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# A NEURAL NETWORK-BASED SYSTEM FOR BRIDGE HEALTH MONITORING

T.K. Lin[1], K.C. Chang[2] and C.C. Chen[3]

## ABSTRACT

A bridge health monitoring system based on neural network technology is proposed in this paper. Nowadays, with the aging of existing bridges all over the world, solutions on how to identify effectively the health conditions of bridges has become a significant issue. The method should offer a rapid and reliable result, immediately after major strikes of events, without using a great deal of time and labor. The demand of this health monitoring system grows rapidly and research on this topic had been discussed widely. Meanwhile, neural networks, originating from artificial intelligence, have also shown their outstanding performance in solving complex problems. For this reason, a monitoring system using a neural network was developed. Two major ground excitations recorded in Taiwan were used to establish the NARX-based system. Analytical results from different methods including transfer function, ARX-based model, and the proposed neural network-based system were used to evaluate the efficiency in health monitoring. The results show that the proposed neural networked-based system can be used successfully with superior advantages after major earthquakes for bridge health monitoring.

## Introduction

Earthquakes have become the most threatening disaster to civil structures. The damage to infrastructures not only causes a loss in economic activity, but also in the life and property of people. Under this circumstance, research on the application of instrumentation on structures to monitor their characteristics during and after earthquakes is always an important issue. Through the development of system identification while monitoring the vibration trait of buildings and bridges, some theories and methods have gradually become more reliable in the last few decades.

Traditionally, the identification methods are developed under a frequency domain. However, two close frequency modes may not be separated effectively by the frequency-domain-based method when noise is contained in the measured data. To solve this problem, the discrete-time domain-based identification technique has been applied to civil engineering in the last two decades. In most methods, structures are considered time-invariant. Specifically, parameters of structures are assumed to be constant during the whole time history.

However, structures might be damaged or might produce nonlinear behavior during an earthquake. To this, neural networks proved to have outstanding performance in solving complex problems and are

[1] Associate Research Fellow, National Center for Research on Earthquake Engineering, Taipei, Taiwan
[2] Professor, National Taiwan University, Taipei, Taiwan
[3] Assistant Research Fellow, National Center for Research on Earthquake Engineering, Taipei, Taiwan

integrated into identification systems. The adaptability and fault tolerance of neural networks have made them good candidates for dealing with incomplete data or of uncertainty. Therefore, the identification of nonlinear systems under major earthquakes may be implemented (Adeli et al., 1995; Masri et al., 1992; Masri et al., 1993).

A neural network-based method is proposed in this paper. This neural network was constructed under the multi-input-single-output structure of the Nonlinear Autoregressive with Exogenous (NARX) model. Similar to the Autoregressive with Exogenous (ARX) model, which has been applied widely in structure system identification, the NARX has offered a different viewpoint in evaluating the behavior of a structure. The nonlinear characteristics of NARX can identify and study the relationship between any input and output node by means of proper training to reflect the instantaneous property of the system. In order to prove the feasibility of the proposed NARX-based system, analytical results were compared with those from transfer function and an ARX-based model.

**System Identification by NARX**

The solution of how to identify precisely the characteristics of structures has always been an important issue. For that reason, new strategies based on neural networks have been studied widely. Generally, a structure system identification model can be described by the following NARX-based network.

$$y(t) = g(y(t-1),..., y(t-n_{y)}, ...x(t),...x(t-n_x)) \tag{1}$$

where $x$ and $y$ are the input and output value of the identification system, $n_x$ and $n_y$ are the maximum time delay step of $x$ and $y$, and $g$ represents a linear or nonlinear function for $y(t)$.

