Locating Structural Damages by Matching of Damage Signatures Utilising Artificial Neural Networks

LAM Heung Fai BEng(Hons) MPhil PhD MASCE
Department of Building and Construction, City University of Hong Kong
Email: paullam@cityu.edu.hk

Eric W M LEE BEng(Hons) PhD MIoP MHKIPD
Department of Building and Construction, City University of Hong Kong
Email: ericlee@cityu.edu.hk

In the recent years, the developments of measurement and data storage devices and high-speed computers are so rapidly that the use of measured vibration data in structural health monitoring is feasible from the hardware point of view. For example, Tsing Ma and Kap Shui Mun bridges in Hong Kong have been comprehensively instrumented for the purpose of vibration monitoring. However, the development of software (ie the methodology for extracting useful information from the measured raw data) has not yet been sophisticated enough for structural health monitoring to put into actual applications. This paper proposes a methodology for detecting the damage locations at an early state by matching the measured damage signature to a set of calculated damage signatures utilising artificial neural networks (ANN). Note that many model updating methods can be used to estimate the damage extents if the damage locations are identified in advance. Therefore, the most difficult task in structural health monitoring is to locate all damages. An ANN model denoted as the GRNNFA, which was particularly developed for working in noisy environment, was employed as a tool for systematically matching the patterns. The proposed methodology, which consists of the damage signature matching method and the ANN design method, were verified in this paper. The results of this study have demonstrated the superior performance of applying the GRNNFA model in handling noisy training data, and the ability of the proposed methodology in structural damage diagnosis in the present of measurement noise.

Keywords: *Structural Damage Detection, Damage Signature Matching, Artificial Neural Network, GRNNFA, Noisy Data Classification*

Introduction

A sound structural health monitoring method, which can detect the damage occurrence, location and extent, is important in the maintenance of structural system. Visual inspection is the most commonly used approach for damage detection. However, the use of visual inspection in complex civil engineering structures is time consuming and certain major incipient damages may occur in inaccessible areas or may be concealed by paint or rust. Many non-destructive evaluation (NDE) techniques, such as ultrasonic and infrared testing, are highly localised methods. Similar to visual inspection, these NDE techniques can only be used to investigate some accessible parts of the structure. Owing to the limitations of the abovementioned methods, researchers started to examine the possibility of using vibration data of a structure to assess its integrity situation in a global sense.

According to the literature, the occurrence of damage can be detected by monitoring the variation of measured modal parameters, such as natural frequencies and mode shapes. Furthermore, many model updating methods can be applied to calculate (or estimate) the damage extent if the damage locations are identified in advance. Therefore, the detection of damage locations is the most difficult task in structural health monitoring. The main objective of this paper is to propose a methodology to identify the damage locations at an early state by matching the measured damage signature [2] to a set of calculated damage signatures utilising artificial neural networks (ANN).

The idea of matching measured dynamic data in locating the damage location is not new. In 1979, Cawley & Adams [1] proved that the ratio between the measured eigenvalue perturbations due to structural damage depends only on the damage location but not the damage extent. Therefore, this ratio can be treated as a 'pattern' for the identification of damage location. Since only natural frequencies are used, the method fails to distinguish the difference among damages at symmetrical locations on the structure. In 1994, Lam [2] extended the works by Cawley & Adams [1], and proved that the ratio between the eigenvector perturbation and the eigenvalue perturbation due to structural damage is a function of damage location but not damage extend. Lam defined this ratio as a damage signature in references [2] to [4], and proposed to use it as a 'pattern' for detecting damage locations following the pattern matching approach. One of the fundamental difficulties of the pattern matching approach is the lack of a systematic way for matching the patterns. In the proposed methodology, ANN technique is employed to overcome this difficulty.

ANN was not specifically developed for the purpose of structural health monitoring, but its pattern recognising and generalisation capabilities make it very suitable to be employed as a tool for structural damage detection following the pattern matching approach. In 1992, Wu, et al [5] proposed to use Fourier spectra as 'patterns' and used ANN to detect structural damage of a 3-story shear building model. However, the result was not satisfactory, and they concluded that Fourier spectra are not suitable 'patterns' for damage detection. Two years later, Elkordy, et al [6] proposed an ANN-based damage detection method by using displacement and strain mode shapes as 'patterns'. Both numerical and experimental verifications gave very encouraging results.

Noisy data classification and regression are major research topics in the field of ANN. Different ANN models for data regression and classification have been developed, including the Multi-layer Perceptron [7] and Radial Basis Function network [8]. However, these models usually require users to define the network structure (eg number of hidden neurons or kernels) prior to network training. Alternatively, the General Regression Neural Network (GRNN) [9] recruits every training sample as a kernel in its model, and thus users do not need to predefine the network structure. Nevertheless, this approach requires extensive computational resources to hold and process the information of kernels if the batch size of training samples is large. Despite this drawback, it still owns the features of simple network structure, fast network training time, powerful regression properties, and ease of implementation.

In order to alleviate the extensive computational requirements especially for large sizes of training sets, Specht [9] proposed the clustering version of the GRNN to reduce the number of kernels. The concept is to compress the training samples into a set of representative kernels; ie similar training samples are grouped and represented by a single kernel. Different clustering approaches can be employed for this grouping process. Examples of popular clustering methods are the Kohonen Self-organising Map [10] and Fuzzy C-Mean clustering [11]. Those methods measure the similarity between samples by Euclidean distance which has been proven to be unstable since the weight vectors and category boundaries may cycle endlessly, as argued by Moore [12]. Furthermore, users of those methods normally need to pre-determine the number of classes, to which the samples are to be clustered, in order to use these clustering procedures.

In this paper, a hybrid ANN model denoted as GRNNFA [13] is introduced. It employs the Fuzzy Adaptive Resonance Theory (FA) [14] as a pre-processor of the GRNN to compress the training samples to fewer numbers of representative kernels. The FA is a powerful unsupervised classification model. The architecture of the FA was developed based on Adaptive Resonance Theory (ART) [15]. Since the FA network structure grows incrementally, it is not required to define the network complexity prior to network training. Instead of utilising Euclidean distance measurement, FA measures the similarity between samples by Fuzzy subsethood [16]. The FA network has been proven to be stable [14] in network training that solves the stability-plasticity dilemma [15]. However, the prototypes created by the FA are represented by hyper-rectangles. They cannot directly be used as kernels of the GRNN model. Thus, we propose a data compression scheme to convert the information of the prototypes to the centers, labels and widths of the kernels in the GRNN model. This compression scheme facilitates the removal of symmetrically distributed noise embedded in the training samples.

