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교량의 건전성 모니터링을 위한 효율적인 접근방법

Effective Approaches for Structural Health Monitoring of Bridges

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ABSTRACT

Two-step identification approach for effective bridge health monitoring is proposed to alleviate the issues associated with many unknown parameters faced in the real structures and to improve the accuracy in the estimate results. It is suitable for on-line monitoring scheme, since the damage assessment is not always needed to be carried out whereas the alarming for damages is to be continuously monitored. In the first step for screening potential damaged members, damage indicator method based on modal strain energy, probabilistic neural networks and the conventional neural networks using grouping technique are used and then the conventional neural network technique is utilized for damage assessment on the screened members in the second step. The proposed methods are verified through a field test on the northern-most span of old Hannam Grand Bridge.

1. Introduction

Bridges may get deteriorated and degraded with time in unexpected ways, which may lead to structural failures causing costly repair and/or heavy loss of human lives. Consequently, structural health monitoring has become an important research topic in conjunction with damage assessment and safety evaluation of structures. The use of system identification approaches for damage detection has been expanded in recent years.

Damage detection methods can be categorized into one of four levels as existence, location, severity, and evaluation (1). Most damage detection methods are based on optimization and parameter identification algorithms comprising one-step scheme. When these conventional methods are applied to large-scale redundant structures, ill-conditioning and non-uniqueness in the solution of inverse problems are inevitable difficulties. Moreover, it is not efficient to perform the multi-purpose damage detection in a single step in the viewpoint of on-line monitoring.

In this study, the neural network (NN) technique based on the estimated modal parameters is utilized for element-level damage detection. When the NN technique is used for damage detection, the number of unknown parameters is related to the complexity of the networks which may cause the ill-conditioning problem. A two-step identification strategy is proposed for effective monitoring of bridge structures to alleviate ill-posedness problem in the neural network-based damage detection. In the first step for screening the potential damaged members, three different methods were utilized: (1) Damage Indicator Method based on the Modal Strain Energy (DIM-MSE), (2) Probabilistic Neural Networks (PNN), and (3) Neural Networks using Grouping technique (NN-Gr). Then, in the second step for damage assessment, the conventional NN technique is utilized to assess the damage locations and severities on the screened members. The proposed methods are applied to the field tests on Hannam Grand Bridge.

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2. Two-step Approaches for Effective Bridge Health Monitoring

2.1 Damage Indicator Method Based on Modal Strain Energy (DIM-MSE)

For damage localization, DIM-MSE has been extensively adopted by constructing indices from various modal parameters. It is a kind of signal-based damage detection methods. The basic scheme is to compare the strain mode shapes (the second derivative of the mode shape) between before and after damages. As it is known, strain (or curvature) mode shape is sensitive to damage because of its local behavior, and has been utilized to locate damage sites in beams or frame structures [(2), (3)]. Li and Yam[(4)] applied the damage indicator method based on modal strain energy to detect damages in thin-plate systems, which is applied in this study.

2.2 Probabilistic Neural Networks (PNN)

PNN is basically a pattern classifier that combines the well-known Bayes decision strategy with the Parzen non-parametric estimator of the probability density functions of different classes [(5)]. PNN has been used for damage detection of bridge structures [(6), (7)]. The application of PNN to damage detection of real structures is rare, since most of researches have been based on the simulation study.

In this study, PNN is utilized to identify damage location based on the modal quantities. The class is defined according to the locations of structural members. Each class represents one of damage locations and the modal quantities of the damaged structure are training patterns belonging to that class; the modal quantities are input and the class number is output. To reduce the number of classes to be identified, some neighboring elements are grouped to the same class. Training patterns representing a certain class are randomly generated by perturbing some element(s) in that class. The identified modal parameters are used as the input to PNN. Then PNN calculates the probability of damage for each class, which indicates the similarity of the input to the training patterns in that class. In this study, the mode shape differences between before and after damage, which are found to be less-sensitive to the modeling errors [(8)], were used as the input to the PNN.

