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Structural Damage Detection Using Neural Network and H_∞ Filter Algorithm

Hesheng Tang*[a] and Tadanobu Sato[b]

a. Visiting Researcher, Dr., Disaster Prevention Research Institute, Kyoto University, Uji, Kyoto 611-0011, Japan

b. Prof., Disaster Prevention Research Institute, Kyoto University, Uji, Kyoto 611-0011, Japan

ABSTRACT

In this paper we propose a neural network -based approach for damage detection of unknown structure systems. Newly developed global H_∞ Filter optimal learning algorithm for the neural network to simulate a structural response is developed. This algorithm is based on the worst-case disturbances design criterion, and is therefore robust with respect to model uncertainties and lack of statistical information to the exogenous signals. Simulation results are presented to identify dynamic response characteristics of nonlinear structural systems corresponding to different degrees of parameters changes, which indicate that damage occurred in the structure. It is shown that the proposed method is highly robust and more appropriate in practical early structural damage detection.

Keywords: Damage detection, neural network, H_∞ Filter

1. INTRODUCTION

Nondestructive damage identification problems have been the focus of research studies for many years; numerous researchers have studied a variety of analytical and experimental techniques. Neural networks have been viewed as potential saviors for the solution of the difficult problems in damage identification typically encountered in the structural dynamics field [1]. Neural networks were originally developed to simulate the function of the human brain or neural system. Subsequently, they have been widely applied to diverse fields ranging from biology to many engineering fields. Currently, NNs are studied vigorously as non-parametric system identification techniques. No prior knowledge about the model is the major advantage of using neural network in system identification. Neural networks are able to treat implicit damage mechanisms, so that it is not necessary to model the structure in detail. In recent years, research on vibration and neural networks based damage identification has been expanding rapidly [1-3].

Although the neural network methods that have been developed are applicable in concept to most simple structural models, with the number of the degrees-of-freedom of the structural models increasing, excessive computation time and computer memory are necessary for the network training, and it may not be practically possible online processing. Due to these reasons, a substructure identification method for the large-scale structure systems was proposed [2-5]. In the case of polynomial-type nonlinear or linear system that is memoryless model, the approach yields virtually exact results. For other types of nonlinear systems, such as the memory-type models, the approach is invalidity. Consequently, we cannot just use the interstory displacement and interstory velocity as the inputs of the neural network to mapping the restoring force function, and the past restoring force should be included in the inputs. Hence, the substructure interstory force identification schemes have been investigated [2-5], which are limited by the chosen parametric model to identifying certain classes of nonlinearities.

A concern in neural network training is in the hope of finding a 'fast' and 'robust' learning method. Error back-propagation (BP) algorithm is commonly used to evaluate connection weights in conventional neural network [6].

Further author information: (Send correspondence to Dr. H. Tang)
H. Tang: E-mail: ths@catfish.dpri.kyoto-u.ac.jp, Tel: +81(0) 774 38 4071
T. Sato: E-mail: sato@catfish.dpri.kyoto-u.ac.jp, Tel: +81(0) 774 38 4069

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However, some disadvantages of this algorithm were found for structural system identification: learning process is unstable when the teaching signals contaminated by measurement noise, and the identified weights sometimes fall into the local minimum solution because the connection weights are adjusted based on the first-order stochastic gradient descent method. For this case, some researchers have put forward extended Kalman filter (EKF) training methods that use higher-order information more efficiently [7-9]. They showed that EKF algorithm converged in fewer iterations than the standard back-propagation algorithm using a few artificial examples. They also showed that in some case when the back-propagation algorithm failed, the EKF converged a good solution. But it should be noted that the EKF method requires the knowledge of the noise covariance metrics, convergence of the algorithm as well as the final values are depend, to great extent, on this initial guess, which is unrealistic in modeling identification. The EKF algorithm might thus diverge, whereas the H_∞ filtering method will always provide the robust predictor of a given arbitrary structure. The H_∞ filtering problem is a state estimation problem of minimizing the maximum energy in the estimation error over all the disturbance trajectories and make no assumptions on the statistics or distributions of the disturbance signals [10]. The H_∞ filter was confirmed to be more efficient and robust than the Kalman filter for the identification of structural system [11].

In this paper, a newly developed learning algorithm for training the neural network method for the structural damage detection has been proposed, the hysteretic nonlinearity system (memory-type model) will be used and the restoring force with one step time lag will be selected as the input. The date sets consisting of interstory displacement, interstory velocity, and the interstory restoring force of the each substructure are used to train neural networks for the purpose of the damage detection corresponding substructures. The approach proposed in this paper relies on the use of vibration measurements from a “healthy” system to train a neural network for identification and prediction purposes. Subsequently, the trained network is fed comparable vibration measurements from the same structure under different episodes of response in order to monitor the health of the structure. The robust and efficiency of such approach for the early structural damage detection will be demonstrated by the simulation results.

