleration at the floors and the control signals at the past time step[9-10]. When AMD is used as controller, the absolute acceleration at the floors and the control signals at the past time step for the emulator neural network are not enough to identify the structure-AMD coupled system. As described in equation (9), in the case of hydraulically actuated systems, a velocity feedback path exists between the velocity of the actuator and the control signal input to the actuator. Through the velocity feedback, the dynamics of the structure directly affect the characteristics of the control actuator. Thus, the measurements that are directly available for forecast dynamic response are the four floor acceleration measurements, the control signal, the coupled force between the structure and AMD, the displacement and acceleration of the AMD, and the valve flow rate of the hydraulic actuator described in Equation(6) at the beginning of the current sampling period. The displacement of the AMD relative to the forth floor is measured using the LVDT mentioned above. The coupled force between the structure and AMD is measured by a piezoelectric force ting or a load cell. The architecture of the three-layer neural networks based on acceleration feedback is presented in **Fig.2**. The number of neurons in hidden layer is set to be two times of those in input layer. The neurons in output layer represent the forecast relative acceleration response at the coupled degree of freedom at the end of current sampling period. The number of input, hidden and output layer includes 9, 18 and 1 neurons.

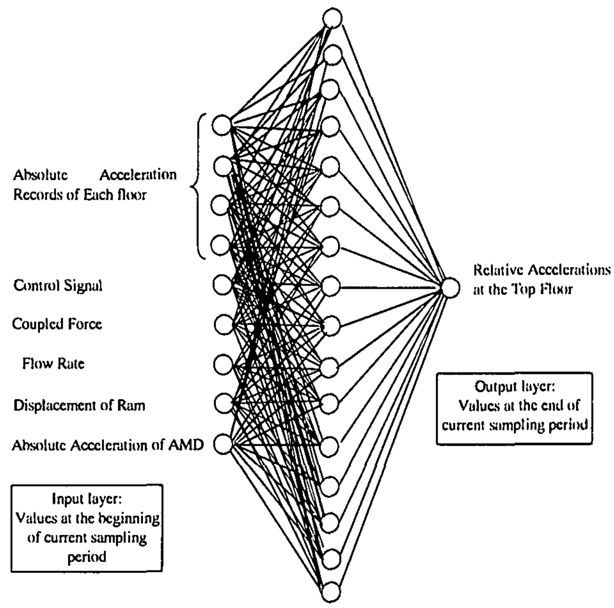


Fig.2 Emulator neural network

4.2 Training of Emulator Neural Networks

The training process of emulator neural network is to establish the appropriate connection weights between neurons of each layer by a form of supervised learning with the help of training cases which are composed of a number of patterns of inputs and desired outputs of coupled system.

