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A Post-Seismic Damage Detection Strategy in Time Domain for a Suspension Bridge with Neural Networks

ニューラルネットワークによる地震後のつり橋の時刻歴損傷同定手法の提案

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A neural-network-based damage detection approach with the direct use of actual incomplete time series of earthquake response is developed for a suspension bridge. Two neural networks are constructed and trained using the segment of the time series of seismic responses on several locations of the bridge, when earthquake is in small level, to identify the transversal and vertical velocities responses at the deck in the middle of the main span of the suspension bridge. The two neural networks are assumed as nonparametric models for the bridge in health condition before the earthquake occurred. The performance of the trained emulator neural network models for the suspension bridge is evaluated by numerical simulation. The RRMS error between the forecast responses and the measurements in different stages are decided. Results show that the RRMS errors corresponding to the transversal and vertical velocities in the middle of the main span have a variance in different segments. This results mean that occurrence of damages in some structural members is possible. This analysis result is testified by inspection result that broken stay cables have been found after the earthquake. The proposed approach is a non-parametric damage detection strategy, in which a prior information about the exact model of the suspension bridge is not needed. The proposed strategy has a significant advantage when dealing with large-scale structures in real-word.
KEYWORDS: identification; earthquake vibration; health monitoring; neural network; suspension bridge; incomplete measurement, damage detection

1. Introduction

Infrastructures are generally the most expensive assets in any country. The major concerns in the operation of in-service infrastructures are the reliability of the structures and the cost associated with maintaining reliability. But the infrastructures such as transportation systems and civil structures (bridges, highways, railways, tunnels, etc.) are deteriorating at an alarming rate. In recent years, structural health monitoring for civil infrastructures has been accepted as an evolving technology to maintain operational availability and productivity, reduce maintenance cost, and prevent catastrophes.

Structural health monitoring and damage detection are extremely important research areas to keep our advanced society functional and challenging topics that are under vigorous investigations by numerous researchers using a variety of analytical and experimental techniques. Most of the current damage detection methods such as acoustic or ultrasonic methods, magnetic field methods, radiography, eddy-current methods and thermal field methods are either visual or localized experimental methods[1]. These experimental techniques require that the vicinity of the damage is known a priori and that the portion of the structure being inspected is readily accessible. The need for quantitative global damage detection methods that can be applied to complex structures has led to research into structural identification methods that examine changes in the vibration characteristics of the structure. Some of these research has been summarized in recent literatures[2,3]. But, the identification and damage detection for large-scale suspension bridges with many uncertainties and complexities in material property, geometry dimension and boundary conditions, represents a difficult and unique problem. Furthermore, former structural identification procedures for damage detection and structural monitoring have seldom been successfully applied to civil engineering infrastructures such as cable-supported bridges subjected to damaging seismic events.

The dynamic response measurements of existing civil structure under earthquake excitations provide useful and economical information for identification or damage detection. In this paper, a neural-network-based damage detection approach with the direct use of actual incomplete dynamic response measurements in time domain under earthquake is developed for a suspension bridge. The incomplete dynamic measurements of the suspension bridge under an earthquake are directly used for the purpose of nonparametric identification and damage detection for real-time damage existence or occurrence alarm.

As a parallel distributed processing methodology, neural network has been regarded as a potential method for large-scale and complex dynamic systems with adaptability. Neural-network-based identification and control algorithms have attributes that make them potentially effective in dealing with most of these problems. Modeling dynamic systems by using neural networks has been increasingly recognized as one of the system identification paradigms. At present, several neural networks with different structures have been proposed to solve the identification and control problems. The most widely used neural network is the feed forward multi-layer neural network, which is trained by the back-propagation algorithm. Numerous engineering applications of neural networks have been reported in the literature of recent years. The applications of neural networks in the field of civil engineering were reviewed by Ghaboussi et al., Chen et al., Smyth et al. and Xu et al [6-13]. In order to deal with the scale problem of large-scale structures, Wu et al. and Xu et al. explored a localized and decentralized damage detection and parametric identification methodology using dynamic response measurements under small-scale earthquakes or dynamic excitations, and carried out a feasibility study by numerical simulations[12,13]. Xu et al. proposed a health monitoring strategy with the direct use of earthquake responses which can be used to not only give qualitative information about damage occurrence but also identify the structural stiffness quantitatively[14]. The feasibility study shows that the proposed parametric identification strategy using dynamic response in the time domain with neural networks has the potential of being a practical tool for health monitoring applied to civil engineering structures.