2. BACKGROUND OF NEURAL NETWORKS

In this study, the most widely used technique, the feedforward neural network (FNN), is adapted for the damage identification shown in Fig.1. Fig.1 shows a typical three-layer FNN: the input layer $u_i (i = 1, \cdots, n)$ with n nodes, the two hidden layers with p and q nodes and the output layer $y_i (i = 1, \cdots, m)$ with m nodes. Between layers, there are weights w_{ij}^1, w_{ij}^2 and w_{ij}^3 representing the strength of connections of the nodes in the network. In Fig.1 we can assign a different activation function of $\gamma(*)$, $\beta(*)$ and $\alpha(*)$ with corresponding bias terms, $\mathbf{b}^1$, $\mathbf{b}^2$ and $\mathbf{b}^3$, for each layer. In this paper, the hyperbolic tangent function

$$f(x) = \frac{1 - e^{-\alpha x}}{1 + e^{-\alpha x}} \qquad (\alpha > 0) \tag{1}$$

is chosen as the activation function.

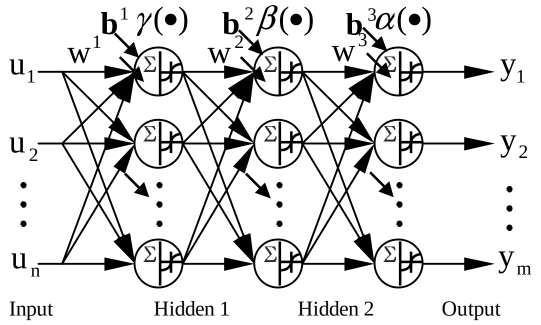

Figure 1. Feedforward Neural Network Model

During this operation, the output vector y is calculated by feeding the input vector u through the hidden layer of the neural network are given as

$$y = \alpha\left(\mathbf{w}^1 \beta\left(\mathbf{w}^2 \gamma\left(\mathbf{w}^3 \mathbf{u} + \mathbf{b}^3\right) + \mathbf{b}^2\right) + \mathbf{b}^1\right) \tag{2}$$

with $\mathbf{w}^1 = [w_{ij}^1]$, $\mathbf{w}^2 = [w_{ij}^2]$, $\mathbf{w}^3 = [w_{ij}^3]$, $\mathbf{b}^1 = \{b_1^1, \cdots b_p^1\}^T$, $\mathbf{b}^2 = \{b_1^2, \cdots b_q^2\}^T$, $\mathbf{b}^3 = \{b_1^3, \cdots b_m^3\}^T$ and $\mathbf{u} = \{u_1, \cdots u_n\}^T$.

The capabilities of the FNN stem from the non-linearities used within nodes. If nodes are linear elements, a single-layer net with appropriately chosen weights can duplicate the results obtained with any multi-layer net.

3. LEARNING ALGORITHM USING THE H∞ FILTER

Without loss of generality, a typical FNN model (Eq.2) can be defined as the following nonlinear discrete state-space model:

$$\mathbf{w}_{k+1} = \mathbf{w}_k \tag{3}$$

$$\mathbf{y}_k = \mathbf{h}(\mathbf{w}_k, \mathbf{u}_k) + \mathbf{v}_k \tag{4}$$

where the vector $\mathbf{y}_k$ is the vector of output values of units in the net at time k, $\mathbf{h}(*)$ denotes the overall state transition mapping performed by the network as a function of unit activities, weights, and input, $\mathbf{w}_k$ is the network's weight matrix at time k, but here we treat $\mathbf{w}_k$ as a single dimensional vector rather than a matrix, and v_k is the measurement noise.

The task of the H_∞ filter learning for the FNN is to estimate the weights from the noise patterns data. The design of discrete H_∞ filter is discussed in [10]. The following linear discrete system is considered

$$\mathbf{x}_{k+1} = \mathbf{A}_k \mathbf{x}_k + \mathbf{B}_k \mathbf{n}_k \quad \text{(State equation)} \tag{5}$$

$$\mathbf{y}_k = \mathbf{C}_k \mathbf{x}_k + \mathbf{v}_k \quad \text{(Measurement equation)} \tag{6}$$