The proposed methodology presented in this paper follows the approach of multi-dimensional classification. The damage locations are identified using the GRNNFA model [13]. Damage signatures [2] are employed as the training and testing samples. In order to demonstrate the procedures of the proposed methodology, a simple numerical case study about the detection of damage locations of a 10-story shear building model is given.

Proposed Methodology

Damage Signature Matching Method

The basic idea of the pattern matching approach is to define a 'pattern' (eg, damage induced modal parameter changes) as a measure of structural damage such that different 'patterns' represent different damage scenarios. Based on computer simulation, the 'pattern' for different damage scenarios can be calculated and stored in a database. When the measured 'pattern' is available, it can be matched with the calculated 'pattern' in the database one by one. The damage scenario corresponding to the best fitted calculated 'pattern' will then be treated as the actual damage scenario.

One outstanding advantage of this approach when it is compared to other existing approaches in the literature is that no matrix condensation and modal expansion techniques are required. Those techniques are important for fitting the dimensions of the measured and theoretically calculated mode shapes. However, the huge number of possible damage scenarios makes the original pattern matching approach impractical in real applications. This is because damage scenarios with single-fault and multiple-fault of different fault extents are, in general, need to be considered. The required computational time and storage space are the problems in the implementation of the pattern matching approach. Let's take a simple structure with 10 possible fault locations as an example to illustrate the computational difficulty. If 5 levels of fault extents are to be considered (eg, 0% 10%, 20%, 30% and 40% reduction in stiffness) at each possible fault location, the total number of damage scenarios to be considered is $5^{10} = 9{,}765{,}625$. For such a simple structure, one needs to calculated and store 9,765,625 patterns in the database. In a general case with N_D possible fault locations and N_L levels of fault extents, the total number of damage scenarios to be considered is $N_L^{N_D}$. It is impractical to include all damage scenarios in real situation with over hundreds and thousands of possible fault locations.

The proposed methodology overcomes this problem by utilising the damage signature [2] as the 'pattern' in order to eliminate the effect of fault extents. Damage signature was proved to be a function of only fault location but not fault extent [2]. With the help of damage signature, the total number of damage scenarios to be considered in the previous example reduces from 9,765,625 to 1,024 ($= 2^{10}$).

Owing to the limited space in this paper, details of damage signature are not given in this paper. The interested readers are directed particularly to reference [2]. Damage signature is the ratio of the eigenvector perturbation of several selected modes to the eigenvalue perturbation of a reference mode. The modal parameters can be obtained experimentally, and the measured damage signature is defined as:

$$\hat{\Lambda} = \frac{\Delta\hat{\Phi}}{\Delta\hat{\omega}_r^2} \tag{1}$$

where $\hat{\omega}_r^2$ is the measured eigenvalue (rad/s)² of the r-th mode and r is the reference mode number; $\Delta\hat{\Phi}$ is a column vector of measured eigenvector perturbation for all selected modes:

$$\Delta\hat{\Phi} = \left\{\Delta\hat{\phi}_1^T,\ldots,\ \Delta\hat{\phi}_i^T,\ldots,\ \Delta\hat{\phi}_{N_s}^T\right\}^T \tag{2}$$

where $\hat{\phi}_i$ for i = 1,...,N_s is the measured eigenvectors of the i-th selected mode; N_s is the total number of modes to be considered in the damage detection process; the superscript T represents the transpose. It must be pointed out that $\hat{\phi}_1$ in equation (2) is not necessary the mode shape of mode 1 but the first selected mode. The selection of modes to be included in the calculation of damage signature depends on several factors [2], such as the sensitivity of a mode to the damage and the accuracy of the measured mode.

With the computer model (eg, a finite element model), the eigenvalue and eigenvector perturbations for different damage scenarios (without the consideration of different fault levels) can be calculated. The calculated damage signatures for different damage scenarios are defined as:

$$\Lambda(k) = \frac{\Delta\Phi(k)}{\Delta\omega_r^2(k)} \quad \text{for } k = 1,\ldots,K \tag{3}$$

where k is the damage scenario index; and K is the total number of damage scenarios to be considered.

The proposed methodology matches the measured damage signature in equation (1) to the K calculated damage signatures in equation (3). The damage scenario corresponding to the best fitted calculated damage signature is the damage scenario detected by the proposed methodology.

Another problem in the implementation of the pattern matching approach is the lack of a systematic and intelligent way to match the measured pattern to all the calculated patterns in the database. Traditional computers are fast in algorithmic computational tasks and precise arithmetic operations. However, they are inefficient at tasks, such as pattern matching and classification, and function approximation and optimisation [17]. The proposed methodology takes the advantage of ANN to overcome this problem.

There are many different ways to employ ANN in structural damage detection. In this paper, the ANN is trained by using the calculated damage signatures in equation (3) for all considered damage scenarios as inputs and the corresponding fault location index vectors **L** as targets, where **L** is defined as:

$$\mathbf{L} = \left\{L_1, L_2,\ldots,L_i,\ldots L_{N_d}\right\}^T \tag{4}$$

where N_d is the total number of possible fault locations to be considered, and L_i is the fault location index for the i-th possible damage location. An index of value 1 stands for a fault at the corresponding location, while 0 represents an undamaged situation.

According to the generalisation property of ANN, the trained ANN can be used to 'estimate' or 'approximate' the fault location index vector of the damaged structure corresponding to a given measured damage signature. Without the help of the damage signature, the number of damage scenarios to be considered in the training process will be increased tremendously. As a result, the time for generating the training input-target data will be unacceptably long and the training of ANN may go forever.

GRNNFA Model Development

Due to the limited pages of this paper, readers may refer to [9] and [14] for the detail formulation of the GRNN and FA models respectively. The development of the GRNNFA model is based on the clustering version of the GRNN model with multiple hyper-spherical kernels (Tomandl and Schober, 2001) as shown in equations (5) and (6). The values of $A_j(t)$ and $B_j(t)$ in equation (6) are incrementally updated each time when the output of the training sample, b, for cluster j is encountered. The clustering module compresses the available training samples to fewer numbers of kernels which significantly reduces the computational burdens of the GRNN model.

$$\hat{y}(x) = \frac{\sum_{j=1}^{n} \frac{A_j}{\sigma_j^m} \cdot \exp\left[-\frac{1}{2\sigma_j^2}(x-\mu_j)^T(x-\mu_j)\right]}{\sum_{j=1}^{n} \frac{B_j}{\sigma_j^p} \cdot \exp\left[-\frac{1}{2\sigma_j^2}(x-\mu_j)^T(x-\mu_j)\right]} \qquad (5)$$

$$\begin{cases} A_j(t) = A_j(t-1) + b \\ B_j(t) = B_j(t-1) + 1 \end{cases} \qquad (6)$$

where $x = \{x_1, \ldots x_m\}$ is the input vector; b is the output of the presented sample; $\hat{y}(x)$ is the predicted output; $\mu_j = \{\mu_{j1}, \ldots, \mu_{jm}\}$ is the center of kernel j; σ_j is the width of kernel j; m is the dimension of input domain; n is the total number of kernels.