2.3 Neural Networks by Grouping Technique (NN-Gr)

Neural network technique, which is a kind of model-based damage estimation methods, can be an alternative for continuous monitoring of bridge structures. This is because, once the networks have been properly trained during the training stage, they do not need much computation time in the operation stage. When the neural network technique is used for damage detection of a bridge structure which is composed of a huge number of structural members, ill-posedness in the inverse problem is inevitable. To mitigate such problem, the grouping scheme can be effectively used. Elements with similar structural behavior or neighboring members can be regarded as one group. Using the grouping technique, the number of unknown parameters can be decreased. Consequently, the complexity of the networks is also reduced. As in the PNN, the mode shape differences between before and after damage are used as the input to the NN, since training patterns are to be generated from inaccurate FE model with modeling errors with considerable size.

2.4 Second Step for Damage Assessment

In view of continuous monitoring of bridges, quick calculation for damage localization is necessary. The accurate damage estimation including the identification of damage location and the assessment of damage severity is needed, only when damage has occurred. Therefore the second step can be carried out according to the results of the first step. Model-based damage detection methods can estimate the damage locations and severities by improving the mathematical model of the structure using experimental data, since the structural damages result in changes of the dynamic characteristics.

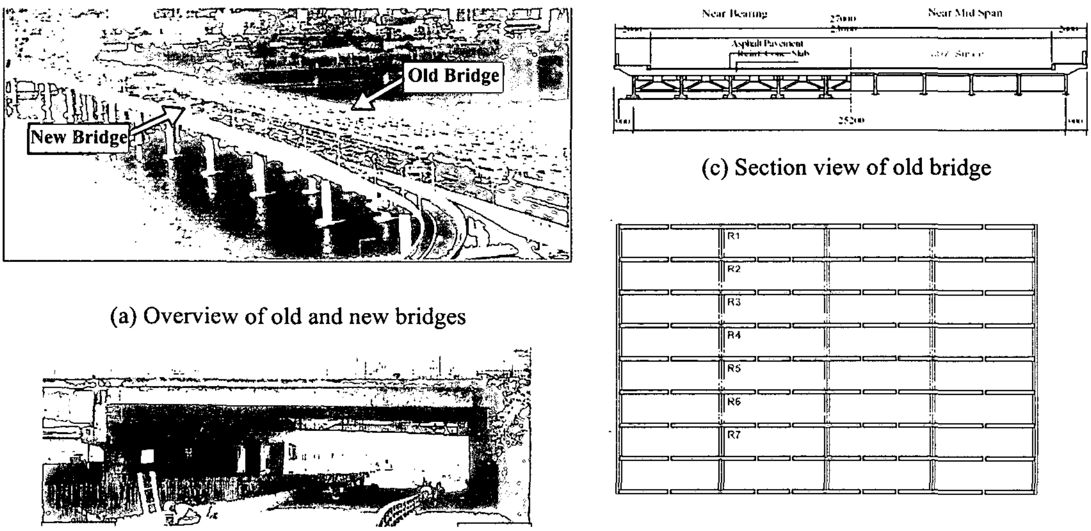
In the second step, the conventional neural networks with back propagation algorithm [(9), (10)] are used for damage assessment. Only the potential damaged members that are identified at the first step need to be considered in this networks configuration. Also, only a few modal components measured at the damage region are necessary for assessing the damage severity. The mode shape differences between before and after damage are used as the input to the neural networks.

3. FIELD TEST ON HANNAM GRAND BRIDGE

3.1 Description of Field Tests

Field tests on damage estimation were performed on the northern-most span of old Hannam Grand Bridge over Han River in Seoul, Korea (Fig. 1), which is to be replaced during bridge renovation. It is simply supported, and the length of the span is 22.7m. It consists of nine steel plate girders and a concrete slab. Originally it had ten girders, but the 10^{th} girder was removed during the construction of the new bridge next to it. Ambient vibration tests were carried out. The vibration was mainly induced by the traffic loads on the adjacent new bridge and the train loads under the test bridge. Seven sets of measurements were carried out on Girders 1 to 7 as shown in Fig. 1d. For each set, vertical accelerations were measured at 11 equally spaced points on the slab just above each girder. Reference signals to correlate each experimental set were obtained at 7 points (R1-R7).