For a multi-input-single-output model, the output value of $y(t)$ in point $j$ can be expressed as $y^{(j)}(t)$ where the input value is described as

$$x(t) = [x^{(a)}(t) \quad x^{(b)}(t) \quad x^{(c)}(t) \quad .........]^T \tag{2}$$

In order to reflect the feature of the global system, only one hidden layer was considered in the structure of the proposed NARX system and the activation functions in the hidden and in the output layers were chosen as the hyperbolic tangent function and the linear function, respectively, in this research. The input vector of the NARX-based neural network are $y^{(j)}(t-1)$, $y^{(j)}(t-n_y)$, $x^{(a)}(t-1)$, $x^{(a)}(t-n_x)$, $x^{(b)}(t-1)$, $x^{(b)}(t-n_x)$ and the output vector is $y^{(j)}(t)$. The relationship between the input and the output can be expressed as,

$$y^{(j)}(t) = s + \sum_{l=1}^{n_h} w_l \tanh(\sum_{k=1}^{n_y}(v_{lk}^{(j)} y^{(j)}(t-k)) + \sum_{m=0}^{n_x}(u_{lm}^{(a)} x^{(a)}(t-m) + u_{lm}^{(b)} x^{(b)}(t-m) + ...) + b_l) \tag{3}$$

where $v_{lk}^{(j)}$ is the $k^{th}$ weighting between the $l^{th}$ node in the hidden layer and the input node $y^{(j)}$. $u_{lm}^{(\eta)}$ is the $m^{th}$ weighting between the $l^{th}$ node in the hidden layer and in the input node $x^{(\mu)}$ ($\mu = a \ldots b$ ....), $w_l$ is the weighting between the $l^{th}$ node of hidden layer and the output node, $n_h$ is the node number of the hidden layer, $s$ is the threshold of the output nodes, and $b_l$ is the threshold of the $l^{th}$ node in the hidden layer.

The output of point $j$ in a multi-degree-of-freedom system can be expressed as (Worden et al., 1997)

$$y^{(j)}(t) = y_1^{(j)}(t) + y_2^{(j)}(t) + y_3^{(j)}(t) + \cdots y_n^{(j)}(t) \tag{4}$$

where $y_n^{(j)}(t)$ is the $n^{th}$ order component of point $j$.

The first-order response of point $j$ is the sum of each first-order response from the input node and the relationship between $y_1^{(j)}(t)$ and the input nodes can be described as,

$$y_1^{(j)}(t) = \sum_{\eta=a,b,\cdots} \int_{-\infty}^{\infty} h_1^{(j:\eta)}(\tau_1) x^{(\eta)}(t-\tau_1) d\tau_1 \tag{5}$$

where $h_1^{(j:\eta)}(\tau_1)$ ($\eta = a \ldots b \ldots$) represents the impulse response function.

The corresponding kernel transformation are then shown as follows,

$$H_1^{(j:\eta)}(\omega_1) = \int_{-\infty}^{\infty} h_1^{(j:\eta)}(\tau_1) e^{-i\omega_1\tau_1} d\tau_1 \tag{6}$$

Similarly, the second-order response in the output point $j$ can be expressed as,

$$y_2^{(j)}(t) = \sum_{\eta_1=a,b\cdots} \sum_{\eta_2=a,b\cdots} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_2^{(j:\eta_1\eta_2)}(\tau_1,\tau_2) x^{(\eta_1)}(t-\tau_1) x^{(\eta_2)}(t-\tau_2) d\tau_1 d\tau_2 \tag{7}$$

where $h_2^{(j:\eta_1\eta_2)}(\tau_1,\tau_2)$ is called the second-order direct-kernel when $\eta_1 = \eta_2$, and $h_2^{(j:\eta_1\eta_2)}(\tau_1,\tau_2)$ is called the second-order cross-kernel transformation when $\eta_1 \neq \eta_2$.

The corresponding core transformation of the second-order direct-kernel and cross-kernel can be written as,

$$H_2^{(j:\eta_1\eta_2)}(\omega_1,\omega_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_2^{(j:\eta_1\eta_2)}(\tau_1,\tau_2) e^{-i(\omega_1\tau_1+\omega_2\tau_2)} d\tau_1 d\tau_2 \tag{8}$$

Moreover, the kernel transformation of a single-input-single-output system with a NARX weighting can be calculated by using the harmonic detection method. The response of the system can be checked by utilizing simple harmonic inputs. For example, if the input signal of points $a$ and $b$ are (Chance et al., 1998)

$$x^{(a)}(t) = e^{i\Omega t} \qquad x^{(b)}(t) = 0 \tag{9}$$

then, the response of point $j$ can then be derived as,

$$y^{(j)}(t) = H_1^{(j:a)}(\Omega) e^{i\Omega t} + H_2^{(j:aa)}(\Omega,\Omega) e^{i2\Omega t} + \cdots \tag{10}$$