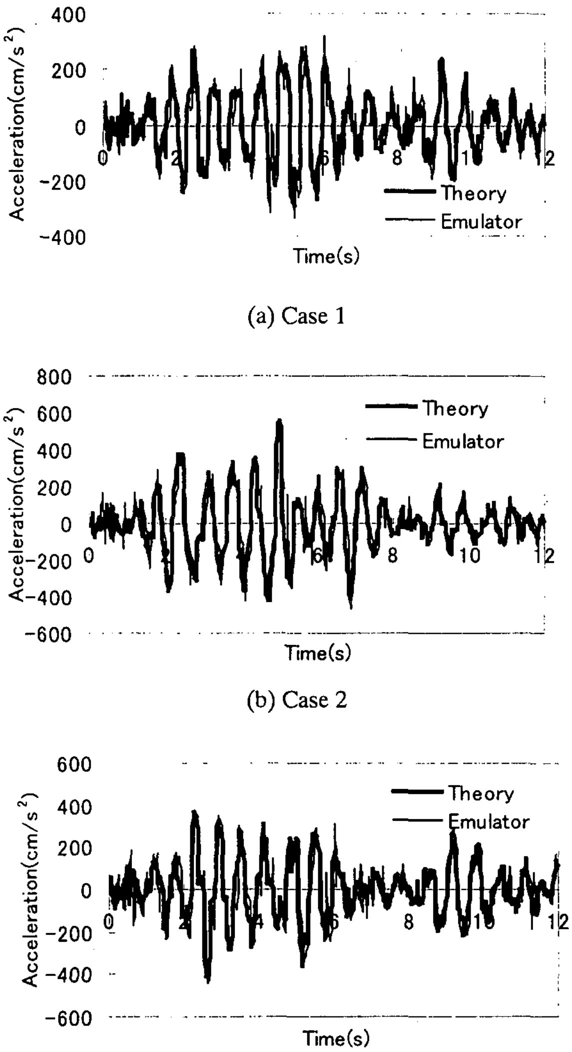
Based on the error back-propagation algorithm, emulator neural network is off-line trained at first. At the beginning of training emulator neural network, the weights are initialized with small random values. The outputs are then computed by feeding forward the inputs through the network. The error function is calculated from the difference between the outputs of emulator neural network and the dynamic response of corresponding subsystem recorded by sensors. By back-propagating the error function to adjust the weights, the emulator neural network can be trained to achieve a desired accuracy for modeling the dynamic behavior of the structure-AMD coupled system.

The training cases for the purpose of training emulator neural network are constructed from the numerical integration analysis results while the structure-AMD coupled system is subjected to random control signals and earthquake excitation. The numerical integration analysis is carried out with integration time step of 0.004s. The training cases are performed with the data taken at the intervals of the sampling period of 0.04s.

Emulator neural network is trained with the results when the structure-AMD coupled system is subjected to 12 seconds of the Taft earthquake (July 21, 1952, Ken Country) with 50% of the amplitude and a 12 seconds random signals with a upper and lower limit of 1.0V and -1.0V. The data sets, used for training the emulator neural networks are the 300 patterns of input and output data taken from the 12 seconds of acceleration response record. The whole off-line training process takes 50000 cycles. By means of the error back-propagation learning rule[7-8], the training cases performed above are enough to train each emulator neural network in order to model the dynamics of the coupled subsystem and to generate the dynamic responses of each subsystem.

In this study, three kinds of load cases, which are the combination of different kinds of earthquakes and random signals, are used to investigate the performance of the neural networks.

(1) Case 1: Taft earthquake with 50% the amplitude and random signal with a upper and a lower limit of 1.0 V and



(a) Case 1

(b) Case 2

(c) Case 3

Fig. 3 Comparison of numerical simulation and emulator network

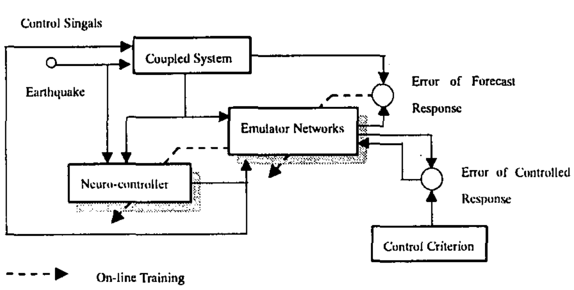


Fig.4 Training method of neurocontroller with the aid of emulator neural networks

-1.0V

(2) Case 2: El Centro earthquake(May 18, 1940, Imperial Valley) with 30% the amplitude and random signal with a upper and a lower limit of 1.0 V and -1.0V

(3) Case 3: Kobe earthquake with 10% the amplitude and random signal with a upper and a lower limit of 1.0 V and -1.0V