Fig. 2 shows the inflicted damage scenarios imposed by torch cuts on the main girders of the bridge for the present damage detection study. Modal parameters for each damage state were identified using the frequency domain decomposition method [11),(12]. Table 1 shows the modal properties obtained from the initial FE model and the experiments for each damage case. Changes in the first three natural frequencies for subsequent damage cases show no significant trend related to damages. This indicates difficulty in using resonant frequencies as a damage indicator for large civil engineering structures, where the environmental effects such as temperature, humidity, etc. may not be ignored. In Table 1, the modal assurance criteria (MAC) values are also shown, which represent the closeness between the calculated and the experimental mode shapes. The first three modes gave close results to the test results: i.e. above 97% in MAC value. Therefore the first three mode shapes were used as inputs for the damage estimation.



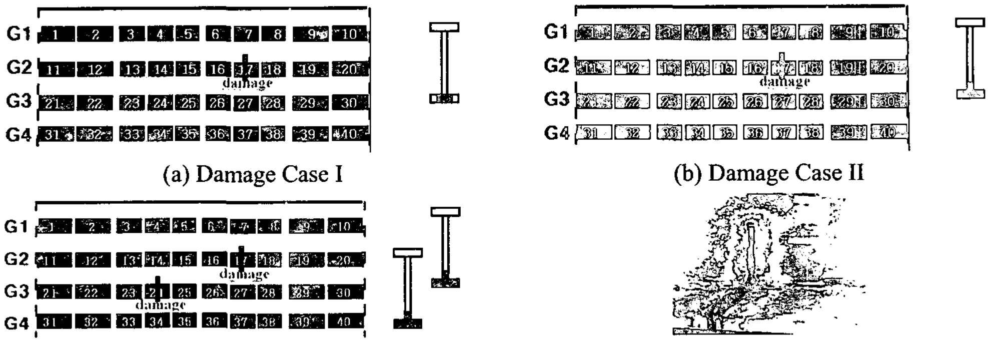
(a) Overview of old and new bridges

(b) Northern-most span of old bridge (L=22.7m)

(c) Section view of old bridge

(d) Measurement locations
(1-77 : Roving sensors, R1-R7 : Reference sensors)

Fig. 1 View of Hannam Grand Bridge in Seoul, Korea

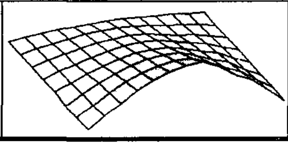
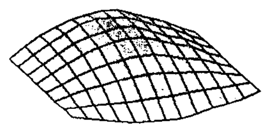
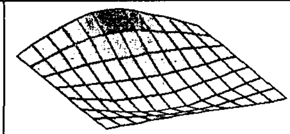


(a) Damage Case I (b) Damage Case II

(c) Damage Case III (d) Inflicted Damage by Torch

Fig. 2 Damage scenarios for Hannam Grand Bridge

Table 1 Natural frequencies and modes of Hannam Grand Bridge for various damage cases

Modes		1^{st} mode	2^{nd} mode	3^{rd} mode
Calculated (Intact)		4.071 Hz	4.452 Hz	5.626 Hz
Measured	Intact	4.247 Hz (99.79)	4.876 Hz (97.86)	5.771 Hz (99.71)
	Damage I	4.188 Hz (99.38)	4.903 Hz (99.45)	5.823 Hz (99.64)
	Damage II	4.196 Hz (99.90)	4.780 Hz (99.35)	5.778 Hz (99.57)
	Damage III	4.218 Hz (99.51)	4.757 Hz (99.56)	5.799 Hz (99.73)
Measured mode shapes (Intact case)				

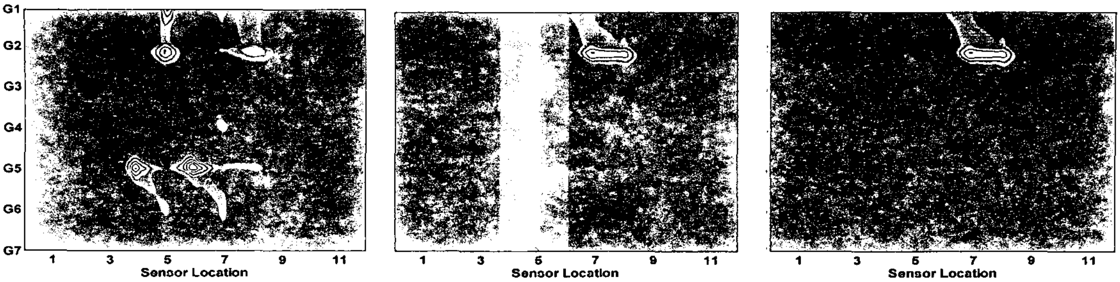
Note: Values in parentheses are the MAC values (%)

