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신경망에 기초한 계측신호처리를 이용한 구조물의 손상감지

Neural Network-based Signal Processing Technique for Structural Damage Detection

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ABSTRACT

이 논문은 계측신호 분석에 의한 교량구조물의 건전성 모니터링에 관한 것으로, 2 단계 인공신경망을 사용한 구조물의 손상발견 기법에 대하여 제안하고 있다. 첫 번째 단계의 인공신경망은 구조물로부터 측정된 가속도 신호를 입력으로 사용하여 각각의 가속도계로부터 측정된 신호의 변형정도를 나타내는 신호변형지수를 출력하도록 설계되었다. 손상의 발생 여부를 나타내는 첫 번째 단계 인공신경망의 출력값은 다시 두 번째 단계 인공신경망의 입력으로 사용되어 손상의 위치와 정도를 파악하는데 쓰여진다. 모형교량을 사용한 실험으로부터 얻어진 가속도신호를 사용하여 제안된 방법의 타당성을 확인하였으며, 향후 실 교량에 대한 실험을 통하여 현장 적용의 가능성을 확인할 계획이다.

1. Introduction

Structural health monitoring requires the processes of system identification and damage assessment to be effective for the purpose of engineering management and maintenance. The vibration-based monitoring has been the major tool to assess the health state of structures and furthermore for their maintenance over the past two decades. However, there still remain many important issues to be solved for the development of the vibration-based structural health monitoring system for practical purpose. They might include: 1) the establishment of damage indices that represent comprehensive state of a structure local as well as global structural safety and reliability; 2) the development of an

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appropriate base line model that frequently inherits errors resulted from measurement and modeling; 3) an economic arrangement of measuring system considering only representative location; and 4) the development of practical identification methodologies during different stages from the undamaged to the damaged.

The main focus of this study is to develop damage identification methodology by utilizing the concept of artificial neural networks (ANN) reflecting the above issues appropriately but implicitly. Especially, hierarchical identification approach is adopted to the development of neural networks for detecting the existence, location and extent of the damage successively.

To investigate the feasibility of the proposed methodology, an experimental test has been made on a simple span three-girder bridge model with span length of 5m. For the 1st level ANN, independent ANNs of the same quantity of sensors are constructed and acceleration signals of undamaged state are used as input data for the corresponding ANN. The output values of the 1st level ANNs are the signal anomaly index for the sensors. The absolute values of the output of the 1st level ANN have been used for detect of damage existence, and the pattern of whole values have been used for the input of 2nd level ANN to identify the location and extent of the damage.