The response of point $j$ under time delay of $k$ steps can also be described as,

$$y^{(j)}(t-k) = \Delta^k y^{(j)}(t) = \Delta^k H_1^{(j:a)}(\Omega) e^{i\Omega t} + \cdots = e^{-ki\Omega\Delta t} H_1^{(j:\eta)}(\Omega) e^{i\Omega t} + \cdots \tag{11}$$

where $x^{(a)}(t-k) = \Delta^k x^{(a)}(t) = \Delta^k e^{i\Omega t} = e^{-ki\Omega\Delta t} e^{i\Omega t}$.

Comparing the coefficients of $e^{i\Omega t}$ with the results from the NARX system, we will have,

$$H_1^{(j;a)}(\Omega) = \sum_{l=1}^{n_h} \omega_l \tanh^{(1)}(b_l)(\sum_{k=1}^{n_y} v_{lk}^{(j)} H_1^{(j;a)}(\Omega)\Delta^k + \sum_{m=0}^{n_x} u_{lm}^{(a)} \Delta^m) \tag{12}$$

and

$$H_1^{(j;a)}(\Omega) = \frac{\sum_{l=1}^{n_h} \omega_l \tanh^{(1)}(b_l) \sum_{m=0}^{n_x} u_{lm}^{(a)} e^{-i\Omega m \delta t}}{1 - \sum_{l=1}^{n_h} \omega_l \tanh^{(1)}(b_l) \sum_{k=1}^{n_y} v_{lk}^{(j)} e^{-i\Omega k \delta t}} \tag{13}$$

Similarly, $H_1^{(j;b)}(\Omega)$ can also be derived by assuming $x^{(a)}(t) = 0, x^{(b)}(t) = e^{i\Omega t}$ .

The kernel transformation would be an important concept for the nonlinear system. The sinusoidal input can cause a response of the same frequency but of different amplitude and phase for the linear system. However, a new frequency component may be produced by the sinusoidal input in the nonlinear system. This nonlinear behavior in a high-order frequency response function can be classified into four groups. The first one refers to the harmonic effect, which is the integer time of the input frequency. The second one is the gain compression and expansion effect. The variation of the system gain function can be described by this effect. Thirdly, the sinusoidal response of frequency $f_1$, which is the first fundamental frequency, can be modified by the second frequency $f_2$, and the phenomenon is called desensitization. The Final one is the combination of two or more than two signals in a nonlinear way to compose a new frequency component which is called intermodulation. By assessing these characteristics, the nonlinear behavior of structure can be identified easily by the proposed NARX-based method (Billings et al., 1989a&b; Billings et al., 1990).

### Practical Application—A Case Study

To demonstrate the performance of the proposed NARX-based system, a bridge in the second southern freeway in Taiwan was selected as the main subject in this research. The distribution of sensors on the bridge is shown in Fig. 1. By utilizing the data collected from major ground excitations, a NARX-based neural network system with a structure of two inputs and one output was established to evaluate the inherent characteristic of the chosen bridge. The input channel was selected as channel 14 and 21, which were the signals from the pile-caps, and the output was labeled as channel 16, which came from the response of the slab on the middle span. All the data were collected in the transverse direction perpendicular to the carriageway.

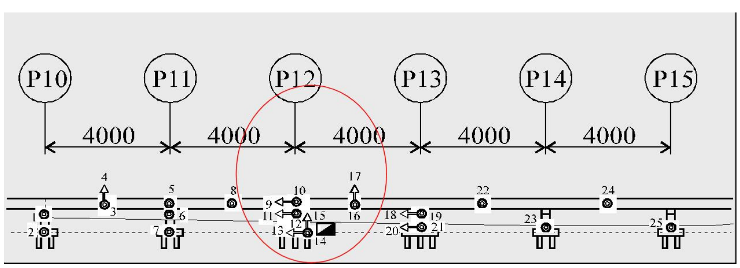


Figure 1. Distribution of sensors on the bridge.