3.2 Two-Step Approach I : DIM-MSE + NN

In the first step, DIM-MSE for plate-like structures was used for screening potential damaged members of the test bridge. The first three modes for all of the intact and damaged cases, which are measured at 77 points on the slab, were interpolated into the finer mode shapes using cubic polynomial function to numerically calculate the mode shape curvatures. Fig. 3a shows the results of screening process using DIM-MSE. The damage locations were identified with good accuracy for all the damage cases, while there were some false alarms at several locations. Twenty members which showed high damage indices were considered in the second step. Also, only a few modal components measured at the damage region are necessary for assessing the damage severity. The potential damaged members considered in the second step were as follows:

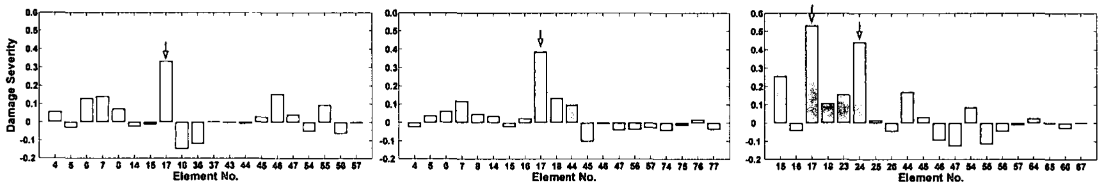
Damage Case I : Elements 4 5 6 7 9 14 15 17 18 36 37 43 44 45 46 47 54 55 56 57
Damage Case II : Elements 4 5 6 7 8 14 15 16 17 18 44 45 46 47 56 57 74 75 76 77
Damage Case III : Elements 15 16 17 18 23 24 25 26 44 45 46 47 54 55 56 57 64 65 66 67

Fig. 3b shows the results of damage assessment. The results of damage assessment showed good estimate for all the damage cases, even though there were lots of false alarms in the first step. The true damaged member(s) showed large value(s) of damage severity and the members with false alarms gave small values, since the noise injection learning algorithm was effectively used to reduce the effect of noise.



Damage Case I　　Damage Case II　　Damage Case III

(a) Results of screening using DIM-MSE



Damage Case I　　Damage Case II　　Damage Case III

(b) Results of damage assessment using NN (↓: damaged locations)

Fig. 3 Results of two-step approach I (DIM-MSE + NN)

3.3 Two-Step Approach II : PNN + NN

In the first step, probabilistic neural network technique was utilized for screening process of the test bridge. For the generation of training patterns, 28 classes were considered as shown in Fig. 4. Training patterns for a certain class consists of 100 randomly generated damage cases. For each damage case, one element among 2 or 3 elements in a class is assumed damaged. For example, if Element 18 is assumed to be damaged, the class number corresponding to such damage scenario is 7. The mode shape differences between before and after damage were used as the input to PNN and NN.

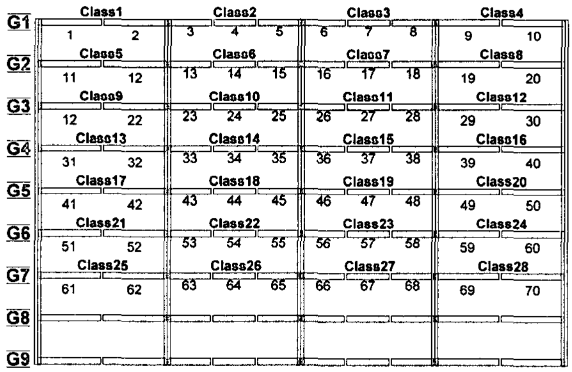
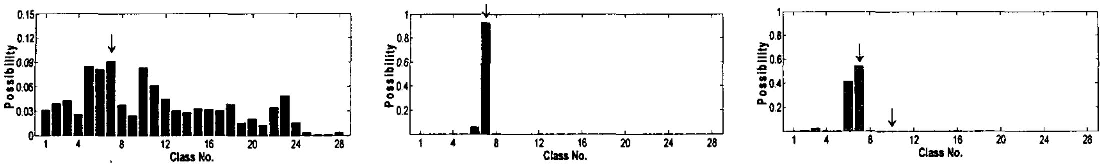