The GRNNFA model employs the FA module to cluster the training samples. The GRNNFA architecture, as shown in Fig 1, consists of two modules. FA is employed for training whereas the GRNN is employed for prediction. The basic approach of combining the GRNN and FA models is to first cluster all training samples to fewer numbers of prototypes by FA. Then, the FA prototypes are converted into the GRNN kernels.

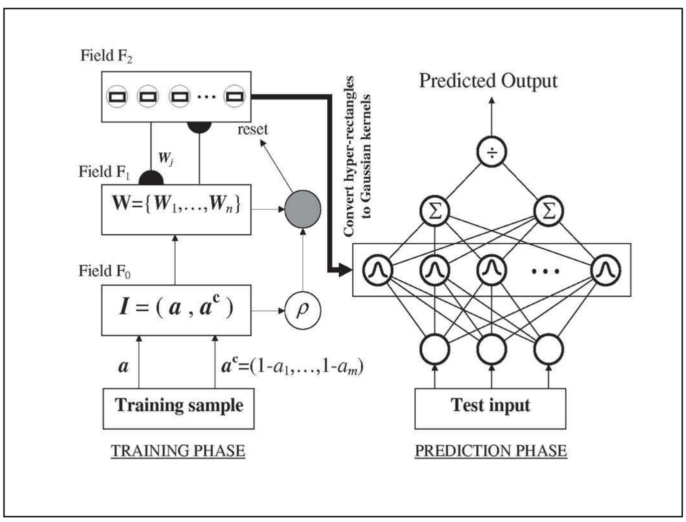


Figure 1 – Architecture of the GRNNFA Model

Since each FA prototype is originally represented by two vertices of the hyper-rectangle, a scheme to obtain the three parameters of each Gaussian kernel (ie the center, label and width) from the respective hyper-rectangle is proposed as follows.

Kernel Center Estimation

The FA is applied to establish prototypes in the input domain according to the distribution of input samples. However, the prototypes created by the FA cannot be used directly as the GRNN kernels since these prototypes, in accordance with the FA learning algorithm, only represent the vertices of hyper-rectangles. As a result, the method proposed in reference [18] for estimating kernel centers of the prototypes created by Fuzzy ARTMAP (FAM) is adopted in GRNNFA. The kernel center x_j of cluster J is determined by equation (7) where a_{Ji} ($i = 1,2,\ldots,N_J$) comprise all N_J samples belonging to J.

$$x_J = \frac{\sum_{i=1}^{N_J} a_{Ji}}{N_J} \qquad (7)$$

Kernel Label Estimation

A statistical regression model can be developed by taking the expected value over kernels as shown in equation (8) where $\hat{y}$, ξ_j, and $P(\theta_j|x)$ are, respectively, the predicted output, the label of the kernel θ_j and the probability of kernel θ_j given the input vector x.

$$\hat{y} = E(y|x) = \sum_{j=1}^{n} \xi_j \cdot P(\theta_j|x) \qquad (8)$$

By applying Bayesian theory to equation (8), the regression model as shown in equation (9) can be obtained.

$$\hat{y} = \frac{\sum_{j=1}^{n} \frac{N_j \xi_j}{\sigma_j^m} \exp\left[-\frac{1}{2}\sum_{p=1}^{m}\left(\frac{x_p-\mu_{jp}}{\sigma_j}\right)^2\right]}{\sum_{j=1}^{n} \frac{N_j}{\sigma_j^m} \exp\left[-\frac{1}{2}\sum_{p=1}^{m}\left(\frac{x_p-\mu_{jp}}{\sigma_j}\right)^2\right]} \qquad (9)$$

The format of equation (9) is similar to the GRNN model. It can be observed that N_j in the denominator of equation (9) (ie the total number of samples of kernel θ_j) is exactly equal to the value of B_j in equation (5) by definition. In order to achieve a statistically justified prediction model, it is proposed to equate $N_j\xi_j$ in equation (9) and A_j in equation (5).

$$\xi_j = \frac{A_j}{N_j} \qquad (10)$$

According to equation (10), the centroid of the outputs vectors of the clustered input samples should be taken as the label of kernel θ_j.

This compression scheme also facilitates the removal of symmetrically distributed noise embedded in the training samples. Let $\Psi_j \in \Re^m$ be a subspace of the input domain covering the prototype j created by the FA to which the samples $\{a_{ji}, a_{j2}, \ldots, a_{jN_j}\} \in \Psi_j$ are clustered where N_j is the total number of samples clustered to the prototype j. In the meantime, let $b = f(a)$ and $\tilde{b}$ be respectively the underlying scalar function and the noise corrupted output corresponding to the input a_{jk} where ($k = 1,2,\ldots,N_j$). The corrupted output can be separated into clean and noisy components as shown in equation (11) where the variable ε is the symmetrically distributed noise with zero mean:

$$\tilde{b}_{jk} = f(a_{jk}) + \varepsilon(a_{jk}) \quad \forall a_{jk} \in \Psi_j \qquad (11)$$

By integrating equation (11) over the subspace Ψ_j, the noise content is removed giving equation (12).

$$\int_{\Psi_j} \tilde{b}\, dx = \int_{\Psi_j} b dx \quad (12)$$

Equation (12) can be discretised and formulated into equation (13).

$$\sum_{k=1}^{N_j} \tilde{b}_{jk} = \sum_{k=1}^{N_j} b_{jk} \quad (13)$$

The centroids of the clean outputs and the corrupted outputs can be obtained from dividing equation (13) by N_j as shown in equation (14).

$$\xi_j = \frac{\sum_{k=1}^{N_j} b_{jk}}{N_j} = \frac{\sum_{k=1}^{N_j} \tilde{b}_{jk}}{N_j} \quad (14)$$

Equation (14) implies that the centroid of the clean outputs over Ψ_j can be obtained by projecting the centroid of the noise corrupted outputs in Ψ_j to the output domain. This determination of clean information from the available noise corrupted information demonstrates the noise removal.