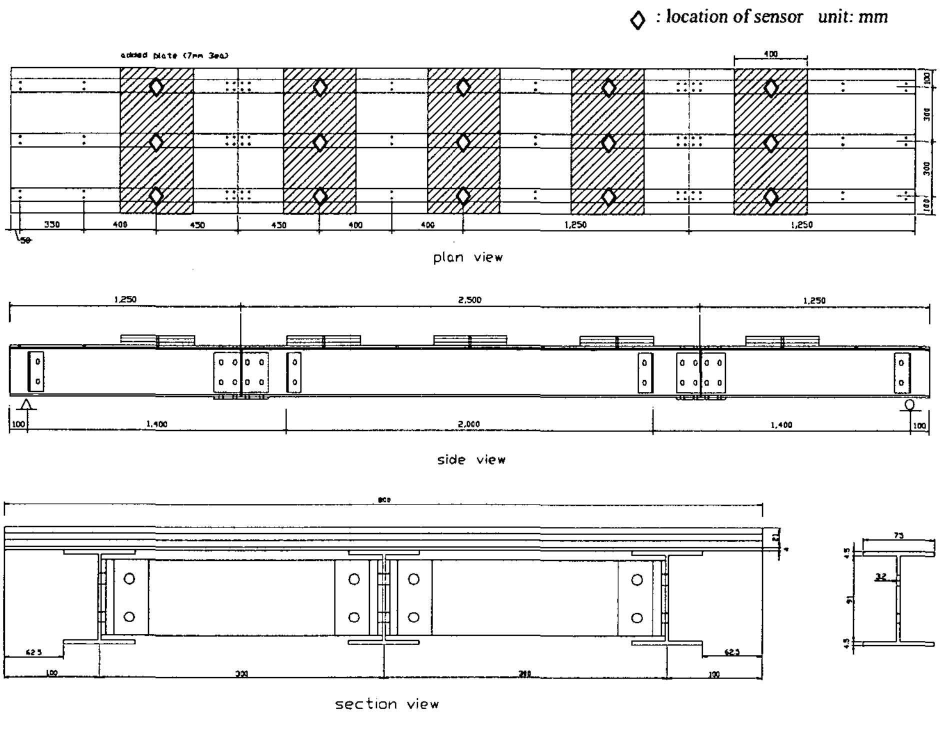

Fig. 1 Bridge Model

2. Experimental Test

For the acquisition of the acceleration signal, simple span three-girder steel bridge model has been tested. The span length of the model bridge is 5.0m, the width 0.8m, and the height of the girder 0.1m. Each girder has two bolt connections at the points of 1/4 and 3/4 of the span. This type of connection was intentionally invented to simulate the second case of damage. A general drawing of the model bridge is shown in Fig.1.

Five accelerometers were used for data acquisition and total 15 points were selected as measurement location as shown in Fig.1. Vibration was induced using impact hammer and 5 hits for each damage case was performed. The sampling rate of the signal was set to 500Hz and 2 seconds of time signal was fed into the ANNs.

This study simulated the 2 different types of damage cases: 1) the connection release at the 1/4 location of the 1st girder that involves 3 steps and 2) the center part damage of the 1st girder involves 6 steps. The damage extents are gradually increased as the steps proceed. The first damage scenario was made by releasing the bolts of the connection while the second damage by cutting the member with different extent. A series of the damage scenario is summarized in Table 1.

Table 1. Damage scenario of experimental test

	Damage extent						Location (plan view)
	1	2	3	4	5	6	
Case1	73%	32%	5%				(0.75, 1.0)
Case2	88%	71%	57%	32%	20%	14%	(0.5, 1.0)

3. The 1st Level ANN

The 1st level ANN is designed to check hardware malfunction and signal anomaly at a time. The network consists of 3 layers of an input, a hidden and an output layer. Each layer has 500, 10, and 3 nodes respectively and all layer uses tangent sigmoid transfer function. The network was trained to output zero for undamaged sensor signal, unity for no signal (connection failure), and minus unity for noise signal (hardware malfunction) as anomaly index. If the signal changes due to the damage of the structure, the anomaly index will change from zero to other value between +1 and −1.

As a pre-processor for the input data, input time signal was transformed to FFT amplitude spectrum and the transformed spectrum was fed into the input layer.