Fig. 4 Classes for PNN in Hannam Grand Bridge

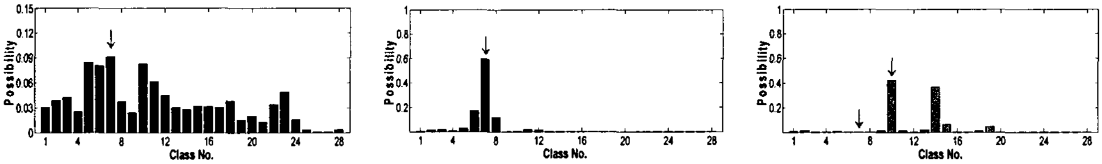
Fig. 5 shows the result for screening potential damaged members using the PNN technique. The class with actual damaged member is successfully identified for the cases with single damage (Damage Case I, II), whereas the screening process failed in Damage Case III with multiple damages. This is because the training patterns were generated for cases with single damage. To overcome this shortcoming, PNN was sequentially applied to detect the newly imposed damages. Fig. 6 shows the results of screening process using sequential identification scheme. The newly imposed damage on Girder 3 in Damage Case III was successfully identified although there was a false alarm at Class 14. From these results, it can be concluded that PNN techniques using sequential estimation scheme can be effectively used to detect multiple damage locations if we assume the damages occur sequentially not simultaneously.

Fig. 7 shows the results of damage assessment for Damage Case I. Four classes which showed high probability of damage in the first step were considered: Class 5 (Elements 11, 12), Class 6 (Elements 13, 14, 15), Class 7 (Elements 16, 17, 18) and Class 10 (Elements 23, 24, 25). Even though there were lots of false alarms in the first step, the results of damage assessment showed good estimate, since the noise injection learning algorithm was effectively used to reduce the effect of noise.



(a) Damage Case I (b) Damage Case II (c) Damage Case III

Fig. 5 Results of damage localization using PNN



(a) Damage Case I (b) Damage Case II (c) Damage Case III

Fig. 6 Results of damage localization using PNN: sequential estimation

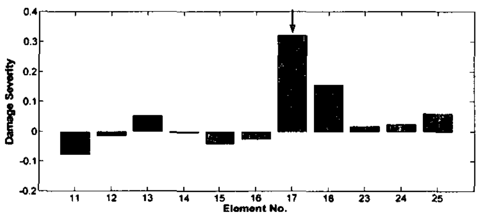


Fig. 7 Results of damage assessment using NN for Damage Case I

3.4 Two-Step Approach III : NN-Gr + NN

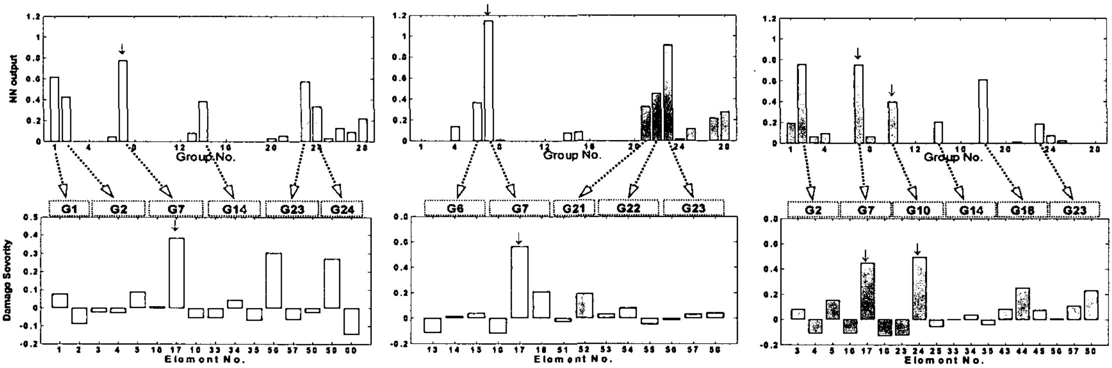
To reduce the number of unknown parameter which is related to the complexity of the neural networks, the neural networks using grouping scheme (NN-Gr) were used in the first step. 28 groups similar to the classes in Fig. 4 were considered. For the generation of training patterns, more than one group was randomly selected and one element among 2 or 3 elements in those groups was assumed to be damaged. The required output for intact case is null vector with the size of 28 which is the same number of total groups. If an element in a certain group is assumed to be damaged, a value of 1 is allocated at the position corresponding to the group in the output vector. For example, if Element 21 and Element 34 in Fig. 4 is assumed damaged, the required output should be $[0^{(1)}\ 0^{(2)}\ \ldots 0^{(8)}\ 1^{(9)}\ 0^{(10)}\ \ldots\ 0^{(13)}1^{(14)}\ 0^{(15)}\ldots 0^{(28)}]$. The number of input nodes in the networks configuration is set to 96 using the selective information scheme excluding the mode shape data near the nodal points, and the number of output node is 28 same as the number of the total groups. In the second step, the conventional NN technique was used for damage assessment. The potential damaged members considered in the second step were;