Kernel Width Estimation

Multiple hyper-spherical kernels similar to that in reference [19] are adopted in the development of the GRNNFA model. Every kernel has its own radii of spread. Hence, the total number of kernel widths to be determined equals to the total number of kernels. Traditional error gradient driven approaches becomes inefficient in determination of large set of parameters. Here, K-nearest-neighbours (kNN) approach is proposed to evaluate the widths of the multiple hyper-spherical kernels by determination of a single parameter. Each kernel width is determined according to equation (15) which is similar to the scheme proposed by [18] but with the number of the nearest neighbours varied.

$$\sigma_j = \frac{1}{2\kappa} \sum_{k=1}^{\kappa} \| x_j - x_k \| \qquad j \neq k \qquad 1 \leq \kappa \leq N-1 \quad (15)$$

The width of kernel j is set to be half of the average distance over κ numbers of the nearest neighbors to kernel j. By using appropriate value of κ and the vigilance parameter of the FA model, a network structure with close minimum validation error can be achieved. The concept of this approach is similar to the smoothing parameter of the original GRNN model. The probability density surface created by the Parzen Density Estimator [20] can be smoothened by the increase in the value of κ. By suitably adjusting the value of κ, the close optimum set of the kernel widths can be obtained.

Numerical Case Study

Example Configuration

A 10-story building model shown in Fig 2 was employed to illustrate the proposed methodology. The behavior of the 'real' structure is simulated by making the following choices of parameters for the shear building model. The values of the interstory stiffness of the first to the tenth stories are 991, 1036, 971, 1109, 993, 1006, 1053, 1003, 995, and 958 N/m, respectively. In generating the set of data for ANN training, a different model with k_i = 1000 N/m for i = 1,...,10, is employed. Such parameterisation introduces model error making this example more realistic. The lumped mass at the i-th story is m_i = 1 kg for i = 1,...,10, for both models. The calculated damage signatures for different damage scenarios are obtained by solving the eigenvalue problem of the shear building model. The measured damage signature is obtained by modal identification of the simulated time-domain responses, which were obtained by assumption the building is subjected to a ground motion. The input ground acceleration history was taken to be the North-South component of the 1940 El Centro earthquake record. The measured output data were taken to be the acceleration time histories at each floor $\ddot{x}_i(t)$ for i = 1,...,10. In order to simulate the effect of measurement

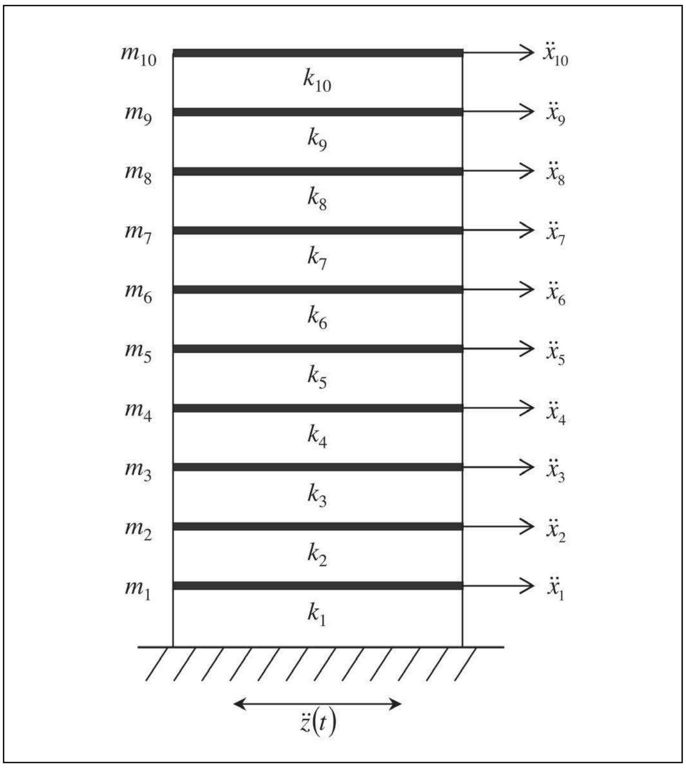


Figure 2 – Structural Model for Demonstration

noise and modeling error, white noise with magnitude up to 20% of the root-mean-square (RMS) of the dynamic responses is added to the calculated responses of the 'real' structure. In computing the response, the system is assumed to be classically damped and the damping ratios for all modes were taken to be equal to 1% of the critical damping (ie ξ = 0.01). With the simulated acceleration at all floors and the measured ground acceleration, the transfer function for the response at each floor can be calculated. The measured natural frequencies and mode shapes can then be obtained by considering the amplitude, phase angle and coherence at different peaks of the transfer functions. In this study, only one mode is considered in constructing the damage signature. Furthermore, two cases are considered in this study. In the first case, 10 sensors are employed to monitor the vibration of all floors. In the second case, the sensors at the third and seventh floors are removed to test the performance of the proposed methodology under the situation of 'incomplete' mode shape.

GRNNFA Model Training

The performances of the GRNNFA model in structural damage detection were evaluated. The samples were represented by a pair of ANN input and output vectors. The i-th component of the output vectors indicates the occurrence of structural damage at the i-th story by the value of '0' and '1' which respectively represents the non-occurrence and occurrence of structural damage. The input vector is the damage signature.

The samples for network training were created by computer simulation. In order to consider the effect of modeling error, Gaussian noise N(0, ε) is introduced into the input components of the training and validation samples. Different values of (ie 5%, 10%, 15% and 20% of the full range) were introduced into the training and validation samples to observe the performance of the GRNNFA model in noise reduction. Since there are 10 possible damage locations at one of the 10 stories, the total number of samples is 1023 (the undamaged case is not considered). Among those samples, 767, 128 and 128 samples were randomly extracted for network training, validation, and testing, respectively. The GRNNFA model was trained by the training samples with the validation samples employed for fast-stop training. The performance of the trained ANN was evaluated by the unseen clean testing samples. The randomisation procedures in samples extractions for network training, validation and