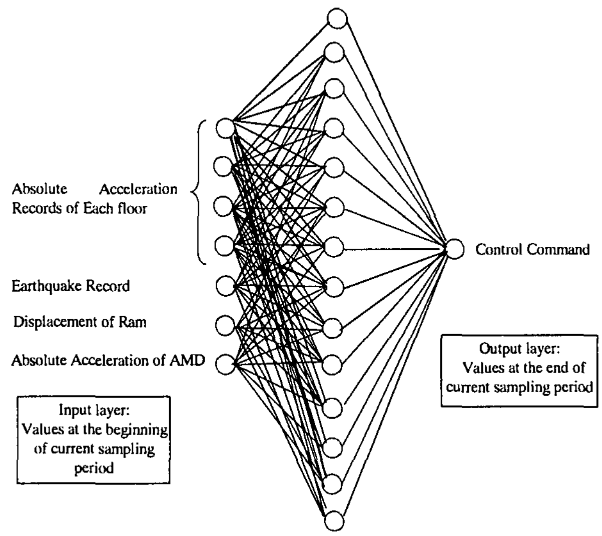


Fig. 5 Architecture of neurocontroller

Evaluation of the prediction capabilities of the trained emulator network is presented in time domain. **Fig.3** gives the result of the comparison between the absolute acceleration response at the control point determined from the numerical integration analysis by FEM and those forecast by the on-line trained emulator neural network in Case 1,2, and 3, respectively. The R.M.S. error of the forecast response in Case 1,2 and 3 are 3.54cm/s^2, 1.82cm/s^2 and 3.43cm/s^2, respectively. Clearly, the emulator network is able to reproduce the structural response under different seismic excitations very accurately. This makes the emulator network independent of the training cases and a generalized model for the structure-AMD coupled system. On the other hand, the input variables for emulator networks are suitable and enough to carry out non-parametric identification for the coupled system.

5. Acceleration Feedback Control For Coupled Systems by Multi-layer Neural Networks

5.1 Outline of Training of Neurocontroller with the aid of Emulator Neural Networks

The concept of neurocontroller is meant to describe the use of a well-specified neural network to issue actual control signal to a designated control system. The neurocontroller replaces the feedback control algorithm in a conventional control method. The neurocontroller receives the feedback information as its inputs to the input layer and issues an appropriate signal to the control system from its output layer. The training method of typical neurocontroller is shown in **Fig. 4.**

In training of any neural network, a set of training cases, consisting of input and output pairs, are needed. The training cases for the emulator neural network can be generated either through numerical simulation of the coupled actuator-structure system or in an experimental setting by sending control signals to the actuator and recording the sensor outputs. But the same procedure can not be used for generating training cases for the neurocontroller, because the correct values of the output are not known. So the neural-action network is trained based on the above off-line pre-trained neural-emulator network. The trained emulator network learns the transfer function between the control signals and the output of sensor measuring the response of the structure. The emulator neural network is used to provide a path for back-propagation of the errors in training of the neurocontroller. At first, the error of signals can be decided by back-propagating the error function E through the trained neural-emulator network without changing the weights. After that, the error of signal is back-propagated to adjust the weights of the neurocontroller network. This training process is repeated until the structural responses reach the desired responses within the specified tolerance. The neurocontroller training method used in this study is the generalized delta rule method described above.

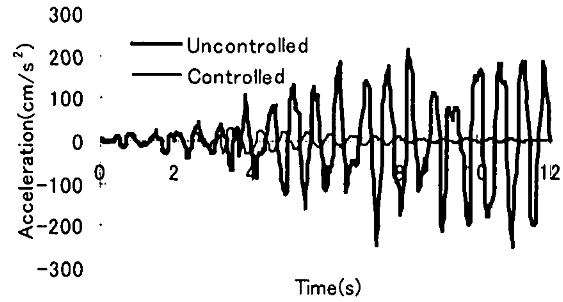
The architecture of neurocontroller is indicated in **Fig.5**. Thus, the measurements that are directly available for control force determination are the acceleration measurements on the four floors, the ground acceleration, and the displacement and acceleration of the AMD. In the numerical simulation of the control problem, the sensor data is received at discrete time intervals, referred to as the sampling period. The output of the neurocontroller is also sent to the control system at the same discrete sampling period.