where the $\mathbf{x}_k$ is the state vector of system at the time k, $\mathbf{y}_k$ is the vector of measurement at time k, $\mathbf{n}_k$ is the process noise, and $\mathbf{v}_k$ is the measurement noise, we make no assumption on the nature of unknown quantities $\mathbf{n}_k$ and $\mathbf{v}_k$, and $(\mathbf{A}_k, \mathbf{B}_k, \mathbf{C}_k)$ are the system matrices. The suboptimal H_∞ estimation problem is interested not necessarily in the estimation of $\mathbf{x}_k$ but in the estimation of some arbitrary linear combination of using the noise-corrupted observations $\{\mathbf{y}_k, k = 0,1,2, N-1\}$ i.e.,

$$\mathbf{z}_k = \mathbf{L}_k \mathbf{x}_k \tag{7}$$

where $\mathbf{L}_k \in R^{q \times n}$. Different from that of the modified Wiener/Kalman filter which minimizes the variance of the estimation error, the design criterion of the $\mathbf{H}_\infty$ filter is to provide a uniformly small estimation error, $\mathbf{z}_k - \hat{\mathbf{z}}_k$, for any $\mathbf{n}_k, \mathbf{v}_k \in l_2$ and $\mathbf{x}_0 \in R^n$. Let the estimation performance measure be

$$J = \frac{\sum_{k=0}^{N-1} \left\| \mathbf{z}_k - \hat{\mathbf{z}}_k \right\|^2}{\left\| \mathbf{x}_0 - \hat{\mathbf{x}}_0 \right\|_{p_0^{-1}}^2 + \sum_{k=0}^{N-1} \left\{ \left\| \mathbf{n}_k \right\|^2 + \left\| \mathbf{v}_k \right\|^2 \right\}} \tag{8}$$

where $((\mathbf{x}_0 - \hat{\mathbf{x}}_0), \mathbf{n}_k, \mathbf{v}_k) \neq 0$, $\hat{\mathbf{x}}_0$ is an a priori estimate of $\mathbf{x}_0$ and $\mathbf{x}_0 - \hat{\mathbf{x}}_0$ represents unknown initial condition error, $\mathbf{p}_0^{-1} > 0$, is the weighting matrices. $\mathbf{p}_0^{-1} > 0$ denotes a positive definite matrix that reflects a priori knowledge on how close the initial guess $\hat{\mathbf{x}}_0$ is to $\mathbf{x}_0$. The notation $\|\mathbf{z}_k\|_{\mathbf{Q}}^2$ is defined as the square of the weighted (by $\mathbf{Q}$) l_2 norm of $\mathbf{z}_k$, i.e., $\|\mathbf{z}_k\|_{\mathbf{Q}}^2 = \mathbf{z}_k^T \mathbf{Q} \mathbf{z}_k$. The H∞ filter will search $\hat{\mathbf{z}}_k$ such that the optimal estimate of $\mathbf{z}_k$ among all possible $\hat{\mathbf{z}}_k$ in the sense that the supremum of the performance measure should be less than a positive prechosen noise attenuation factor γ^2, i.e., the worse-case performance measure

$$\sup_{\mathbf{x}_0, \{\mathbf{n}_k\}, \{\mathbf{v}_k\}} J < \gamma^2 \tag{9}$$

The above problem formulation shows that $\mathbf{H}_\infty$ optimal estimators guarantee the smallest estimation error energy over all possible disturbances of finite energy. They are, therefore, overly conservative, which results in a better robust behavior to disturbance variations.

To apply the H_∞, the linearization of the nonlinear model (Eqs.3-4) should be required. Then the optimal H_∞ state filter-learning algorithm for estimation of the neural network weights is given by (herein the state $\mathbf{x}_k$ will be replaced by the neural network weights vector $\mathbf{w}_k$)

$$\hat{\mathbf{w}}_k^- = \hat{\mathbf{w}}_{k-1} \tag{10}$$

$$\mathbf{P}_k^- = \mathbf{P}_{k-1} + \mathbf{B}_k \mathbf{B}_k^T \tag{11}$$

$$\mathbf{K}_k = \mathbf{P}_k^- (\mathbf{I} + \mathbf{C}_k^T \mathbf{C}_k \mathbf{P}_k^- - \gamma^{-2} \mathbf{L}_k^T \mathbf{L}_k \mathbf{P}_k^-)^{-1} \mathbf{C}_k^T \tag{12}$$

$$\hat{\mathbf{w}}_k = \hat{\mathbf{w}}_k^- + \mathbf{K}_k (\mathbf{y}_k - \mathbf{h}(\hat{\mathbf{w}}_k^-, \mathbf{u}_k)) \tag{13}$$

$$\mathbf{P}_k = [\mathbf{I} - \mathbf{K}_k \mathbf{C}_k] \mathbf{P}_k^- \tag{14}$$

where $\mathbf{C}_k = \left.\dfrac{\partial \mathbf{h}}{\partial \mathbf{w}}\right|_{w=\hat{w}_k^-}$, and the attenuation factor γ must be tuned so as to satisfy the $\mathbf{P}_k$ positive definite.