Even though some identification methods for large-scale structures, such as model reduction and conventional approach of substructural method, have been proposed, a neural network based nonparametric identification and damage detection strategy with incomplete dynamic responses in time domain is introduced in this study.

A neural-network-based damage detection approach with the direct use of actual incomplete dynamic response measurements in time-domain under an earthquake is developed for a suspension bridge is presented in this paper. The incomplete dynamic measurements of the suspension bridge under an earthquake are directly used for the purpose of nonparametric identification. The purpose of this study is to construct a neural network model (nonparametric model) for the bridge in the situation before earthquake occurred, which can be used for the purpose of health monitoring (alarm) system when damage exists, and control system design in which an identification model is necessary.

The first segment of the measurements before the peak of the earthquake acceleration occurred are used for the nonparametric identification for the bridge in health condition, which is treated as a reference state, before earthquake occurred. Two neural networks are constructed and trained with the dynamic responses before the peak of the earthquake acceleration occurred to identify the transversal and vertical velocity at the deck in middle of the main span of the Bridge. And the two neural networks can be treated as nonparametric models for the bridge in health condition before the earthquake occurred. The suspension bridge has a very great deal of degree of freedom and should be treated as a large-scale and complex system. Part of the time series of the velocity response at the deck in middle of the main span, and the earthquake records are used to train the two emulator neural networks by BP algorithms without the support of the Finite Element Model of the bridge.

The performance of the trained emulator neural network model for the suspension bridge is evaluated by numerical simulation in which the forecast response from the neural emulator is compared with the measurement during different segments of the earthquake. The RRMS error between the forecast responses and the measurements in different stages are decided. Results show that the RRMS errors corresponding to the transversal and vertical velocity in the middle of the main span have a variance in different segments. This results means that possible damages occurred in some structural members. This analysis result agrees with the inspection results after the earthquake, broken stay cables were found.

The proposed approach is a non-parametric system identification method for damage detection, in which a prior information about the exact model and Finite Element Model are not needed, so it has significant advantage when dealing with real-word situations where the selection of a suitable parametric model for identification is usually a demanding task. And the proposed neural networks nonparametric model is can be treated as a promising method for the design of the control system for a suspension bridge for which the modeling and control system design is difficult.

2. Problem Description and Neural Networks

2.1 Bridge Description and Vibration Measurements

Figure 1 gives the side-elevation of the suspension bridge studied in this study. 1A and 4A anchorage and 2P tower pier were constructed as spread foundation. 3P tower pier was constructed as piled foundation. The characteristics of this bridge are as follows:

(1) Narrow decked bridge: The ratio of span length and girder width is about 1/40.

(2) Short and unbalanced side span length: side span length differ each other because location of foundations were decided by topological conditions. As the countermeasure, 2 extra strands were placed at the side span to use cable efficiently, and escape from cable slip at the top of 3P tower.

To ensure its structural integrity and operational safety, the bridge has been equipped with a monitoring system that includes instruments such as accelerometers, velocity and displacement transducers, anemometers. The transducer set-up is described in Table 1. In the table, "√" means the dynamic response at the position was measured. The available dynamic responses record in time domain including velocity response at the deck in the middle and 1/4 of the main span in longitudinal, transverse and vertical direction, the acceleration response at the top and in the middle of the tower in transverse and longitudinal direction, and the acceleration response at the basement of 3P pier and 4A anchor were measured by the existing monitoring system on the bridge. The sampling period was set to be 0.01 second, and 120 seconds of dynamic responses under an earthquake was measured. It is clear that just very limited earthquake responses were used. Part of the observed dynamic responses are used to identification the bridge structure.

2.2 Preprocessing of the Measurements

The response measurements were noise polluted, a digital data preprocessing is carried out first for identification by the following procedures:

(1) conveying the time-domain responses to frequency-domain by FFT(Fast Fourier Transform);

(2) filtering the Fourier spectrum by a high-pass filter of 0.05Hz;

(3) getting the time-domain responses by IFFT(Inverse Fast Fourier Transform).