5.2 Case Studies

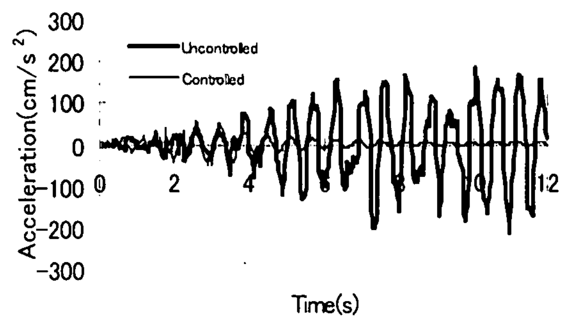
In this study, control criteria is to reduce the acceleration response to a small value of 0.03g. A neurocontroller was trained with this control criterion and was applied to control the structure response subjected to earthquake. In this section we present the results of three case studies in which the structure is subjected to three different earthquake ground accelerations.

In the first case study the structure is subjected to 50% of the Taft earthquake record which is used to produce the training data for training emulator neural network. The numerical results are summarized in **Fig.6** and **7**, it is indicate that the neurocontroller was successfully in mitigating and reducing the system vibrations effectively. Clearly the acceleration and displacement response on each floor have been reduced. **Fig. 8** shows the control force produced by AMD.

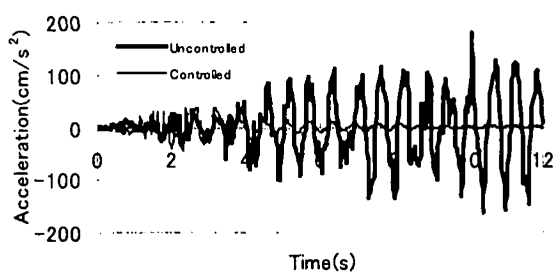
In control problem, we must take into account the time delay. In this study, the dynamic performance is considered, the time delay of each sampling period includes the time for digitizing the observed input of neural networks, the time for calculating the control signal and converting it to analogous control signal. The consumed time of deciding control signal in each sampling period is indicated in **Fig. 9**. It is clear that the maximum consumed time is far less than the sampling period of 0.04 second. In order to consider the influence of the time delay for digitizing the observed input of neural networks, calculating the control signal and converting it to analogous signal , a time delay of a sampling period has been included in the numerical simulation of the dynamic response of the controlled system.



