A New Damage Identification Strategy for SHM based on FBGs and Bayesian Model Updating Method

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Abstract One of the difficulties of the vibration-based damage identification methods is the nonuniqueness of the results of damage identification. The different damage locations and severity may cause the identical response signal, which is even more severe for detection of the multiple damage. This paper proposes a new strategy for damage detection to avoid this nonuniqueness. This strategy firstly determines the approximates damage area based on the statistical pattern recognition method using the dynamic strain signal measured by the distributed fiber Bragg grating, and then accurately evaluates the damage information based on the Bayesian model updating method using the experimental modal data. The stochastic simulation method is then used to compute the high-dimensional integral in the Bayesian problem. Finally, an experiment of the plate structure, simulating one part of mechanical structure, is used to verify the effectiveness of this approach.

Keywords structural health monitoring, damage detection, fiber Bragg grating, Bayesian model updating, stochastic simulation

1. Introduction

The nonuniqueness of the results of damage identification is the one of the difficulties of the vibration-based damage identification methods. The different damage locations and severity may cause identical response signal. This problem is even more severe for the detection of the multiple damage. The reason is that, the number of the measured points in real application is limited and only the limited modes could be estimated. Furthermore, the modelling error and the measurement noise is usually inevitable, some erroneous modes could have modal parameters closer to the estimated modal parameters than the model with the correct damage locations and amount [1].

By explicitly considering the modelling error and the measurement noise, Bayesian model updating approach is an excellent way to model prediction error and provide the uncertainty information of the damage identification results [2]. Based on the Bayesian formula, Bayesian model updating approach could incorporate the engineering judgments, the mathematical models and the measured data together to make robust identification for damage. The results of damage identification are expressed though the post probability density function (PDF), rather than pinpointing a single solution in the traditional deterministic approach. The post PDF quantifies the confidence level of the identified results, which usually provides an important reference for maintenance decision.

The fiber Bragg grating (FBG), considered to be a promising technology, has been increasingly applied to the SHM process. FBG has several advantages, such as immunity to electromagnetic interference, high sensitivity, light weight, and so on. The excellent multiplexing capability of the FBG facilitates its use as a distributed sensor system, which not only monitors the local key parts of the structure but also captures the overall dynamic information. Panopoulou et al. [3] developed a complete damage detection system using FBGs. The dynamic strain response data from the FBG is first measured, then the feature indices are extracted by various signal processing methods, and finally an artificial neural network is utilized to detect and locate damage. This system has been demonstrated by a thin composite panel and a honeycomb structure and is planned for use in a future application of an antenna reflector.

This paper uses the distributed FBG as the sensor network and proposes a new strategy for damage detection though two steps, which firstly estimate the approximate damage area from the dynamic strain signal using the statistical pattern recognition method, and then accurately evaluates the damage based on Bayesian model updating method using experimental modal data. Lastly, the stochastic simulation method is used to solve the Bayesian computation issue and generate the samples of the damage parameters identified.

The following paper is organized as follows. Section 2 summaries the new damage detection strategy. Section 3 is the experimental verification section: firstly describes the experimental apparatus and procedures, and then presents the detection results of Step 1 and Step 2, respectively. A few conclusions are discussed in Section 4.

2. Theoretical Background

2.1. New Damage Identification Strategy

The traditional damage detection methods for SHM can be classified into model-based method and non-model-based method [4]. Here, the "model" refers as the physical model of the real mechanical or civil structure. The non-model method usually directly uses the signal processing or statistical method to determine whether the damage occurs. This method is simple and straightforward, but helpless for quantifying the damage, such as the size, orientation and trends of the crack. Alternatively, the model-based method requires an accurate physical model and could quantify the damage but on the cost of intensive computation.

Absorbing both advantages of the non-model method and the model-based method, a new damage detection strategy is proposed based on FBG and Bayesian model updating method. This process consists of the following two phases. (1) Roughly estimate damage area based on the distributed dynamic strain signal with the recognition accuracy of the gage lengths of FBG without a detailed analytical model. (2) Accurately identify the size, direction and depth of the damage with the recognition accuracy of the accuracy of the physical model based on Bayesian model updating method. The details of the process are showed in Fig. 1.