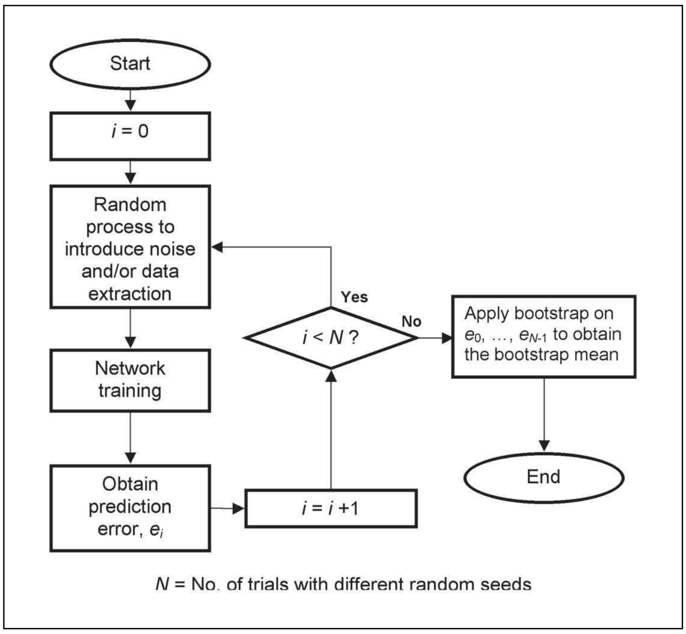


Figure 3 – Algorithm of the Bootstrapping Approach. It Facilitates the Mitigation of the Randomisation Effects to the Performance Evaluation of the GRNNFA Model

testing were involved in the generation of noise-corrupted data and extraction of samples for network training and testing. However, there exists a chance that one may luckily draw the 'best' training samples from the available samples. The ANN model being trained by these 'best' samples may be able to describe the system behaviour accurately and results a good performance of the ANN model. Hence, the performance evaluation based only on one set of random sampling was considered unfair. In order to mitigate this randomisation effect, bootstrapping [21] technique was employed to quantify the performance indicators statistically. Bootstrapping is an approach for estimating the statistical variations of a parameter in situations where the underlying sampling distribution of the parameter is unknown or difficult to estimate. It has been proven useful to compute the population parameters statistically in problems with small data samples. Fig 3 shows the procedures used to mitigate the effect of randomisation in this study. Instead of a single run, several experiments were conducted and bootstrapping was applied to obtain the bootstrapped mean of the prediction errors. The principle of bootstrapping for computing mean of a set of data samples is as follows.

a. A set of data $X = x_1,\dots,x_n$ is collected. Suppose that n is the size of the sample observed from a completely unspecified probability distribution F, $\hat{\mu}$ is the mean of all the values in X, and N is the number of repeated times of bootstrapping.

b. Draw a random sample of n data points independently, with replacement, from X. The new set of data X* is the bootstrap sample.

c. The bootstrap sample mean of X*, $\hat{\mu}^*$, is calculated.

d. Steps b. and c. are repeated N times to obtain bootstrap estimates of $\hat{\mu}_1^*,\dots,\hat{\mu}_N^*$.

Also, the above performance evaluation procedure was conducted not only for the cases with full components of the input vectors (ie 10 numbers of input components). The performance of the ANN model with 8 numbers of components (ie 2 numbers of missing input components) was also tested.

Results and Discussions

The simulation results are summarised in Table 1, which shows the bootstrap mean and its 95% confidence limits of the number of samples for different number of correctly predicted locations under different noise strengths. For easy illustration, the prediction results are plotted in Fig 4. Each bin height indicates the bootstrap mean of the number of samples with the corresponding number of locations at which the structural health state (ie damaged or undamaged) are correctly predicted. All samples can be predicted with at least 6 numbers of correctly predicted locations. Furthermore, the figure shows that over 50% of the samples own at least 9 numbers of correctly predicted locations.

No of Correctly Predicted Locations	Noise Strength			
	5%	10%	15%	20%
0	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
1	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
2	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
3	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
4	0.10 (0.00, 0.25)	0.05 (0.00, 0.15)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
5	0.10 (0.00, 0.25)	0.05 (0.00, 0.15)	0.20 (0.05, 0.40)	0.7 (0.35, 1.05)
6	0.30 (0.10, 0.50)	0.65 (0.30, 1.00)	1.80 (1.15, 2.45)	3.90 (3.05, 4.85)
7	5.55 (4.40,6.75)	5.19 (4.35, 6.05)	8.04 (7.25, 8.75)	14.58 (12.80, 16.45)
8	43.26 (41.90, 44.65)	35.66 (33.75, 37.55)	35.11 (32.85, 37.25)	39.99 (37.95, 41.95)
9	66.87 (65.10, 68.60)	75.03 (73.00, 77.10)	72.21 (70.05, 74.25)	59.81 (57.25, 62.25)
10	11.86 (10.50, 13.20)	11.37 (10.20, 12.60)	10.65 (9.75, 11.55)	9.01 (7.80, 10.30)

Table 1 – Bootstrapped Results of Correct Predictions under Different Noise Strengths (Bracketed Figures are the Lower and Upper Limits of the 95% Confidence Interval)

Let's consider a special situation when the actual damage is at, say, the second story and the prediction of the GRNNFA model indicates both of the second and third stories are damaged. Although the prediction at the third story is not correct, this result is on the safe side, and it is acceptable from the structural safety point of view. The wrong predictions, at which

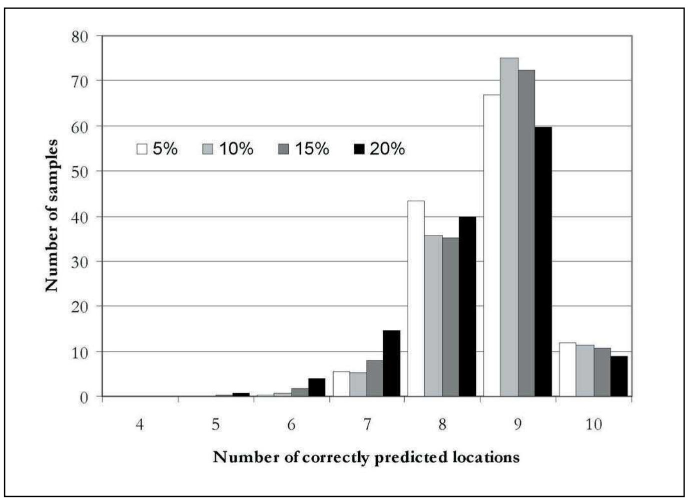


Figure 4 – Bootstrap Mean of Number of Samples with Different Numbers of 'Correctly' Predicted Locations

some of the identified undamaged locations are, in fact, damaged, are dangerous. Here we define the so-called 'safe' predictions as all the correct predictions together with the wrong predictions, at which all the identified undamaged locations are correct.