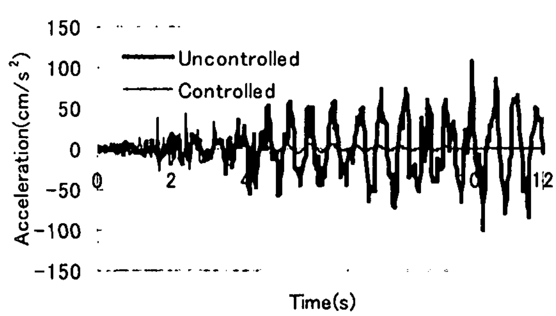
(a) The fourth floor



(b) The third floor

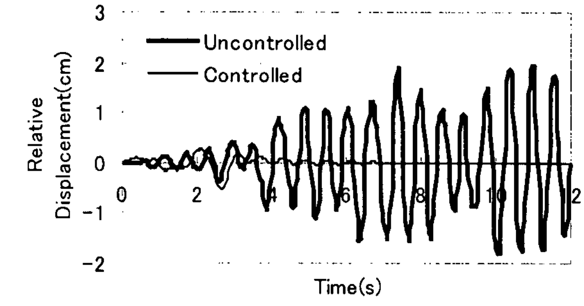


(c) The second floor

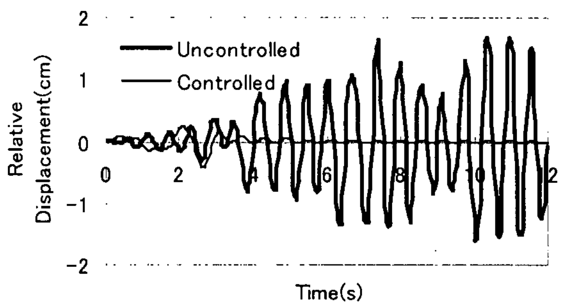


(d) The first floor

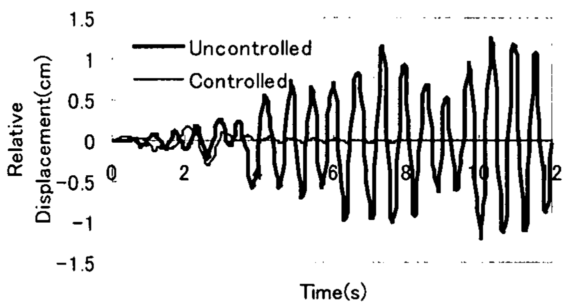
Fig. 6 Comparison of acceleration response of each floor



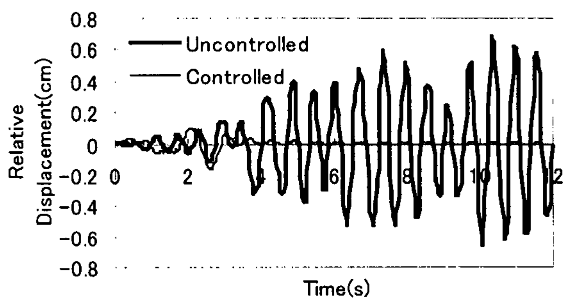
(a) The fourth floor



(b) The third floor



(c) The second floor



(d) The first floor

Fig. 7 Relative displacement of each floor

In the previous case study, the structure is subjected to 50% of the Taft earthquake record, which is the same earthquake record as that used in the training of the neurocontroller. The performance of the neurocontroller, when the structure is excited by other earthquake records and controlled by the neurocontroller that has been trained with the 50% of the Taft earthquake record, is demonstrated in the following case studies by numerical simulation.

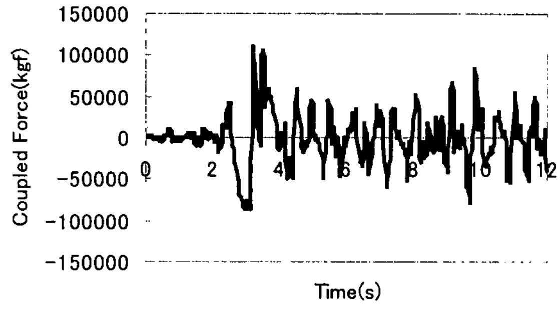


Fig.8 Control force

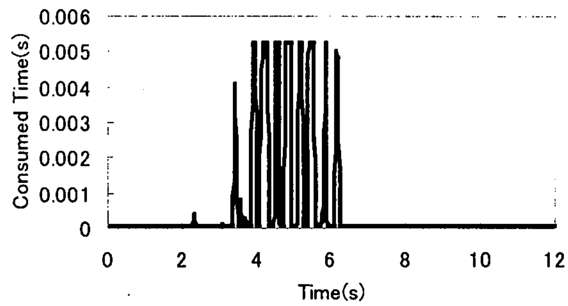


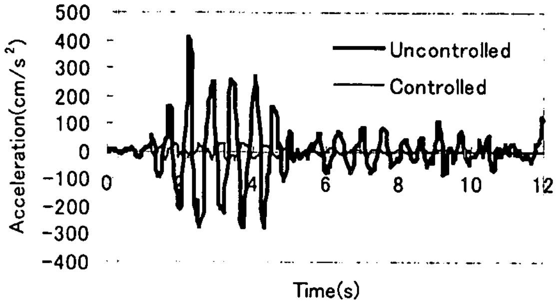
Fig. 9 Consumed time for determining control signal