The established NARX-based neural network has 212, 1, and 1 node/s in its input, hidden, and output layer, respectively. The variables of the input nodes are $y^{(j)}(t-1)$ , $y^{(j)}(t-70)$ , $x^{(a)}(t-1)$ , $x^{(a)}(t-70)$ , $x^{(b)}(t-1)$, $x^{(b)}(t-70)$ and of the output is $y^{(j)}(t)$. The kernel transformation and the characteristic of the structure can be obtained by the weighting method after training successfully the network.

The first-order kernel transformation of channel 14 to 16 is shown in Fig. 2 after training by the Chi-Chi earthquake time history with sampling rate of 200 Hz. The kernel transformation of channel 21 to channel 16 is shown in Fig. 3. As shown in these figures, the fundamental frequency of the structure is approximately 3.4 Hz (Fig. 2) and 3.5 Hz (Fig. 3) while the second fundamental frequency can be identified as 9.1 Hz from channel 14 and 9.3 Hz from channel 21. To evaluate the effect of multi-support input, the comparison of the two kernel transformations was coincided in Fig. 4. The result on the comparison of the transformation shows that the structure characteristic of the first-order kernel transformation was found very close when each support was chosen as the input signal under the Chi-Chi earthquake. That is, the structure may not be damaged under this major event.

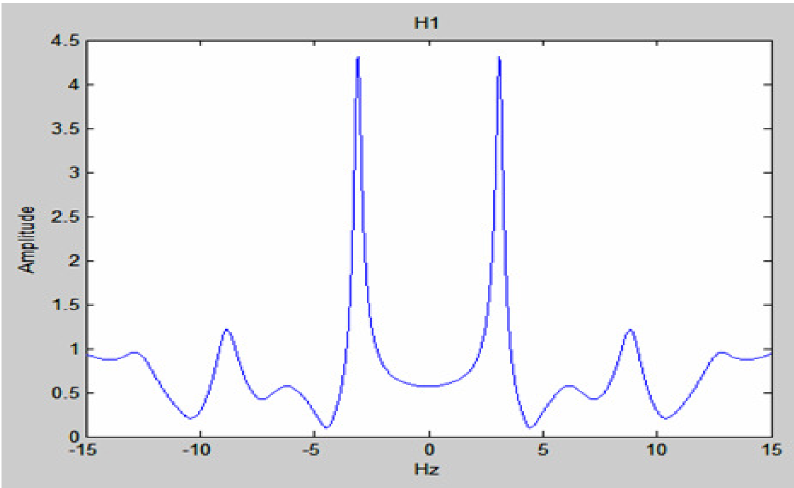


Figure 2. First-order kernel transformation of channel 14 to channel 16 under Chi-Chi earthquake.

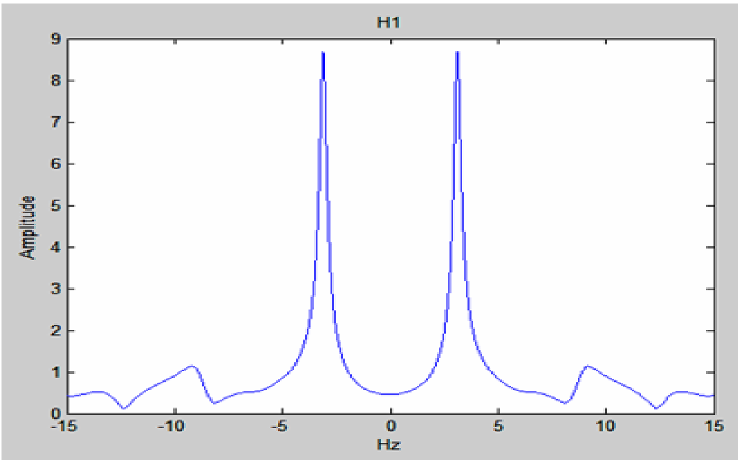


Figure 3. First-order kernel transformation of channel 21 to channel 16 under Chi-Chi earthquake.