The predicted results were manipulated from 'correct' prediction to 'safe' prediction. Bootstrapping was applied to the 'safe' predictions and the results are shown in Table 2. The histogram in Fig 5 shows that the results of 'safe' predictions are better than that of 'correct' predictions. It is due to the fact that some of the incorrect predicted samples are classified as 'safe' in definition. In 'safe' predictions, Fig 5 shows that all samples can achieve 6 'safely' predicted locations. Over 82% of the samples were 'safely' predicted with at least 9 locations.

The results were further analysed by the evaluations of the expected number of 'correctly' or 'safely' predicted locations under different noise strengths. Assuming, under noise strength ϕ, the number of samples with k numbers of 'correctly' predicted locations be N_k^ϕ where k = 0,1,...,10. The expected number of 'correctly' predicted locations E_ϕ can be evaluated by equation (16).

$$E_\phi = \frac{\sum_{k=1}^{10} kN_k^\phi}{\sum_{k=1}^{10} N_k} \qquad (16)$$

The expected numbers of 'correctly' and 'safely' predicted locations were evaluated and summarised in Fig 6. It shows the bars with upper and lower limits of the 95% confidence limits of the bootstrap means in the cases of 'correct' and 'safe' predictions. In both cases (ie 'correct' and 'safe' predictions), the cases with 10% noise strength own the highest number of correct/safe predicted locations. Furthermore, the 95% confidence intervals of 5% and 15% noise strengths are overlapped. This implies that the number of 'correctly' predicted locations for 5% and 15% noise strengths are comparable. The number of correctly/ safely predicted locations with 20% noise strength is the lowest. This is because the noise strength is too high for the GRNNFA model to capture the genuine behavior of the system. In fact, 20% noise strength is higher than most of the errors in normal practice.

The analysis was repeated with only 8 sensors (sensors at the third and seventh floors were removed) installed on the building. The results of the cases with 2 missing input components are shown in Fig 7 and 8 showing, respectively, the correctly and safely predicted results. Fig 7 shows that, with only 8 numbers of input components, over 50% of the samples own at least 8 numbers of correctly predicted locations. It was considered not as high as the case with 10 numbers of input components (ie over 50% of the samples own at least 9 numbers of correctly prediction locations). However, the result was still encouraging since it was obtained from the samples with 2 missing components of the input vector. Fig 8 shows that over 80% of the samples own at least 8 numbers of correctly prediction locations. Again, the performance was not as high as that of the cases without missing components but still considered encouraging from the practical engineering point of view.

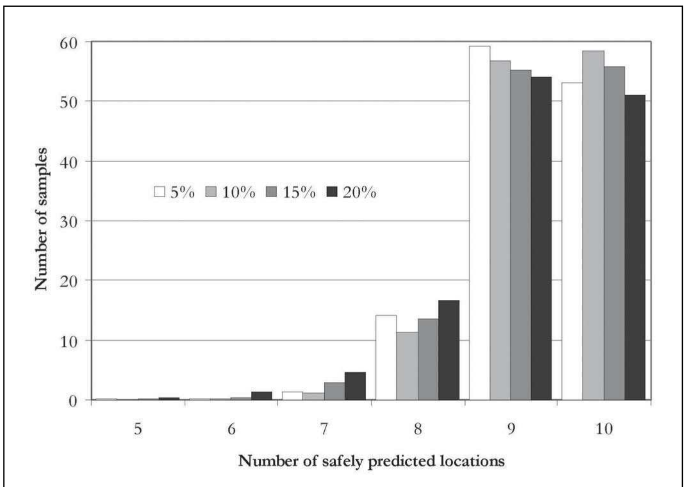


Figure 5 – Bootstrap Mean of Number of Samples with Different Numbers of 'Safely' Predicted Locations

No of Safely Predicted Locations	Noise Strength			
	5%	10%	15%	20%
0	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
1	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
2	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
3	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
4	0.10 (0.00, 0.25)	0.05 (0.00, 0.15)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
5	0.10 (0.00, 0.25)	0.05 (0.00, 0.15)	0.20 (0.05, 0.40)	0.30 (0.10, 0.50)
6	0.10 (0.00, 0.25)	0.10 (0.00, 0.15)	0.35 (0.15, 0.55)	1.35 (0.90, 1.80)
7	1.25 (0.80, 1.70)	1.20 (0.70, 1.75)	2.85 (2.15, 3.60)	4.66 (3.70, 5.75)
8	14.19 (12.60, 15.80)	11.30 (9.80, 12.85)	13.54 (12.10, 15.10)	16.61 (14.55, 18.60)
9	59.17 (56.50, 61.75)	56.84 (54.70, 59.00)	55.23 (52.95, 57.55)	54.02 (51.25, 56.95)
10	53.08 (50.25, 55.80)	58.46 (55.55, 61.30)	55.77 (54.05, 57.45)	51.10 (48.35, 53.70)

Table 2 – Bootstrapped Results of Safe Predictions under Different Noise Strengths (Bracketed Figures are the Lower and Upper Limits of the 95% Confidence Interval)