4. NEURAL NETWORK FOR DAMAGE DETECTION

4.1 Basic Idea

The expression of the equation of motion for a generic multi-degree-of-freedom non-linear system can be written in the form

$$\mathbf{m}\ddot{\mathbf{x}}(t) + \mathbf{r}(\dot{\mathbf{x}}(t), \mathbf{x}(t), \mathbf{r}(t)) = \mathbf{u}(t) \tag{15}$$

where $\mathbf{m}$ is the mass matrix, $\ddot{\mathbf{x}}(t)$, $\dot{\mathbf{x}}(t)$ and $\mathbf{x}(t)$ are the relative acceleration, velocity and displacement, $\mathbf{u}(t)$ is the system's external excitation, and $\mathbf{r}(t)$ the non-linear restoring force.

The reduced-order equation of motion for ith active degree of freedom for a shear-type structure (Fig.2) subjected to earthquake-induced ground excitations ($\ddot{x}_g$) can be written as:

$$m_i \ddot{x}_i + r_i - (1 - \delta_{in}) r_{i+1} = -m_i \ddot{x}_g \tag{16}$$

where if $i \neq n$ then $\delta_{in} = 0$ else $\delta_{in} = 1$.

In this paper, one of the more widely used models for hysteretic nonlinearities is studied, because it can capture many commonly observed types of hysteretic behavior, is the Bouc− Wen model[12]. In this case, the ith component of interstory restoring force vector is expressed by

$$r_i(\dot{u}_i, u_i, r_i) = c_i \dot{u}_i + z_i \tag{17}$$

and hysteretic force z_i is satisfied by

$$\dot{z}_i = k_i \dot{u}_i - \alpha_i |\dot{u}_i| |z_i|^{n_i - 1} z_i - \beta_i \dot{u}_i |z_i|^{n_i} \tag{18}$$

where $\dot{u}_i$ is the relative velocity between the i-1th and ith mass point, c_i is the damping, k_i the stiffness, α_i, β_i and n_i are the nonlinear parameters.

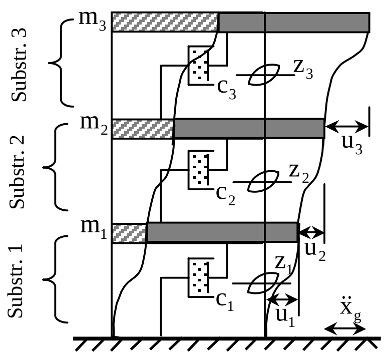

Figure 2. Model of 3 DOF structural system

Table 1. Parameters of structural model

m_i (kgfs²/cm)	k_i (kgf/cm)	c_i (kgfsec/cm)	α_i	β_i	n_i
0.12553	24.5	0.07	1.0	0.5	2

(Note: i=1,2,3)

Because in reality the hysteresis restoring force is not simply a function of the states $\mathbf{x}$ and $\dot{\mathbf{x}}$ but also of the past restoring force $\mathbf{r}$. (This was written generically as $\mathbf{r}(\dot{\mathbf{x}}(t), \mathbf{x}(t), \mathbf{r}(t))$ in Eq. (15).) In other words, for hysteresis there is not a unique surface in the $\mathbf{x}$ and $\dot{\mathbf{x}}$ space [13]. Ref. 14 also demonstrated that using the "memoryless" non-parametric method for identification of nonlinear system with general hysteretic properties leads to a "drift" effects in hysteretic systems, because the hysteretic system is a memory-type model. For the polynomial-type nonlinearity system that is memoryless model, the approach yields virtually exact results, which will be proven in detail later for substructure modeling. In this paper, consider the hysteretic nonlinearity system is a memory-type model; the restoring force with one step time lag will be selected as the input. This approach can cope with a much broader family of unknown nonlinear response behaviors.

Assume that the mass are known and the experimental measurements for $\ddot{\mathbf{x}}$ and $\ddot{x}_g$ are available and that the corresponding $\dot{\mathbf{x}}$ and $\mathbf{x}$ can be found by direct measurements or through integration of $\ddot{\mathbf{x}}$. Hence, the interstory restoring force values r_i can be calculated using the Eq.16. Eq.16 also tells us that i-th interstory restoring force function $r_i(\dot{u}_i, u_i, r_i)$ is determined just by the properties of the i-th substructure, and which shown the proposed method is localization damage detection method.