Figure 2 gives some of the acceleration response results in transversal, longitudinal and vertical direction of the 4A anchor. The peak of the transversal and vertical component of the acceleration at 4A anchor occurred at 19.42 second, 17.93 second, respectively.

A nonparametric identification strategy for generating the velocity response at the deck in the middle of the main span by neural network using the incomplete earthquake responses is proposed, and the proposed strategy can be used for alarming system to detect whether damage occurs or not.

Figure 3 gives the results of the observed velocity and preprocessed measurement with high-pass filter both in transversal direction and vertical direction at the deck in the middle of the main span.

2.3 Emulator Neural Network

The emulator neural networks for the purpose of forecasting the dynamic responses at the deck in the middle of the main span of the suspension bridge can be regarded as an identification problem for a complex and unknown nonlinear system. In this study, two three-layer neural networks called as emulator neural networks are constructed and trained to identify the dynamics of the bridge in the form of forecasting the velocity responses in transversal and vertical direction at the deck in the middle of the main span in a nonparametric manner.

The emulator neural networks designed in this study are two typical three-layer back-propagation neural networks with l nodes in the input layer, m neurons in the hidden layer and n neurons in the output. 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.

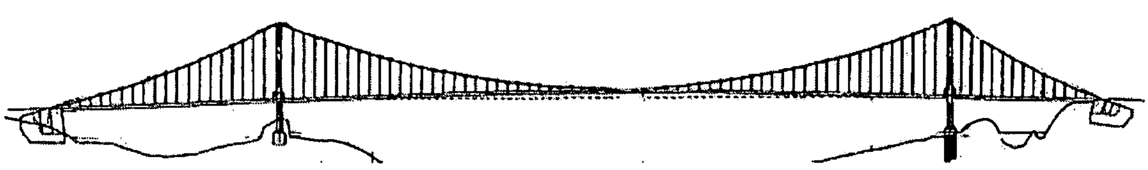
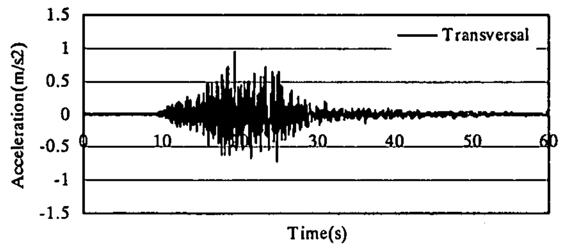


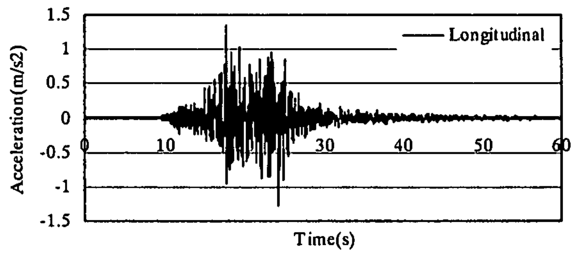
Figure 1. Side-elevation of the suspension bridge

Table 1 Transducer Set-up

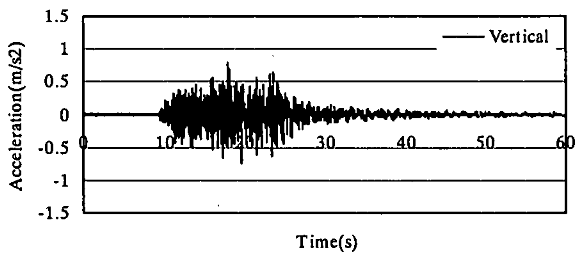
		Accelerometer			Velocity Transducer		
Direction		Transversal Direction	Longitudinal Direction	Vertical Direction	Transversal Direction	Longitudinal Direction	Vertical Direction
Position	Deck in Middle of the main span				√	√	√
	Deck in 1/4 of the main span				√	√	√
	Top of 3P tower	√	√				
	Middle of the 3P tower		√				
	Top of the basement of 3P pier	√	√	√			
	4A anchor	√	√	√			