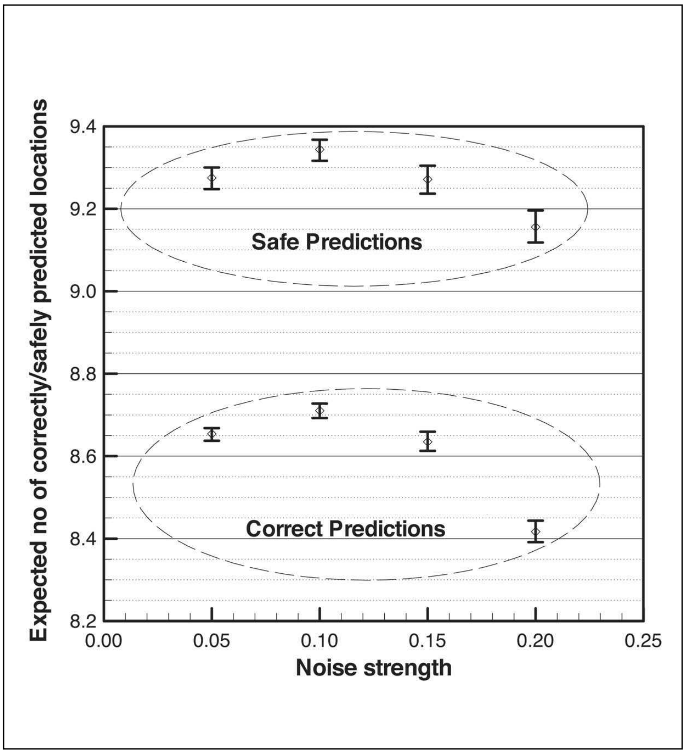


Figure 6 – Expected Number of Correctly/Safely Predicted Locations

No of Correctly Predicted Locations	Noise Strength			
	5%	10%	15%	20%
0	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
1	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
2	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
3	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.16 (0.05, 0.31)
4	0.10 (0.00, 0.25)	0.00 (0.00, 0.00)	0.26 (0.10, 0.44)	0.70 (0.47, 0.96)
5	0.31 (0.13, 0.55)	0.57 (0.36, 0.78)	1.64 (1.30, 1.98)	3.62 (3.07, 4.17)
6	1.15 (0.86, 1.46)	2.45 (1.88, 3.02)	5.65 (4.87, 6.43)	11.90 (11.09, 12.73)
7	14.80 (13.78, 15.86)	13.41 (12.58, 14.24)	18.58 (17.34, 19.82)	22.52 (21.20, 23.83)
8	18.11 (16.74, 19.45)	24.22 (22.94, 25.52)	30.90 (29.69, 32.14)	30.84 (29.71, 31.93)
9	62.81 (61.41, 64.24)	56.33 (54.92, 57.73)	40.40 (38.98, 41.82)	27.95 (26.67, 29.27)
10	2.84 (2.40, 3.31)	3.02 (2.50, 3.57)	2.58 (2.14, 3.05)	2.32 (1.77, 2.89)

Table 3 – Bootstrapped Results of Correct Predictions under Different Noise Strengths with 8 Numbers of Input Components (Bracketed Figures are the Lower and Upper Limits of the 95% Confidence Interval)

No of Safely Predicted Locations	Noise Strength			
	5%	10%	15%	20%
0	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
1	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
2	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
3	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
4	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)	0.05 (0.00, 0.13)
5	0.00 (0.00, 0.00)	0.05 (0.00, 0.13)	0.13 (0.03, 0.26)	0.47 (0.26, 0.70)
6	0.10 (0.03, 0.21)	0.13 (0.03, 0.23)	0.76 (0.49, 1.04)	2.34 (1.80, 2.92)
7	0.34 (0.18, 0.52)	1.09 (0.78, 1.43)	3.43 (2.73, 4.14)	7.23 (6.51, 7.94)
8	10.71 (9.84, 11.54)	11.99 (10.91, 13.07)	17.06 (15.91, 18.18)	21.09 (19.77, 22.42)
9	51.83 (50.16, 53.44)	52.16 (50.73, 53.70)	47.50 (46.07, 49.04)	42.55 (40.73, 44.38)
10	37.03 (35.42, 37.75)	34.59 (33.05, 36.15)	31.12 (29.64, 32.58)	26.24 (24.48, 28.05)

Table 4 – Bootstrapped Results of Safe Predictions under Different Noise Strengths with 8 Input Components (Bracketed Figures are the Lower and Upper Limits of the 95% Confidence Interval)

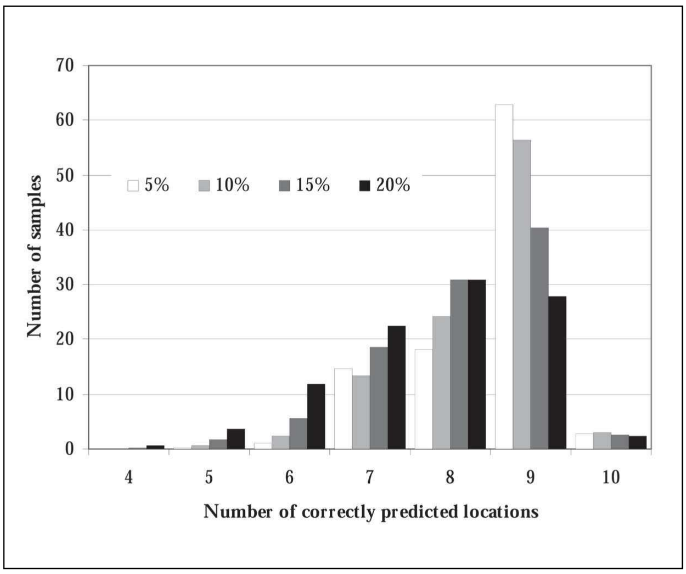


Figure 7 – Bootstrap Mean of Number of Samples with Different Numbers of 'Correctly' Predicted Locations (8 Numbers of Input Components)

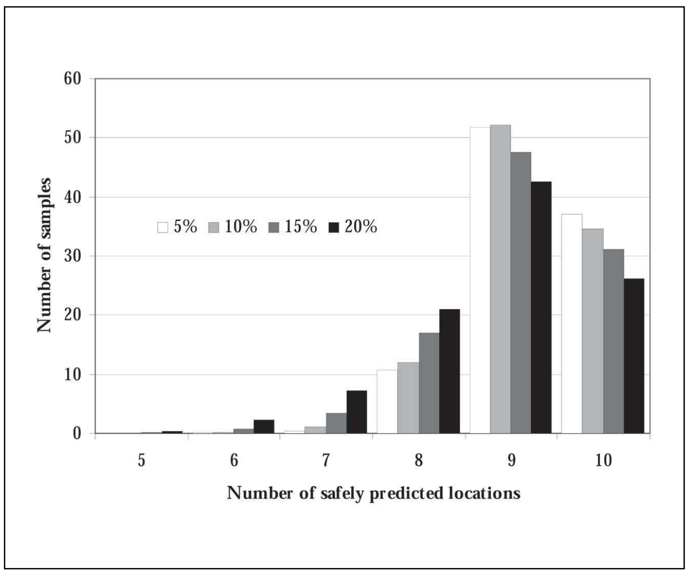


Figure 8 – Bootstrap Mean of Number of Samples with Different Numbers of 'Safely' Predicted Locations (8 Numbers of Input Components)

Conclusions

Structural health monitoring using ANN has attracted much attention in the last decade. However, only very little publications in the area of ANN-based SHM address the problem of ANN design. The lack of a practical ANN design method is one of the main reasons for the delay in the applications of ANN in the structural damage detection industry. There are two main objectives in this paper. The first one is to develop a practical and rational ANN design method, while the second one is the application of the developed ANN design method in matching the measured and calculated damage signatures and so as to identify the damage locations on the target structure.

The GRNNFA model was developed for noisy data regression. It has been proven to be effective in the tasks of regression and classification in noisy environment. The 'safe' prediction concept was employed to evaluate the practical performances of the GRNNFA model in structural health monitoring through the numerical case study. The analysis results show that the prediction results with different noise strengths were quite close to each other. This result is very important since it implies that the GRNNFA model is not sensitive to input noise and the robustness of the proposed methodology.