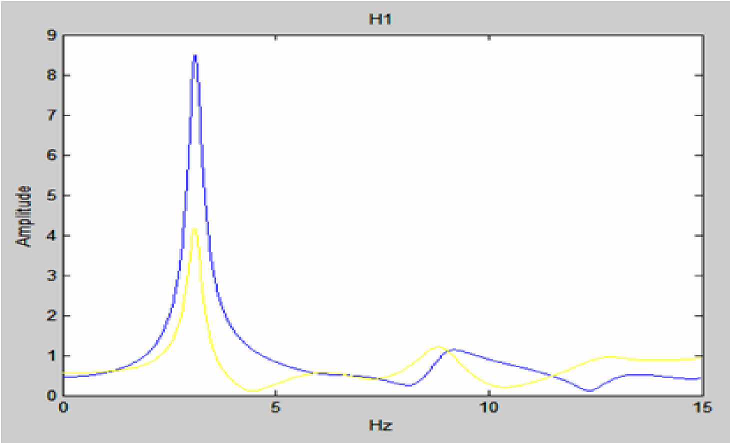


Figure 4. Comparison on the first-order transformations of channels 14 to 16 and channel 21 to 16 under Chi-chi earthquake.

The plan view and the contour of the second-order kernel transformation of channel 14 to 16 is shown in Figs. 5 and 6, and $f_1$ and $f_2$ were the frequencies imposed on the structure. As described in the previous section, the possibility of structure resonance may be probed by the combination of these frequencies. According to the figures, the interaction phenomena can be observed easily in $f_1$=3.4 Hz (21.35 rad/sec) with arbitrary $f_2$ value, in $f_2$=3.4 Hz (21.35 rad/sec) with arbitrary $f_1$ value, and in the combination $f_1$ + $f_2$ =3.4 Hz (21.35 rad/sec). The second-order response of the structure can be amplified largely under these three cases. Thus, it is expected that the bridge will be damaged by an excitation or summation of 3.4 Hz in channel 14.

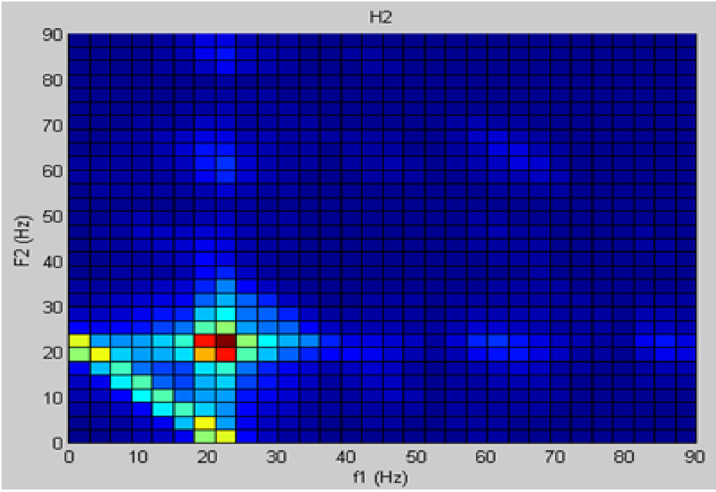


Figure 5. Second-order kernel transformation: Plan view of channel 14 to 16.

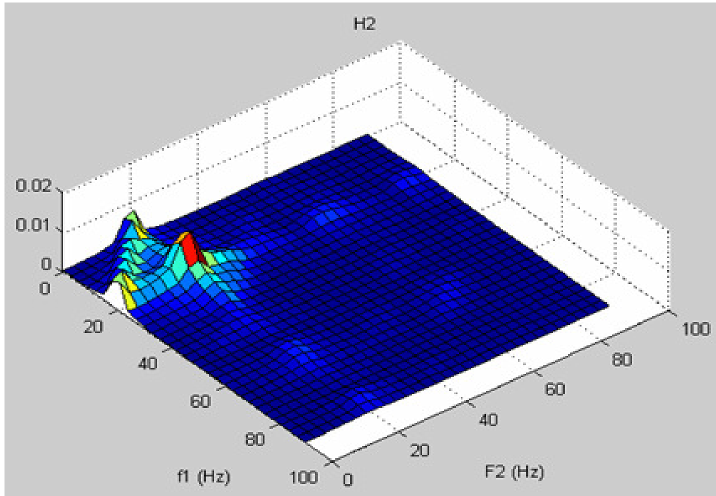


Figure 6. Second-order kernel transformation: contour view of channel 21 to 16.