(a) Acceleration in transversal direction

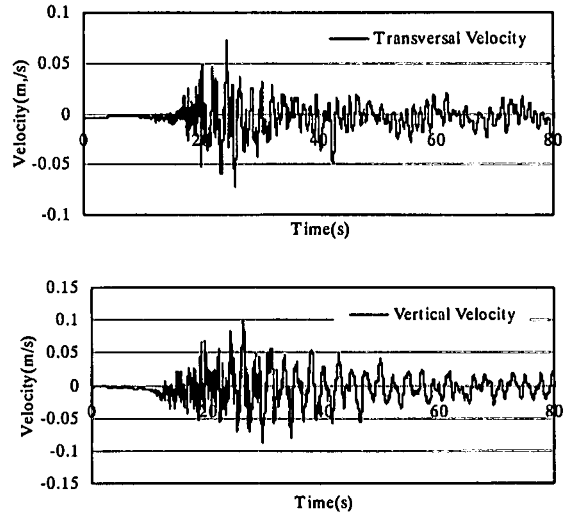


(b) Acceleration in longitudinal direction

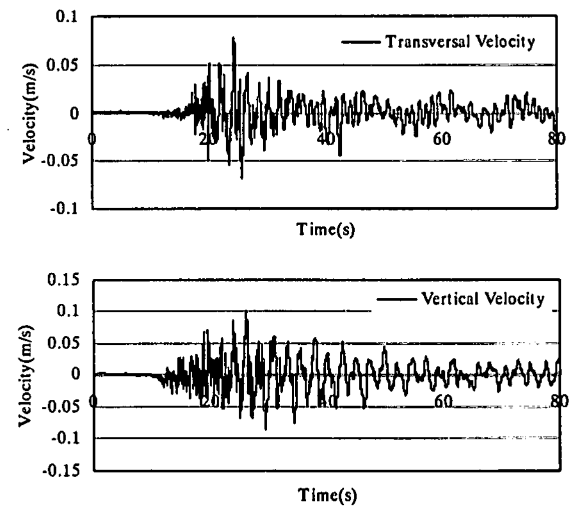


(c) Acceleration in vertical direction

Figure 2. Acceleration measurements at 4A anchor



(a) observed velocity



(b) preprocessed measurement of Velocity

Figure 3. Observed velocity and the pre-processed measurement with high-pass filter at the deck in the middle the main span

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

$$x_i = f\left(\overline{x}_i^N\right) \tag{1}$$

$$\overline{x}_i^N = \sum_{j=1}^{J} w_{ij}^{N,N-1} x_j^{N-1} - h_i^N \tag{2}$$

$$f(x) = \frac{1}{1+e^{(-x)}} \tag{3}$$

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, J is the number of neurons in Layer $N-1$.

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

$$E = \sum_p \sum_i \frac{\left(d_i - x_i^F\right)^2}{2} \tag{4}$$

where d_i, x_i^F are the desired output and the output of the i-th neuron in output layer respectively; i, p are the number of output neurons of output layer and the total number of patterns (examples) contained in the training sets.

Usually, the widely used learning algorithm for training neural networks is delta rule, which is based on the gradient steepest decent method. 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 layer N at iteration $k+1$ and it at iteration k as follows,

$$\begin{aligned}&\Delta w_{ij}^{N,N-1}(k+1)\\&= \eta \delta_i^N x_j^{N-1} + \alpha \Delta w_{ij}^{N,N-1}(k)\end{aligned} \tag{5}$$

$$\delta_i^N = -\frac{dE}{d\overline{x}_i^N} \tag{6}$$

where $\Delta w_{ij}^{N,N-1}(k+1)$ 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 =0.8. Moreover, the momentum constant must be restricted to the range $0 \leq |\alpha| < 1$, here let α=0.6 here.

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

$$w_{ij}^{N,N-1}(k+1) = w_{ij}^{N,N-1}(k) + \Delta w_{ij}^{N,N-1}(k+1) \tag{7}$$

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.

It is important to choose a proper network size for identification problems, it is not a efficient method to determine the best network size for a given system. Usually, the size of a neural network can be decided through a trial-and-error process. And the input and output variables should be selected logically with the consideration of physical meaning.

3. Numerical Simulations on Nonparametric Identification and Damage Detection

3.1 Construction of Emulator Neural Networks

In this study, two neural emulators are constructed to identify the transversal velocity and the vertical velocity of the deck in the middle of the main span of the suspension bridge in health condition before the earthquake occurred, respectively. It is reasonable that damage did not occur during the first segment when the earthquake acceleration was not great, therefore, part of the dynamic responses measurements under the earthquake before peak acceleration occurred are used to identify the transversal velocity and the vertical velocity at the deck in the middle of the main span of the suspension bridge in health condition. The inputs for the two emulator neural networks are selected from the limited available information shown in Table 1. So, only very limited incomplete earthquake responses on few location of the suspension bridge are used for the purpose of nonparametric identification.