By taking advantages from the damage signature matching method and the ANN design method using GRNNFA model, the proposed methodology solves many difficulties of the original pattern matching approach. The numerical case study demonstrates the ability of the proposed methodology in locating damages not only in single-fault scenarios but also multi-fault scenarios.

The numerical case study also shows that the ANN, which is trained by a sub-set of the complete set of training data, can still locate the damages to an acceptable accuracy. The authors are now studying the relationships between the amount of information employed in ANN training and the accuracy of the trained ANN in locating damages. This is an important step to extend the proposed methodology to be applicable for large-scale civil engineering structures.

Acknowledgements

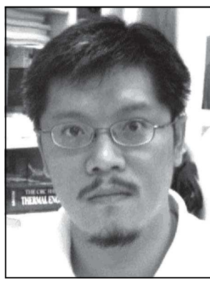
The work described in this paper was fully supported by a grant from CityU (Project No 7001617).

References

1. Cawley, P. and Adams, R. D., The Location of Defects in Structures From Measurements of Natural Frequencies, *Journal of Vibration and Acoustics*. Volume 2, pp. 49-57 (1979).
2. Lam, H.F., Detection of Damage Location Based on Sensitivity and Experimental Modal Analysis, MPhil Thesis, Department of Civil Engineering, Hong Kong Polytechnic University (1994).
3. Lam, H.F., Ko, J.M. and Wong, C.W., Detection of Damage Location Based on Sensitivity Analysis, *Proceedings of the 13th International Modal Analysis Conference (IMAC)*, pp.1499-1505 (1995).
4. Lam, H.F., Ko, J.M. and Wong, C.W., Localisation of Damaged Structural Connections based on Experimental Modal and Sensitivity Analysis, *Journal of Sound and Vibration*, Volume 210, No.1, pp.91-115 (1998).
5. Wu, X., Ghaboussi, J. and Barrett, J.H., Use of Neural Networks in Detection of Structure Damage, *Engineering Structures*, Volume 42, No.4, pp.649-659 (1992).
6. Elkordy, M.F., Chang, K.C. and Lee, G.C., A Structural Damage Neural Network Monitoring System, *Microcomputers in Civil Engineering*, Volume 9, pp.83-96 (1994).
7. Rosenblatt, F., *Principles of Neurodynamics*, Spartan Books, New York (1962).
8. Broomhead, D.S. and Lowe D., Multi-variable functional interpolation and adaptive networks, *Complex Systems*, Volume 2, pp.321-355 (1988).
9. Specht, D.F., A general regression neural network, *IEEE Transaction on Neural Networks*, Volume 2, No.6, pp.568-576 (1991).
10. Kohonen, T., The Self-Organizing Map, *Proceedings of the IEEE*, Volume 78, No.9, pp.464-1480 (1990).
11. Bezdek, J.C., A Convergence Theorem for the Fuzzy ISODATA Clustering Algorithms, *IEEE Transaction on Pattern Analysis and Machine Intelligence*, Volume PAMI-2, pp.1-8 (1980).
12. Moore, B., ART 1 and pattern clustering, In Touretzky D, Hinton G and Sejnowski T (Eds.), *Proceedings of the 1988 Connectionist Models Summer School*, San Mateo, CA, Morgan Kaufmann Publishers, pp.174-185 (1989).
13. Lee, E.W.M., Lim, C.P., Yuen, R.K.K. and Lo, S.M., A hybrid neural network for noisy data regression, *IEEE Transactions on Systems, Man and Cybernetics - Part B: Cybernetics*, Volume 34, No.2, pp.951-960 (2004).
14. Carpenter, G.A., Grossberg, S. and David, B.R., Fuzzy ART: Fast Stable Learning and Categorisation of Analog Patterns by an Adaptive Resonance System, Neural Network, Volume 4, pp.759-771 (1991).
15. Grossberg S., Adaptive Pattern Recognition and Universal Recoding I: Parallel Development and Coding of Neural Feature Detectors, *Biological Cybernetics*, Volume 23, pp.121-134 (1976).
16. Kosko, B., Fuzzy Entropy and Conditioning, Information Sciences Volume 40, pp.165-174 (1986).
17. Lin, Chin Teng and Lee, C. S. George, Neural Fuzzy Systems: A Neuro-Fuzzy Synergism to Intelligent Systems, Prentice Hall PTR, Upper Saddle River, NJ 07458, Section 9.1. (1996).
18. Lim, C.P. and Harrison, R.F., Modified Fuzzy ARTMAP approaches Bayes Optimal Classification Rates: An Empirical Demonstration, *Neural Networks*, Volume 10, No.4, pp.755-774 (1997).
19. Tomandl, D. and Schober, A., A modified general regression neural network (MGRNN) with new, efficient training algorithms as a robust 'black box' -tool for data analysis, *Neural Networks*, Volume 14, pp.1023-1034 (2001).
20. Parzen E., On estimation of a probability density function and mode, *Annal Mathematical Statistics*, Volume 33, pp.1065-1076 (1962).
21. Efron, B., Bootstrap Methods: Another Look at the Jackknife, *The Annals Of Statistics*, Volume 7, pp.1-26 (1979).

LAM Heung Fai

Dr Lam Heung-fai is currently an Assistant Professor in the Department of Building & Construction at City University of Hong Kong (CityU). He received his PhD (1999) and MPhil (1994) in Civil Engineering at the Hong Kong University of Science & Technology (HKUST) and the Hong Kong Polytechnic University (PolyU), respectively. He is currently the Associate Editor of the International Journal of Applied Mathematics and Mechanics (IJAMM). Furthermore, he is the committee member of the ASCE Structural Health Monitoring (SHM) Task group and is one of the main contributors in developing the IASC-ASCE SHM Benchmark Study.



Eric W M LEE

Dr Eric W M Lee is currently a Lecturer in the Department of Building and Construction, City University of Hong Kong (CityU). He received the BEng with first class honors in building services engineering and the PhD degree in fire engineering from CityU in 2000 and 2003 respectively. Before joining CityU, he worked in the field of building construction in Hong Kong for over 13 years and was an Executive Engineer in one of the leading building services engineering consultant firm. His major research interests are the application of artificial neural network to building fire development, evacuation, and risk studies. Dr Lee was awarded the Sir Edward Youde Memorial Fellowship and the Croucher Foundation Research Studentship. He is also one of the winners of the Emerald Literati Club 2004 Highly Commended Award.