In this paper, a shear-type structure subjected to earthquake-induced ground excitations is studied in this study

(Fig.2). Based on the concept of the substructure damage detection, the structure will be divided into several substructures (simplified, one active DOF is a substructure), and using the neural network to model the dynamic behaviors of the substructures, namely that the neural network is trained to identify a substructure model of $r_i(\dot{u}_i, u_i, r_i)$. We compose a three layers feed-forward neural network, in which the input signals are $\dot{u}_i$ and u_i at time step k, and r_i at the time step k –1 and the outputs are the calculated values of r_i at the time step k. Hence, the network has 3 input nodes, 1 output node, and one hidden layer with 20 nodes and a hyperbolic tangent function like Eq.1 was used as the node nonlinearity. The size of the network become very small, computation cost decreasing correspondently.

If the network has been well trained, and if the substructure system characteristics have not changed, both the substructure system and the network will have matching outputs. On the other hand, if the substructure system has changed, the output from the substructure system will not correspond any more to the output of the trained network, consequently, the network will yield an output 'error'. Therefore, the deviation between the output from the substructure system and the output from the network provides a quantitative measure of the changes in the physical substructure relative to its 'healthy' condition. The detection procedure is that we will get the reference configuration through the "health" dynamic substructure system training at first, then, the well-trained network is employed to predict the responses of the "damage" system. The output of this prediction will differ from the system observed output, given the same input. One standard, overall performance measure was used for different case, namely the normalized mean-square-error or NMSE defined by

$$\mathrm{NMSE} = \frac{100}{N\sigma_r^2}\sum_{i=1}^{N}(r_i - \hat{r}_i)^2 \tag{19}$$

where r_i is actual value, σ_r^2 is its variance and $\hat{r}_i$ is the neural network output.

4.2 Structural Identification

To verify the effectiveness of the proposed algorithm, a shear-type structure subjected to earthquake-induced ground excitations is studied. We use system's parameters, as shown in Table 1.

In order to verify the generalization of the H_∞–learning neural network, two load cases are used in this paper, El-Centro earthquake (May. 18, 1940, Imperial Valley) and Takochi-oki earthquake (May, 16, 1968, Hachinohe). Both of these two earthquakes with modified maximum amplitude of 25 cm/sec^2 and 30s time histories were selected. The sampling interval of the structural responses to be used for identification is 0.02s.

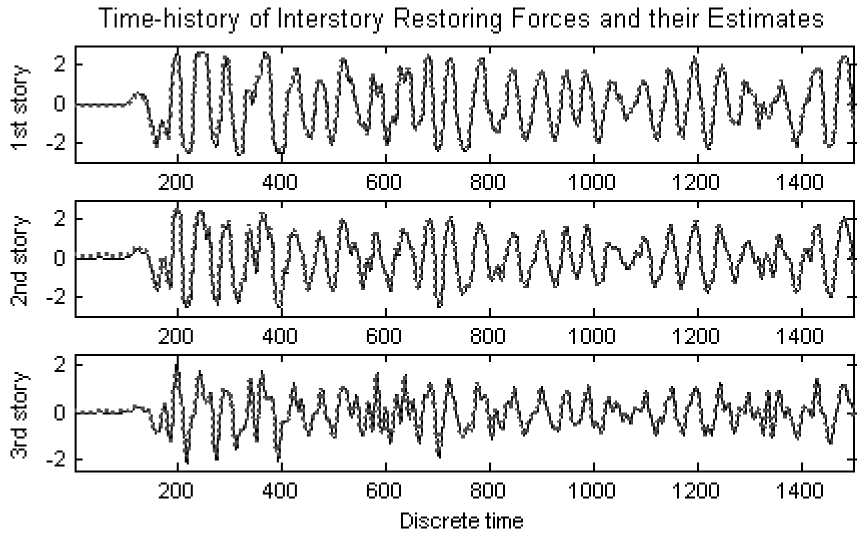

Figure 3. Time History of actual (solid curve) and estimated (dashed curve) restoring forces (using this paper method).

The structure subjected to El-Centro earthquake-induced ground excitations, excellent restoring force estimation results using the proposed approach shown in Fig. 3. (Corresponding, NMSE=0.7550, 0.7532, 0.2221) It is shown that the network is performing extremely well in matching the system. When the interstory force with one step time delay not included in the input of network, the estimation results shown in Fig. 4 (Corresponding, NMSE=17.9907,43.2239, 7.9225). We have tried to increase the number of the weights, but the estimation errors existing almost the same with shown in the fig.4, which further verify that there is not a unique surface in the interstory displacement, interstory velocity space, which defines the interstory restoring force for the hysteretic nonlinearity system.