The emulator neural network for the identification of the transversal velocity (called as NN-T) at the deck in the middle of the main span shown in Figure 4 is constructed with a ten-neuron input layer, a thirty-neuron hidden layer and a one-neuron output layer. The input data of the ten neurons in the input layer are designated to be the two consecutive transversal component of the accelerations at the 4A anchor, the top of 3P tower and the top of the basement of 3P pier, velocities at the deck in the middle of the main span and the 1/4 main span, the output of the network is the transversal component of the velocity of the deck in the middle of the main span the bridge at the next time step.

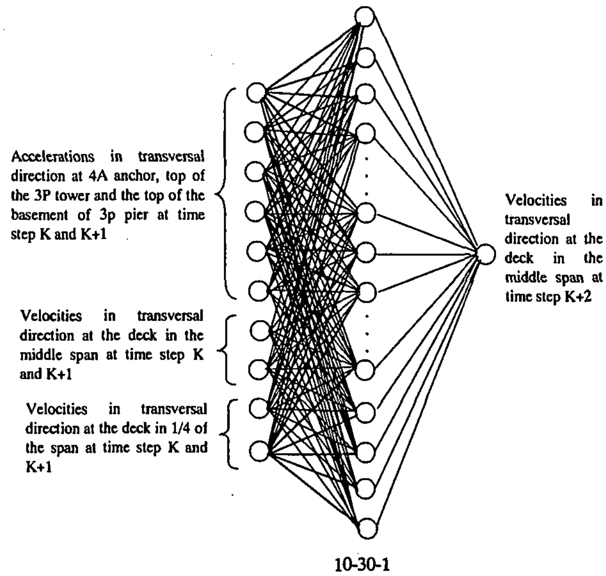


Figure 4. Architecture of emulator neural network for the identification of the transversal velocity at the deck in the middle of the main span

Neural emulator for the identification of the vertical velocity (called as NN-V) at the deck in the middle of the main span shown in Figure 5 is constructed with an eight-neuron input layer, a twenty-four-neuron hidden layer and a one-node output layer. The input data of the eight neurons in the input layer are designated to be the two consecutive vertical component of the accelerations at the 4A anchor and the top of the basement of 3P pier, velocities at the deck in the middle of the main span and the 1/4 main span, the output of the network is the vertical component of the velocity of the deck in the middle of the main span the bridge at the next time step.

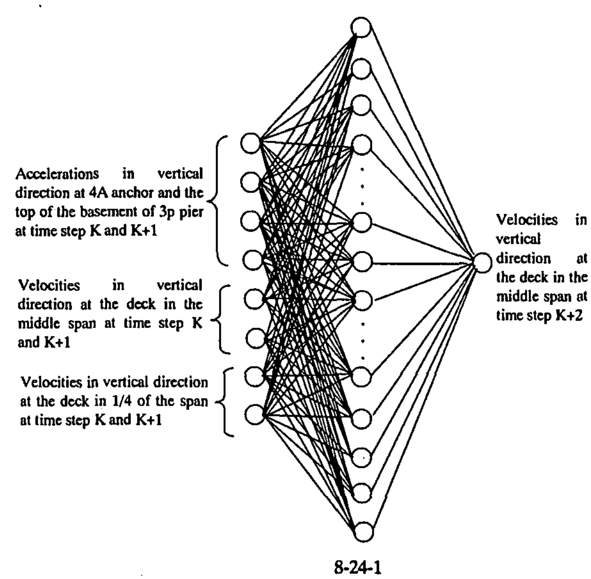


Figure 5. Architecture of emulator neural network for the identification of the vertical velocity at the deck in the middle of the main span