The NARX-based system was also tested by another major earthquake of magnitude 6.4 (labeled as 1022 earthquake) with sampling rate of 200 Hz. The first-order kernel transformation of channel 14 to channel 16 and channel 21 to channel 16 is shown in Fig. 7. As shown in this figure, the fundamental frequency of the structure is approximately 3.7 Hz under the earthquake. Due to its smaller acceleration response than the Chi-Chi earthquake's, the identified fundamental frequency of the bridge was raised slightly as expected. No significant change of the frequency was investigated and the structure characteristic from the first-order kernel transformation was very close in comparison by choosing each support as the input signal. The structure may be assessed as undamaged under the ground excitation based from the analytical result.

The plan view and the contour of the second-order kernel transformation of channel 14 to 16 under the 1022 earthquake are shown in Figs. 8 and 9. The interaction phenomena can be observed easily in $f_1$=3.7 Hz (23.25 rad/sec), in $f_2$ =3.7 Hz (23.25 rad/sec), and in the combination $f_1 + f_2$=3.7 Hz (23.25 rad/sec). The second-order response of the structure can be amplified largely under these three cases. That is, the bridge will be resonated by an excitation or summation of 3.7 Hz in channel 14.

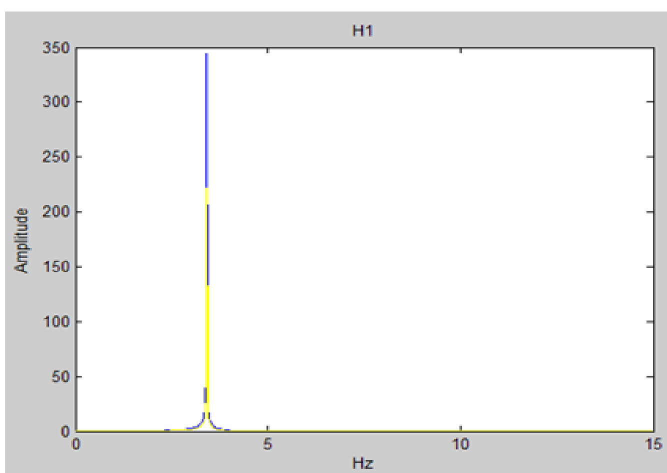


Figure 7. Comparison on the first-order transformations of channel 14 to 16 and channel 21 to 16.

In order to demonstrate the performance of the proposed NARX-based system, two different methods, including the transfer function and ARX-based model, were used and also to offer the reference value of comparison. The transfer function and ARX-based model have been developed maturely and researches have shown that these two methods can be applied easily to identify the basic property of linear structure. Therefore, results from the transfer function and ARX-based model were used here as the reference value. The evaluation consequences under two different major earthquakes are shown in Table 1. For Chi-Chi earthquake, results from these three methods were found very close and the fundamental frequency of the bridge was obtained approximately as 21.4 rad/sec. The structure can be evaluated as undamaged with its linear behavior under the Chi-Chi earthquake. Similarly, the identified frequency during 1022 earthquake was measured approximately as 22.3 rad/sec. Due to the smaller ground acceleration, the frequency has risen slightly in the 1022 earthquake.

Though similar results were obtained in the three methods under two major earthquakes, two specific characteristics can be expected by the new proposed method, namely, 1) The nonlinear behavior which can not be achieved by the traditional methods can be implemented by the new NARX-based method; and 2) Traditionally, only structure with dramatic change or damage can be detected by the transfer function or ARX-based model. With the newly proposed method, the nonlinear response of the structure can be evaluated precisely for its workability. Moreover, structures with multiple input points such as bridges were not monitored completely using conventional techniques. By the illustration of the higher-order kernel transformation, the resonant phenomenon of bridges can be illustrated successfully and be avoided during the design process.