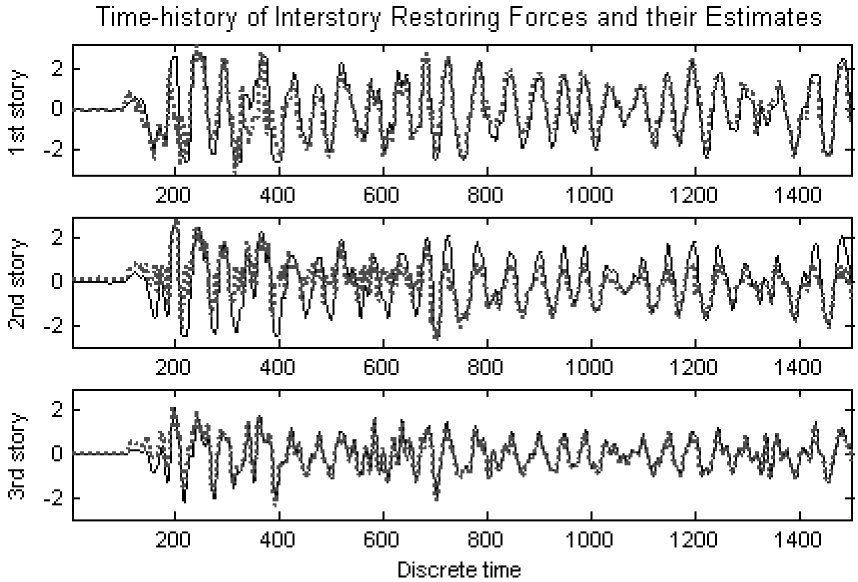

Figure 4. Time History of actual (solid curve) and estimated (dashed curve) restoring forces (which not adopted as network input).

To verify the effects of measurement noise on the proposed algorithm, random white noise signals have been added to both the simulated structural response and the ground-induced accelerations. The level SNR (signal-to-noise ratio) of the noise is defined as

$$\mathrm{SNR} = 10\log_{10}\frac{\sigma_{\mathrm{signal}}}{\sigma_{\mathrm{noise}}}\mathrm{dB} \tag{20}$$

where σ_{noise} and σ_{signal} are the standard deviations of the added noise and the structural responses.

To study these effects, three noise levels simulations were carried out for the interstory restoring force identification of the 1st story (1st substructure), noise was added to the data in the training stage, the network output NMSEs are shown in Table 2. As shown in the Table 2, the performance of the networks is not significantly affected by the additive noise in the training data.

Table 2. Network output NMSE for different level added (1st story or substructure identification)

SNR	no noise	46	30	24
NMSE	0.7550	0.7932	0.8258	0.8301

In the following, we discuss about the nonuniqueness for the H_∞–learning neural network, which has been described in Ref. 3. The time histories of partial network weights are shown in Fig. 5 with different four sets of initial weights values, Fig.5 shows the identified values of weights are converged to the different values. Although having a different set of weights after the well trained, the neural network models the nonlinear substructure system successfully. The nonuniqueness of the weighting matrices for successful solutions of the same system has been demonstrated by Ref. 3, the proposed H_∞–learning neural network with the same property, which precludes the use of this neural network approach for health monitoring by comparing individual weighting terms for damaged and undamaged systems.

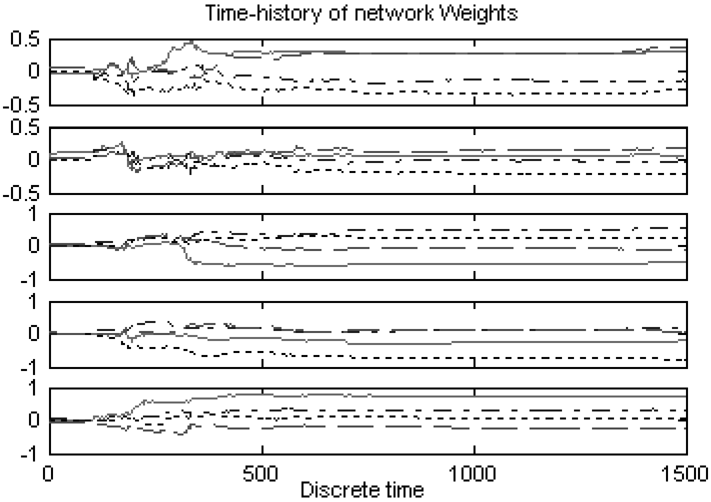

Figure 5. Time histories of a subset neural network weights with a different sets of initial weight values

To check the generalization ability of the H_∞–learning neural network, the trained well network is used to predict responses to different external excitation. The time histories of predicted interstory restoring forces shown in Fig.6 are in very good agreement with the true results for the Hachinohe earthquake, Which shows that the network performs extremely well in the reference unknown system when given the random inputs, on which it has never been trained.