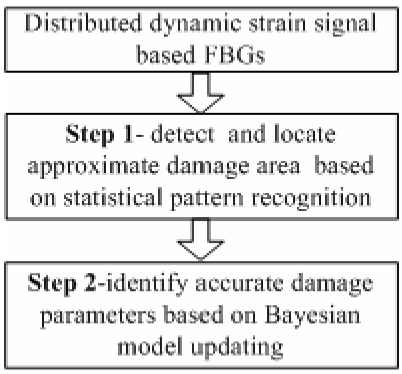

Figure 1. Detailed process of the new damage detection strategy

Based on the strain measurement, the dynamic strain response of FBG is more sensitive to the local small damage than the traditional displacement or acceleration measurements. But the environmental and operational variations, such as the change of temperature, usually disguise the signal variation induced by damage and cause the false-positive indication. So in Step 1, the dynamic strain signal is decomposed into the damage-sensitive signal component using the Hilbert-Huang Transform (HHT) method, the autoregressive (AR) model is then used to exact damage sensitive features, and lastly the Mahalanobos distance-based method is used to determine the approximate damage area, named as the damage suspicious region. But the identification accuracy of this region is low, because that is mainly affected by the grating length of FBG and the layout density of the sensor network.

In Step 2, the Bayesian model updating method is further used to identify the detailed damage parameters. The damage parameters are identified only from the damage suspicious region of Step 1.

There are several advantages for this new damage identification strategy. First, the number of the parameters to be identified has been reduced, which make the cost of the computation greatly drop. Second, the search targets of the damage identification only focus to the damage suspicious area, rather other the entire structure. The "output-equivalent" issue in the damage mechanism modelling can be effectively relieved, which refer to the problem that different damage assumes may produce identical out parameters [1].

2.2. Bayesian Model Updating Framework

Assume the damage could be expressed by the reduction of the element stiffness, but independent from the element mass. Therefore, introducing the parameter vector $\boldsymbol{\theta} = [\theta_1, ..., \theta_i, ..., \theta_N]$, which represents the contribution of the element stiffness to the system stiffness matrix, the system stiffness matrix $\mathbf{K}$ can be written as:

$$\mathbf{K}(\boldsymbol{\theta}) = \mathbf{K}_0 + \sum_{i=1}^{N} \theta_i K_i \tag{1}$$

where N is the degrees of freedom (DOFs) of the linear discrete system, θ_i ($0 < \theta_i < 1$) is non-dimensional, and the smaller the size of θ_i , the more serious the damage of element, other words, deeper the crack. The combination of adjacent damage element constitutes the shape and direction of the crack. Obviously, the accuracy of crack identification depends on the sizes of finite elements which can be controlled artificially but usually at the cost of the computation effort [5].

Based on Bayesian theorem, when given the measured data $\mathbf{D}$ and the probabilistic models M, the post PDF of $\boldsymbol{\theta}$ can be expressed as:

$$p(\boldsymbol{\theta} \mid \mathbf{D}, M) = cp(\mathbf{D} \mid \boldsymbol{\theta}, M) p(\boldsymbol{\theta} \mid M) \tag{2}$$

where c is a normalizing constant, $p(\boldsymbol{\theta}| M)$ is the prior PDF of $\boldsymbol{\theta}$, and $p(\mathbf{D}| \boldsymbol{\theta}, M)$ is the likehood function. Because that the measured modal frequency usually has the more precision than the other modal parameters. Moreover, the most algorithms including the mode shapes have to deal with the problems of the finite element (FE) model reduction or mode shape expansion to bridge the gap between the real structure and the simulated model. So the modal frequencies are used to construct the likelihood function, assume the N_m ($\leq N$) modes of natural frequency are considered here:

$$\begin{gathered} p(\mathbf{D} \mid M) = \frac{1}{(2\pi)^{N_s N_m/2}} \frac{1}{\Sigma^{1/2}} \exp \\ \left\{ -\frac{1}{2} \sum_{n=1}^{N_s} \left[\hat{\psi}(n) - \psi(\boldsymbol{\theta}) \right]^T \Sigma^{-1} \left[\hat{\psi}(n) - \psi(\boldsymbol{\theta}) \right] \right\} \end{gathered} \tag{3}$$

where $\sum$ is the variance matrix of the measured modal frequency, N_s is the number of the measured modal frequency sets, $\hat{\psi}$ is the measured modal frequency of the monitoring structure under unknown health status, and the $\psi(\boldsymbol{\theta})$ is computed modal frequency of the FE model.