Damage Case I : Groups 1 2 7 14 23 24
Elements 1 2 3 4 5 16 17 18 33 34 35 56 57 58 59 60 (16 elements)

Damage Case II : Groups 6 7 21 22 23
Elements 13 14 15 16 17 18 51 52 53 54 55 56 57 58 (14 elements)

Damage Case III : Groups 2 7 10 14 18 23
Elements 3 4 5 16 17 18 23 24 25 33 34 35 43 44 45 56 57 58 (18 elements)

Fig. 8 shows the results of damage localization using NN-Gr and damage assessment using NN. The results of damage localization showed a lot more false alarms than the results of using PNN. This is because there are lots of local minima of the networks in the training process. The non-uniqueness of the solution due to the local minima during the parameter estimation, noise, and limited number of measurements may be resolved by employing the committee technique, which is a statistical approach averaging the damage indices (Perrone and Coper, 1993). This topic is beyond the scope of this thesis. Nevertheless, Damage Case III with multiple damages was reasonably identified, not missing the actual damaged members, when NN-Gr was utilized in the first step. In the second step, the actual damaged member(s) showed large value(s) of damage severity and the members with false alarms gave small values, since the noise injection learning algorithm was effectively used to reduce the effect of noise.



(a) Damage Case I (b) Damage Case II (c) Damage Case III

Fig. 8 Results of damage detection using NN-Gr + NN

4. Concluding Remarks

In this study, two-step identification strategy is proposed for effective monitoring of bridge structures to alleviate ill-posedness problem in the neural network-based damage detection. Three different methods were utilized for the first step: (1) Damage Indicator Method based on the Modal Strain Energy (DIM-MSE), (2) Probabilistic Neural Networks (PNN), and (3) Neural Networks using Grouping technique (NN-Gr). In the second step, the conventional neural network technique was utilized to assess damage locations and damage severities.

Two-step approach is applied to the field test on a Hannam Grand Bridge to demonstrate the effectiveness of the present methods. Three different combinations of damage localization and damage assessment methods have unique characteristics depending on the first step method utilized. The results can be summarized in Table 2. The modal strain energy-based damage indicator method has an advantage of being sensitive to damage, whereas it has a disadvantage of being sensitive to noise. To overcome the noise-sensitive feature, it is recommended to use the continuously monitored data, since the measurement data sets can be easily accumulated in the monitoring process. The effect of measurement noise can be reduced by noise injection learning algorithm in PNN and NN, but it is difficult to obtain an accurate baseline model to be used for the generation of training patterns. This problem can be overcome by using the modal quantities less sensitive to the modeling errors. It has been found that the multiple damages can be detected by using DIM-MSE or NN-Gr in the first step. To detect multiple damages using PNN, it has been suggested to use the sequential estimation scheme. Two damage locations for Damage Case III were successfully identified using the sequential estimation scheme. To make the bridge health monitoring system more applicable and reliable, it is recommended to use various damage detection methods available to avoid the damage missing errors at the first step.

Table 2 Summary of the results for two-step approach

	DIM-MSE + NN	PNN + NN	NN-Gr + NN
Advantage	sensitive to damage can detect multiple damages	can deal with noise can use various input good estimate for single damage	can deal with noise can use various input can detect multiple damages
Disadvantage	sensitive to noise accurate modes need to be evaluated	difficult to detect multiple damages	time consuming in training lots of local minima
Remedies for shortcomings	obtain strain mode shapes directly use average of many data sets	sequential estimation for multiple damages	parallel computing committee neural networks

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