In the second and third case studies, the structure is subjected to 30% of the El Centro earthquake record and 10% of the Kobe earthquake record, respectively. **Fig.10** and **11** give the results of acceleration and relative displacement response at each floor when structure is excited by 30% of the El Centro earthquake record and controlled by the neurocontroller that has been trained with 50% of the Taft earthquake. **Fig.12** and **13** give the results when structure is excited by 10% of the Kobe earthquake record and controlled by the neurocontroller that has been trained with 50% of the Taft earthquake. This demonstrates that the neurocontroller learns to control the motion of the structure in both cases. In summary, for different earthquake records, similar observations have been made. This demonstrates that the fact that the neurocontroller learns to control the motion of the structure, regardless of the source of excitation. The adaptability of the neurocontroller was investigated and verified.

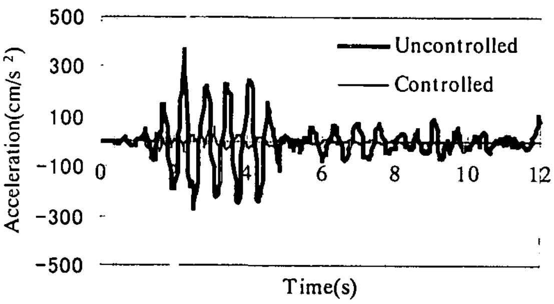
In the study of active tendon system for structural control by using neural networks by Bani-hani et al.,[9-10] the robustness with different types of uncertainties and delays, and relative stability were presented and discussed by numerical and experimental method. It is necessary to carry out study deeply on the robustness with different types of uncertainties and delays and stability of the AMD system.

6. CONCLUSIONS

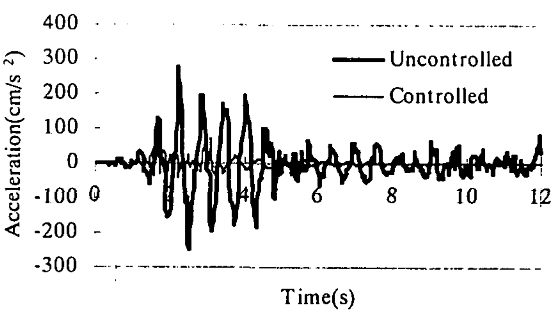
A multi-layer neural-networks-based AMD system for structural control was proposed in this paper. The dynamics of a typical hydraulic actuator is considered. In this proposed control method, a neurocontroller is used to replace the control