3.2 Training, Performance Evaluation of Emulator Neural Networks and Damage Detection

Form the time series of acceleration measurements, it is clear that the peak of the earthquake record in transversal direction occurred at time of 19.42 second. In order to train emulator neural network of NN-T, 1000 pairs of data sets taken from the dynamic responses from 8 second to 18 second are used. The NN-T neural network is trained by the method of back-propagation algorithm. The error function is calculated from the difference between the outputs of the neural emulator and the observed measurement. At the beginning of training the emulator neural nètwork, the weights are initialized with small random values. The whole off-line training process takes 10,000 cycles. Figure 6 gives the result of comparison between the observed velocity responses in transversal direction and those forecast by the trained neural emulator from 8 second to 18 second. It can be seen that the proposed neural network based nonparametric identification can be carried out with high accuracy. So this neural network model can be regarded as a nonparametric model of the suspension bridge before the earthquake occurred. And Figure 7 (a)-(f) give the results of the comparison between the observed velocity responses and those forecast by the trained emulator neural emulator in different segments from 18 second to 78 second. It can be found that the error between the observed velocity responses in transversal direction and those forecast by the trained neural emulator from 18 second to 78 second becomes greater.

Table 2 gives the errors between the observed and the forecast velocity of transversal component, as described by Wu et al. and Xu et al.[10-13], a Relative Root Mean Square(RRMS) error can be used as a useful index for damage detection, it is clear that the light damage on the stay rods of the bridge affect the velocity response in transversal direction of the deck in the middle of the main span. The maximum variance of RRMS error reaches 9.4%. The variance of the RRMS error can be treated as a symbol of the occurrence of damage.

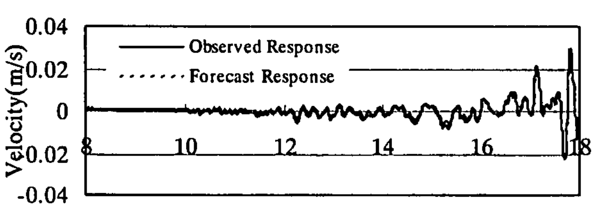
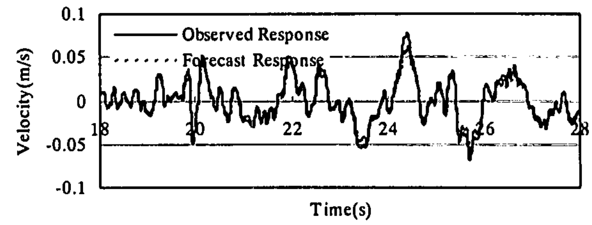
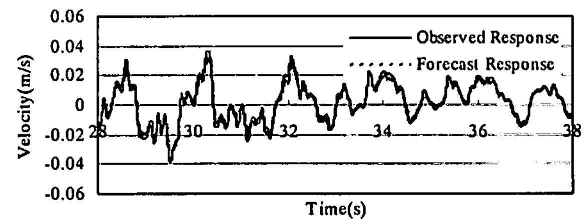


Figure 6. Comparison of velocity in transversal direction at the deck in the middle of the main span

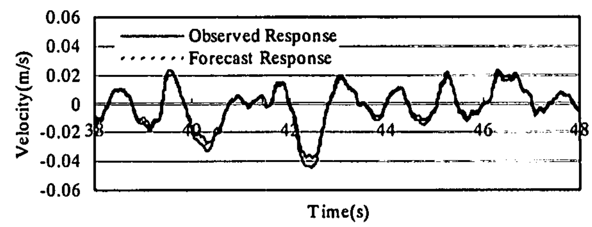
In order to train emulator neural network of NN-V, 1000 pairs of data sets taken from the dynamic responses from 8 second to 18 second are used. Based on the error back-propagation algorithm, the NN-V neural network is off-line trained. Figure 8 gives the result of the comparison between the observed velocity responses in vertical direction and those forecast by the trained neural emulator at the deck in the middle of the main span from 8 second to 18 second. It can be seen that proposed iden-



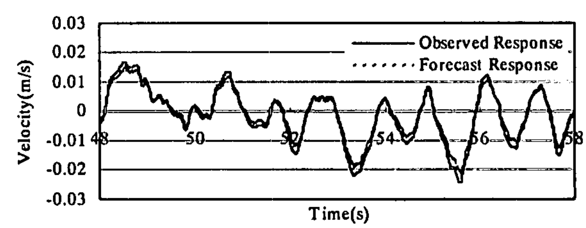
(a) Duration from 18 second to 28 second