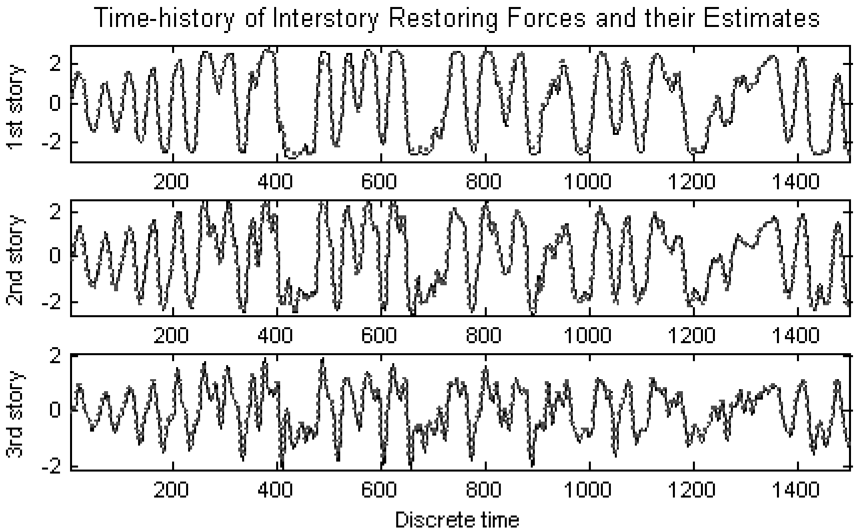

Figure 6. Time History of actual (solid curve) and predicted (dashed curve) restoring forces with well-trained network

4.3 Damage Detection

As described in above, the same structure subjected to El-Centro earthquake-induced ground excitations is presented for the purpose of damage detection. An individual network is prepared for each story or substructure, the training and detection are done for each individual story described in the previous section.

Without loss of generality, the structural damage is simulated with decreasing in stiffness at every story, a set of damaged cases and corresponding NMSEs of the prediction output error are presented. The results for the different damaged stories with different damage degrees of the structure are shown in the Figures 7,8,and 9. Fig. 7 shows the NMSEs of all the three stories network output errors that normalized by undamaged case when damages have occurred in the 1st story with different levels; correspondingly, Fig.8 and Fig.9 show the results when damages have occurred in the 2nd story and 3rd story, respectively. All of three figures show that increases as the damage level of considered story increases NMSE value of certain story, and also show when the damage has occurred in one story, corresponding the network prediction output NMSEs for this story become significantly larger than that of the other without damage story networks. This indicates that the proposed substructure damage detection method works well for localized damage detection.

Due to its nonparametric nature, the network prediction output errors magnitude don't have directive relationship with the degree of the damages, it is to say, the proposed method cannot quantify the level of the damage.

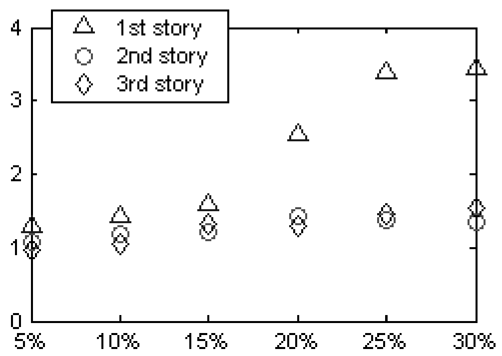

Figure 7. Network output NMSEs (damaged in the 1st story case) for system normalized by undamaged case

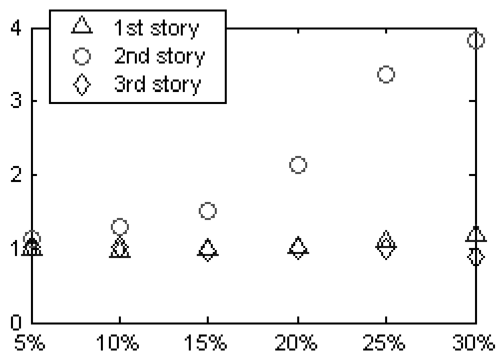

Figure8. Network output NMSEs (damaged in the 2nd story case) for system normalized by undamaged case