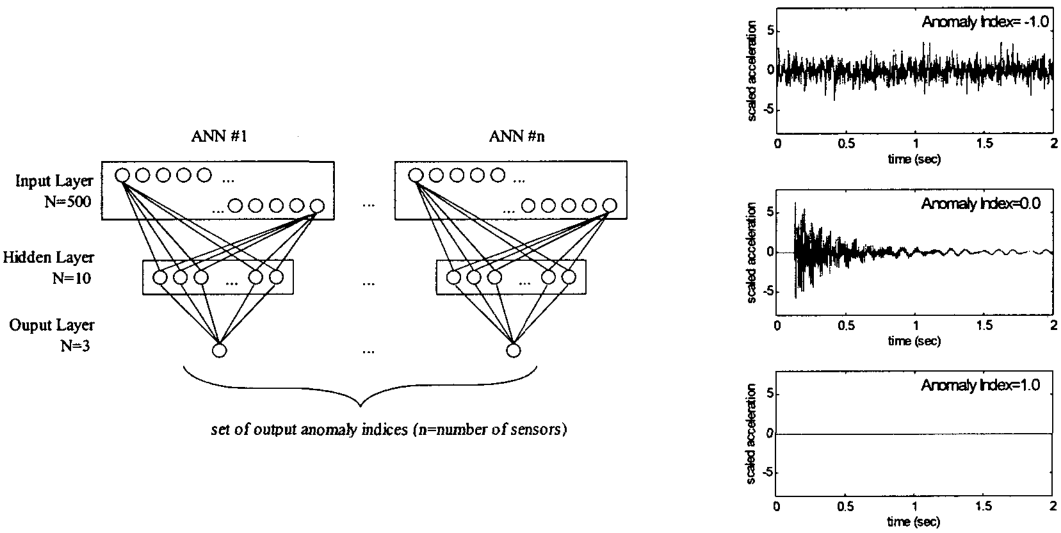

Fig.2 Architecture and Sample Input of the 1st Level ANN

Because there were 15 measurement points, ANNs of the same quantity were constructed for the individual sensor. Each network will output the anomaly index for the corresponding sensor, thus total 15 anomaly indices are obtained as a result.

The signal measured on the damaged model was tested to the 1st level ANN that was trained using the acceleration signal of undamaged model. The signals for 5 times of hammering obtained at the 15 sensors location were used as inputs and their outputs shows very similar pattern for the same damage case of model but different patterns for different cases of damage cases as shown in Fig.3. Based on the simulation results for the 1st level ANN, the outputs of the 1st level ANN are possible to be used as inputs to the 2nd level ANN that predicts the damage location and degree.

4. The 2^{nd} Level ANN

The 2^{nd} level ANN is designed to identify damage location and extent using the outputs of the 1^{st} level ANN as inputs. The structure of the 2^{nd} level ANN consisting of 4 layers in total including two hidden layers is described in Tables 2 and 3. Squashing types of function of the tansig and the logsig function are used as transfer functions. The output nodes represent damage location in the direction of longitudinal and transverse respectively and its damage extent.

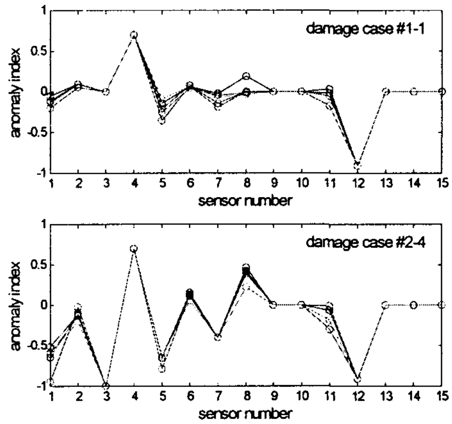

Fig.3 Output pattern of the 1^{st} Level ANN

Experimental results were used to train the 2^{nd} level ANN and verified as shown in Fig.4. The learning process was repeated in thousands of times of epoch until their results were finally converged within the error limit of 0.001 in SSE. All the three outputs were appeared to be almost identical to the corresponding target values. Therefore it was verified that the outputs of the 1^{st} Level are possible as inputs to identify the damage location and extent. To investigate the performance of the trained network under noisy signal condition, two noise cases were tested. The noisy vectors have noise of 1% and 5% respectively. Fig.5 shows the results obtained from the 2^{nd} Level ANN with 1% noise and Fig. 6 with 5% noise. Regarding the identification of the damage location, the degree of noise does not affect the results of the 2^{nd} level ANN but affect largely to the prediction of the damage extent.

Table 2. Architecture of the 2^{nd} Level ANN

	# of Nodes	Transfer Func.
Input Layer	15	
1^{st} Hidden Layer	5	Tangent Sig.
2^{nd} Hidden Layer	5	Log Sig.
Output Layer	3	Log Sig

Table 3. Output nodes of the 2^{nd} Level ANN

Node #	Meaning
1	Longitudinal Location Index
2	Transverse Location Index
3	Damage Extent Index

However, considering that the measured values of most structural responses in reality are less than 1% of signal-noise ratio, such discrepancy may not become a big trouble in practical application. Moreover, an automated health monitoring system will be done mostly in parallel with visual inspection and therefore it seems more realistic and feasible to identify the damage location using the bi-level ANN rather than damage extent and location together.