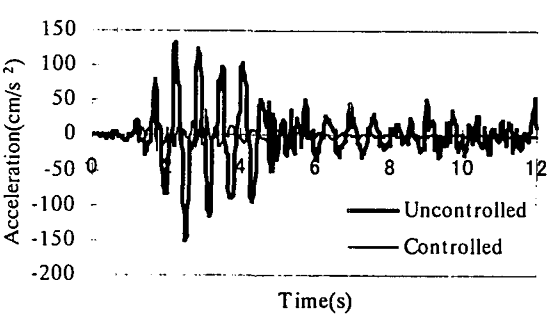
(a) The forth floor



(b)The third floor

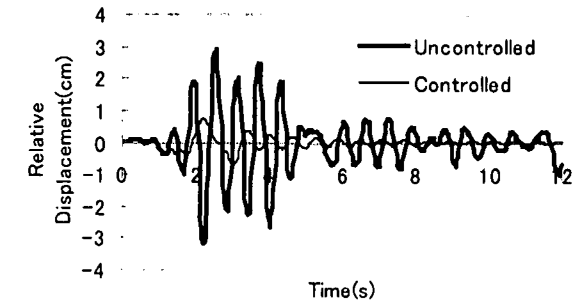


(c) The second floor

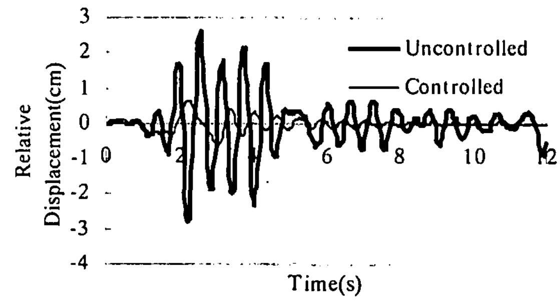


(d) The first floor

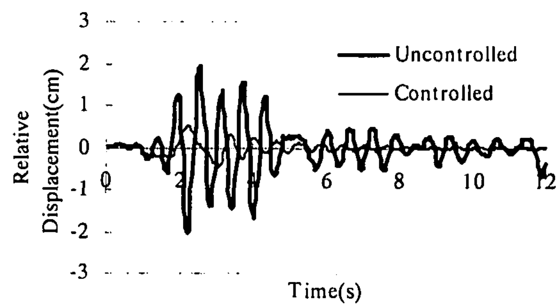
Fig. 10 Control and uncontrolled response of structure subjected to 30% of the El Centro earthquake record



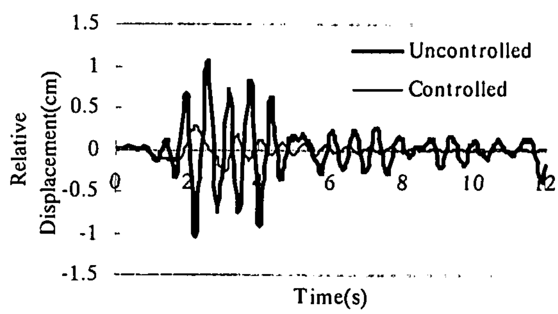
(a) The forth floor



(b) The third floor



(c) The second floor

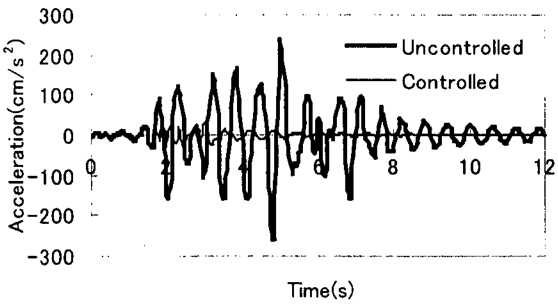


(d) The first floor

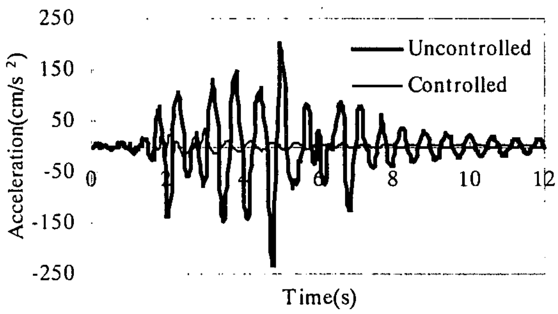
Fig. 11 Control and uncontrolled response of structure subjected to 30% of the El Centro earthquake record

algorithm of the conventional control. From the present study, the following conclusions can be drawn:

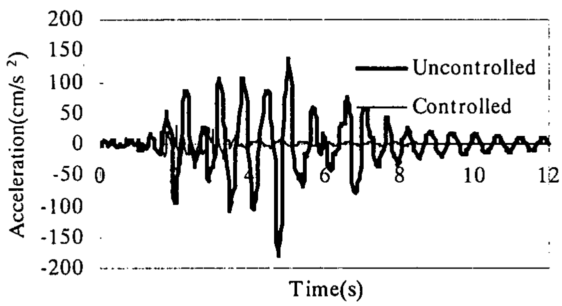
(1) Based on the generalized delta rule training method, an emulator neural network can be trained to predict the future response according to absolute acceleration, control signal, the coupled force between the structure and AMD, the displacement and acceleration of the AMD, and the valve flow rate of the hydraulic actuator. The emulator neural network is trained to learn the mapping between the control signal and the response of the structure. In other words, the identification can be carried out successfully by the multi-layer neural networks for structure-AMD coupled system when the dynamics of the actuator is considered.