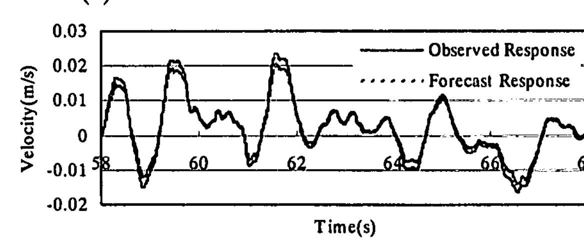
(b) Duration from 28 second to 38 second



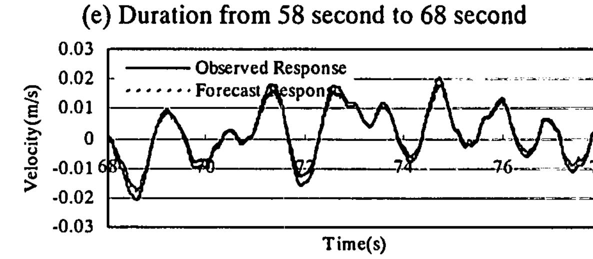
(c) Duration from 38 second to 48 second



(d) Duration from 48 second to 58 second



(e) Duration from 58 second to 68 second



(f) Duration from 68 second to 78 second

Figure 7. Comparison of velocity in transversal direction at the deck in the middle of the main span

tification strategy can be carried out with high accuracy.

And Figure 9 (a)-(f) give the results of the comparison between the observed velocities responses and those forecast by the trained neural emulator at the deck in the middle of the main span from 18 second to 28 second, from 28 second to 38 second, from 38 second to 48 second, from 48 second to 58 second, from 58 second to 68 second, and 68 second to 78 second, respectively. It is clear that the trained neural emulator cannot forecast the velocity responses accurately during the period after 18 second. It can be explained the damage in the stay rods affect the dynamic responses in vertical direction of the deck greatly.

Table 2 Errors Between the Observed and Forecast Velocity of Transversal Component

Durations	RMS Error (mm/s)	RRMS Error(%)	Change of RRMS Error
8s-18s	0.76	18.1	-
18s-28s	4.24	19.8	9.4%
28s-38s	2.05	16.8	-7.2%
38s-48s	2.26	17.9	-1.1%
48s-58s	1.52	19.0	5.0%
58s-68s	1.38	17.4	3.9%
68s-78s	1.44	17.9	-1.1%

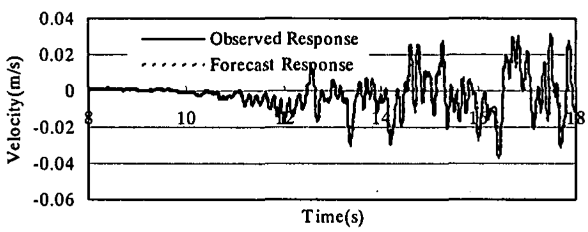
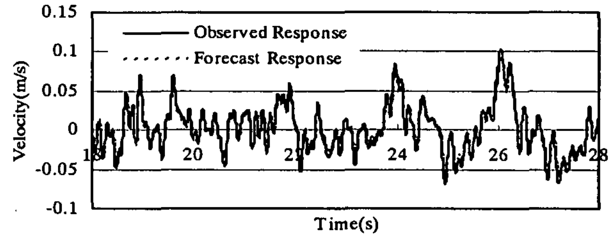


Figure 8. Comparison of velocity in vertical direction at the deck in the middle of the main span

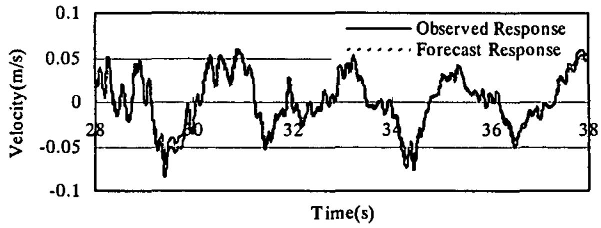
Table 3 gives the RRMS errors between the observed measurements and the forecast velocities of vertical component during different segments, it is clear that the RRMS errors become greater. The RRMS error gives a quantitative instruction that damage in the suspension bridge is possible. The inspection after the earthquake shows that damage in stay rods had been found. The results of this study meet the inspection results.