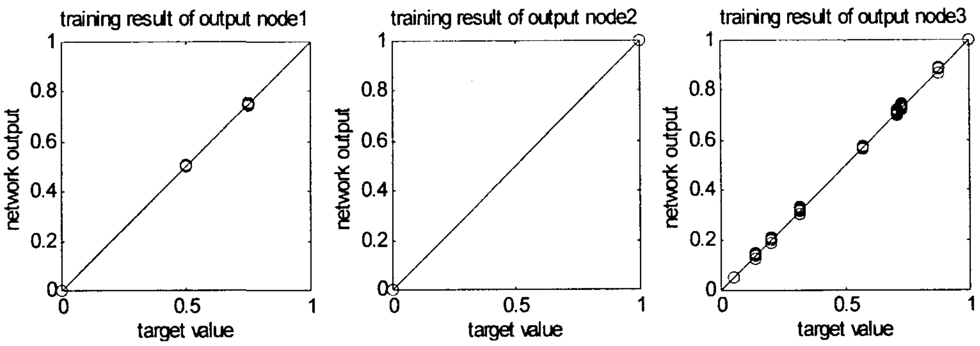

Fig.4 Training results of the 2nd Level ANN

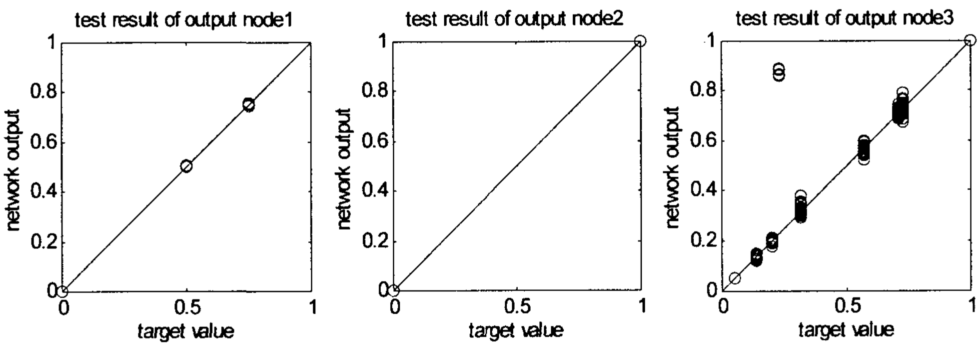

Fig.5 Test result of 2nd Level ANN (with 1% noise)

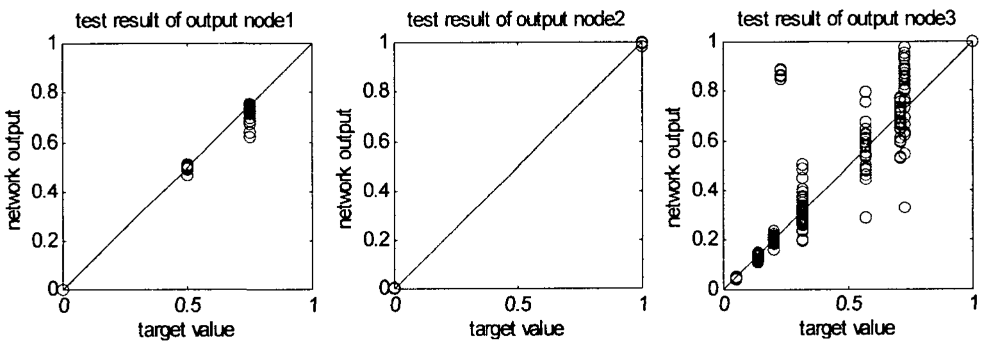

Fig.6 Test results of the 2nd Level ANN (with 5% noise)

5. Conclusions

This study has proposed the bi-level artificial neural network (ANN) for determining structural damage using the inputs of acceleration signals measured directly by the accelerometer sensors. As a first step, the first level ANN detects the damage existence of the model structure in terms of signal anomaly index ranged from -1 to $+1$ at the location of sensor installed. And then the 2nd level ANN identifies the damage location and extent using the anomaly indexes of the 1st level ANN. The bi-level ANN has been approved as a promising tool to predict the damage existence and location fairly well. This study provides an initial step toward the development of monitoring-based structural health assessment and there still remains a lot of comprehensive study needed to complete the assessment system suitable for more practical purpose.

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