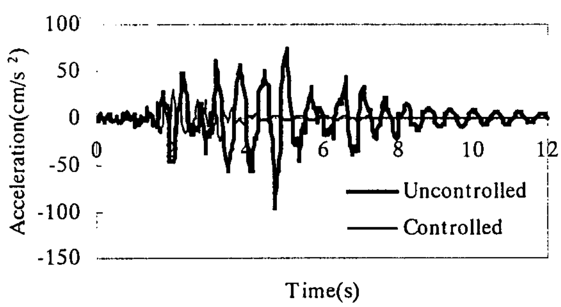
(a) The top floor



(b) The third floor

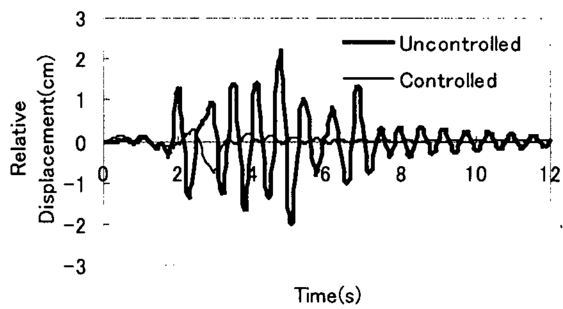


(c) The second floor

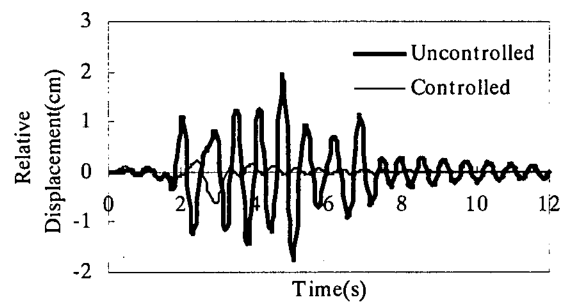


(d) The first floor

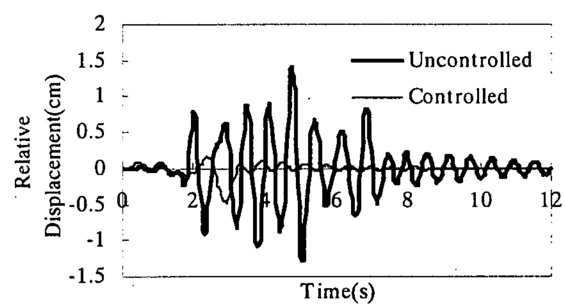
Fig. 12 Control and uncontrolled response of structure subjected to 10% of the Kobe earthquake record



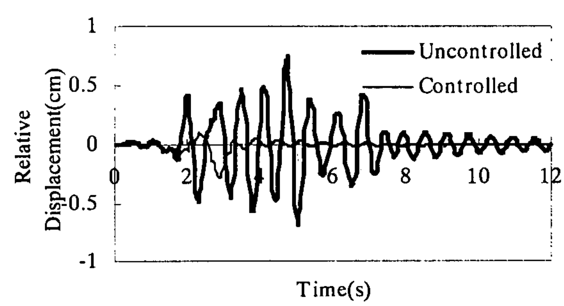
(a) The top floor



(b) The third floor



(c) The second floor



(d) The first floor

Fig. 13 Control and uncontrolled response of structure subjected to 10% of the Kobe earthquake record

(2) During the vibration control of coupled system under earthquake excitation, based on the trained emulator neural network, a neurocontroller can also be trained to decide the necessary control signals, and the dynamic response can be controlled successfully by the neurocontroller.

(3) The method of vibration control using multi-layer neural network is adaptable for the cases that the structure is subjected to different earthquakes from it used for training the neurocontroller. The learning capabilities of the neurocontroller make it an adaptive controller.

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