On the other hand, light damage on the stay rods of the bridge greatly affected the velocity response in vertical direction of the deck in the middle of the main span. The light damage in stay rods gives a maximum of 32.8% of change in RRMS error corresponding to the velocity responses in vertical direction. The damages in stay rods affect the stiffness in vertical direction of the suspension bridge greater that it affect the stiffness in transversal direction. It is clear that the RRMS error corresponding to suitably selected dynamic responses can be a sensitive index for health monitoring of structure-unknown large structure system.

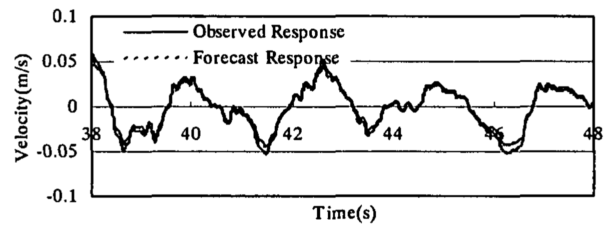
4. Conclusions



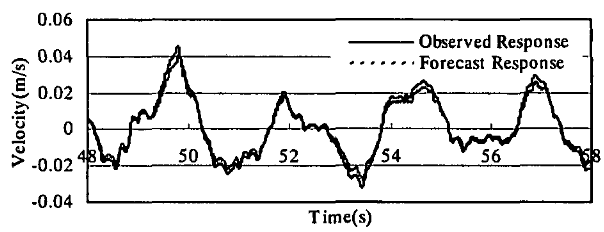
(a) Duration from 18 second to 28 second



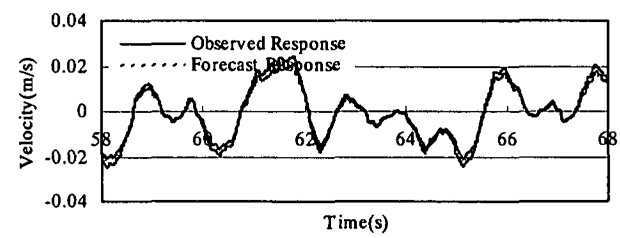
(b) Duration from 28 second to 38 second



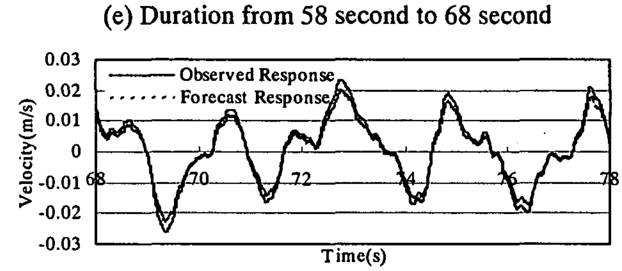
(c) Duration from 38 second to 48 second



(d) Duration from 48 second to 58 second



(e) Duration from 58 second to 68 second



(f) Duration from 68 second to 78 second

Figure 9. Comparison of velocity in vertical direction at the deck in the middle of the main span

Table 3 Errors Between the Observed and Forecast Velocity of Vertical Component

Duration	RMS Error (mm/s)	RRMS Error (%)	Change of RRMS Error
8s-18s	1.32	13.4	-
18s-28s	4.03	14.9	11.2%
28s-38s	4.66	16.8	25.4%
38s-48s	3.67	16.8	25.4%
48s-58s	2.32	16.1	15.7%
58s-68s	1.81	16.9	26.1%
68s-78s	1.72	17.8	32.8%

In this paper, a neural network based nonparametric identification strategy with the direct use of incomplete earthquake measurements for the health monitoring and damage detection of a suspension bridge was proposed. Two emulator neural networks were constructed to identify the transversal and vertical component of the velocity responses of the deck in the middle of the main span under an earthquake excitation. Numerical simulation results show that neural-network-based nonparametric model can be used to forecast the velocity responses with high accuracy even though very limited responses are used. On the other hand, the proposed strategy is not a mathematical model based method. Simulations verify that the proposed method can be used to detect the damage occurrence based on the evaluation index of RRMS corresponding to suitably selected dynamic responses. These characteristics of the neural network model make it a potential strategy for damage detection for health monitoring and control system design for large-scale structures, for example, suspension bridges.

The proposed strategy can decide whether damage occurred or not, and can be used for alarm system for large-scale and structure unknown structures, but it cannot give the answer of the position of the damaged elements and the extent of the damage.

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