The computation of the high-dimensional integral in the Bayesian method is difficult and has attracted the attention of many researchers over the decades. Several improved stochastic simulation methods have been developed to solve the high-dimensional and complex posterior PDF, such as the adaptive Metropolis-Hastings (AMH) [6], the transitional Markov chain Monte Carlo (TMCMC) [7], the Hybrid Monte Carlo (HMC) [8], and so on. Inherited from the AMH that introduced a series of intermediate PDFs, the TMCMC can not only automatically select the intermediate PDFs but also conveniently evaluate the evidence in the Bayesian model class selection. However, the proposal distribution of the TMCMC is the random walk of Gaussian distribution, which cannot explore the local properties of the posterior PDF well. So the slice sampling is used as the algorithm of the candidate value for TMCMC, which is named as TMCMC-slice.

The improved TMCMC-slice algorithm, which has integrated the advantages of the TMCMC and slice sampling method, is used to generate the sample of the unknown parameters. Based on slice sampling, the generation of the candidate value can automatically adapt to the local features of the post PDF with fewer user-adjusted parameters. Though the gradually transitioning from the prior PDF to the post PDF, TMCMC can easier sample from the intermediate PDFs than other methods. And the ratio of Metropolis-Hasting in each iteration step could make the sample concentrate the region of high probability, which improves the convergence properties of the TMCMC-slice algorithm.

3. Experimental verification

3.1. Experimental apparatus and procedure

A 304 stainless steel plate, which is attached by four bolts on a support, was used to simulate one part of the mechanical structure. The geometric parameters of the plate are 500 mm by 500 mm and 3 mm thick. Twenty-nine gratings were bonded on the surface of the plate according to the symmetry of the structure. These gratings were assigned to four individual fibers in order to facilitate wiring, and then connected with the four channels of the optical demodulator produced by the Micron Optics Inc. The sampling rate of the FBGs was set to 2 kHz. There were also 15 accelerometers to monitor the modal parameters of the structure. The sampling rate of the accelerometer was also set to 2 kHz. The arrangement of the FBGs and accelerometers sensor network is shown in Fig. 2.

Providing the excitation for the plate structure, a vibration exciter was attached to the center of the plate using a screw with a 3mm diameter. This vibration exciter was controlled by the LMS modal testing system, which produced the 0~8 kHz broad-band stochastic excitation.