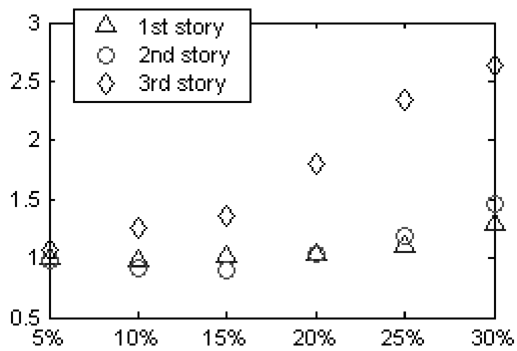

Figure 9. Network output NMSEs (damaged in the 3rd story case) for system normalized by undamaged case

CONCLUTION

In this paper, we a presented neural network with H_∞ filter training algorithm for nonlinear structural dynamic model identification and damage detection. Because the hysteretic nonlinearity system is considered a memory-type model, the restoring force with one step time lag as one of the inputs to the network. Since the design criterion of the H_∞ filtering algorithm is based on the worst case disturbances, the method is less sensitive to uncertainty in the exogenous signal statistics and system model dynamics, the proposed algorithm is more robust than EKF training based neural network. Remarkable success has been achieved in training the networks to learn the nonlinear structural responses, and thereby to make accurate responses predictions identify dynamic response characteristics of nonlinear structural systems corresponding to different degrees of parameters changes, which indicate that damage occurred in the structure. It is shown that the proposed method is highly robust and more appropriate for practical structural damage detection.

REFERENCES

1. S.F. Masri, M. Nakamura, A.G. Chassiakos, and T.K. Caughey. "Neural Network Approach to Detection of Changes in Structural Parameters," *Journal of Engineering Mechanics*-ASCE 122, 4, pp. 350-360, 1996.
2. M. Nakamura, S. F. Masri, and T.K. Caughey. "A Method for Non-Parametric Damage Detection through the use of Neural Networks," *Earthquake Engineering & Structural Dynamics* 27, 9, pp.997-1010, 1998.
3. S.F. Masri, A.W. Smyth, A.G. Chassiakos, T.K. Caughey, and N.F. Hunter. "Application of Neural Networks for Detection of Changes in Nonlinear Systems," *Journal of Engineering Mechanics*-ACSE 126, 7, pp. 666-676, 2000.
4. H. M. Chen, G. Z. Qi, J. C. S. Yang, and F. Amini. "Neural Network for Structural Dynamic Model Identification," *Journal of Engineering Mechanics*-ACSE 121, 12, pp. 1377-1381, 1995.
5. Z. Wu, B. Xu, and K. Yokoyama. "Decentralized Parametric Damage Detection Based on Neural Networks," Computer-Aided Civil and Infrastructure Engineering, 17, pp.175-184, 2002.
6. S. Haykin, *Neural Networks: A Comprehensive Foundation*, Prentice Hall, Inc. 1999.
7. S. Singhal and L. Wu. "Training multiplayer perceptrons with the extended Kalman algorithm," *Advances in Neural Information Processing Systems*, Touretzky, Ed., pp.133-140, 1989.
8. Y. Iiguni, H. Sakai, and H. Tokumaru. "A real-time learning algorithm for a multilayered neural network based on the extended Kalman filter," IEEE *Trans. Signal Processing*, vol. 40, pp. 959–966, 1992.
9. T. Sato, and M. Sato, "Structural identification Using neural Network and Kalman Filter Algorithms," *Journal of Structural Mechanics and Earthquake Engineering*, JSCE, No. 563/I-39, pp.23-32, 1997.
10. B. Hassibi, A.H. Sayed and T.Kailath, *Indefinite-Quadratic Estimation and Control: A Unified Approach to H2 and H_∞ Theories*, SIAM, 1998.
11. T. Sato, K. Qi. "Adaptive H_∞ fillter: Its application to structural identification," *Journal of Engineering Mechanics* (ASCE) 124:1233-1240, 1998.
12. Yi-K. Wen, "Method for Random Vibration of Hysteretic Systems," *Journal of Engineering Mechanics Division*, Vol.102, No.EM2, pp.249-263, 1976.
13. A.W. Smyth, S. F. Masri, E. B. Kosmatopoulos, A. G. Chassiakos, T. K. Caughey. "Development of adaptive modeling techniques for non-linear hysteretic systems," *International Journal of Non-Linear Mechanics*, 37, pp.1435 –1451, 2002.
14. S.F. Masri, J.P. Caffrey, T.K. Caughey, A.W. Smyth, A.G. Chassiakos. "Identification of the state equation in complex non-linear systems," *International Journal of Non-Linear Mechanics*, 39, pp.1111 –1127, 2004.