Table 1. Fundamental frequency under different methods.

| Frequency (rad/sec) /Method | Chi-Chi earthquake | 1022 earthquake |
|---:|---:|---:|
| Transfer Function | 21.5 | 22.37 |
| ARX | 21.43 | 22.32 |
| NARX | 21.35 | 22.28 |

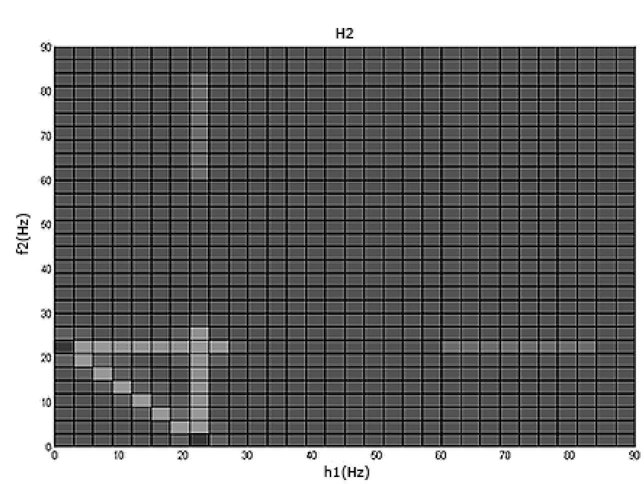


Figure 8. Second-order kernel transformation: Plan view of channel 14 to 16.

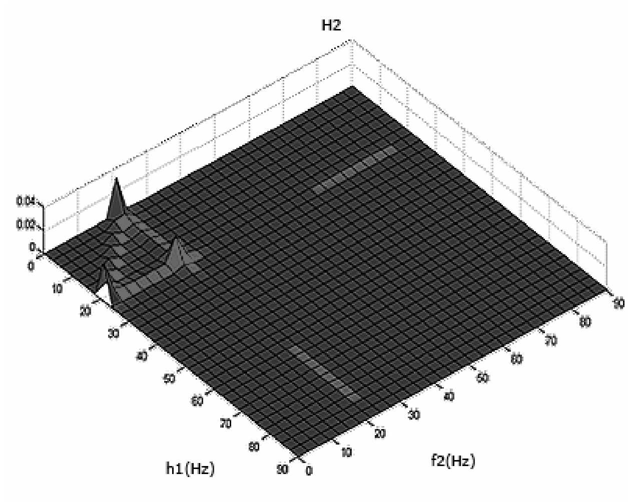


Figure 9. Second-order kernel transformation: Contour view of channel 14 to 16.

## Conclusions

This study proposed a bridge health monitoring system based on neural network technology. In order to identify the nonlinear behavior of structures, a NARX-based system was established from the data collected from major earthquakes. The relationship between the input and output channels can be reflected by the weighting of the neural network, thereby, the fundamental period of the structure can be derived. By applying this system to bridges, the multiple-support characteristic can be evaluated and the combination of specific frequencies causing resonant phenomenon can also be obtained. Results from this study would be an important basis for verifying the damage on structures.

To demonstrate the performance of the proposed system, a bridge in the second southern freeway of Taiwan was chosen. By utilizing the data collected from two major ground excitations, the NARX-based system, with a structure of two input nodes and one output node, was established to evaluate the property of the bridge. The input channels were the signals from the pile-cap and the output was the response of the slab on the middle span. Analytical results of different methods including the transfer function and ARX-based model were also compared with the proposed neural networked-based system to evaluate their efficiencies in health monitoring.

The result shows that besides identifying the fundamental frequency of a structure, the proposed neural networked-based system can also be applied successfully in bridge health monitoring after major earthquakes. The combination of specific frequencies causing resonant phenomenon was shown clearly in the kernel transformation diagrams. Therefore, the damage on structures could then be estimated. Moreover, a larger volume of information can be studied in the complex high-order kernel transformation.

The capability of the NARX-based system in dealing with the nonlinear behavior of structures would be another research focus in the future. By the proposed method, bridges with nonlinear bearing such as lead rubber bearing or visco-elastic dampers can be monitored precisely during major earthquakes. The function of these elements can be assessed, so as to prepare effectively these devices in improving the performance of bridges under earthquakes.

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