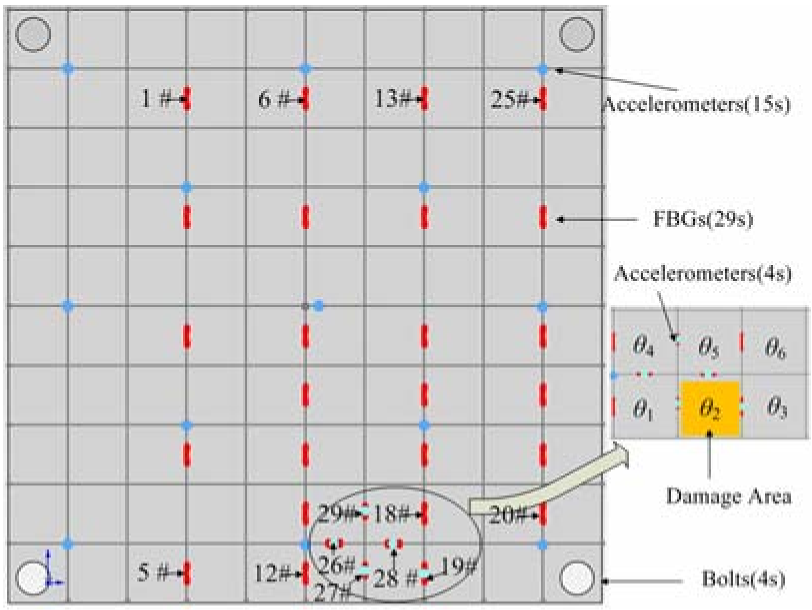

Figure 2. Layout of the FBG and accelerometer sensor network

The structural defect usually appears in most mechanical structures because of stress concentration, fatigue, or corrosion. Therefore, the experiment here was mainly designed to identify this form of damage. The structural defect was simulated by a notch at different depths, which was directly machined on a milling machine, as shown in the upper left corner of Fig. 3. Based on the severity of the damage, there were four groups. The first group represents the baseline health state without any defect; the second group induces a defect whose size is 46 mm by 48 mm with a depth of 1.5 mm (50% thickness), as shown in the yellow region of Fig. 2. In the third group, the size of the defect remains the same, but the depth is increased to 2.4 mm (80% thickness). Finally, in the fourth group, the defect is completely though the plate (3 mm depth). The torque of the four bolts connecting the plate and the support was 80 Nm, which was strictly controlled by the torque wrench in each experimental group. The image of the experimental real objects can be observed in Fig. 3, and the details of the different health states simulated are summarized in Table 1.

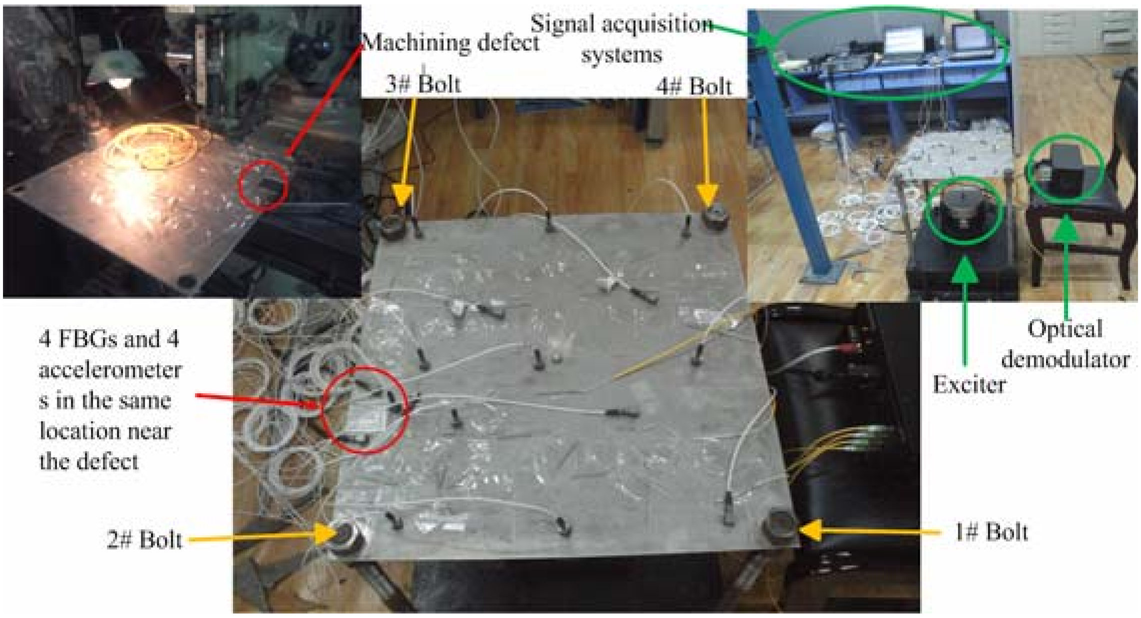

Figure 3. Picture of the experiment

Table 1. Details of different health conditions

State	Label	Description
Health state	State 1	Baseline state, no defects
Damage state 1	State 2	Defect size: 46mm × 48mm × 1.5mm
Damage state 2	State 3	Defect size: 46mm × 48mm × 2.4mm
Damage state 3	State 4	Defect size: 46mm × 48mm × 3mm

3.2. Detection Results of Step 1

For each damage state, 50 sample records are collected as damage identification according to the periodicity characteristics of the response signal. In Step 1, the dynamic strain signal from FBG is first decomposed into several intrinsic mode functions (IMFs), then the AR-based model is applied on the second level IMF component to extract the damage sensitive features and Mahalanobis distance-based pattern classification method are used to detect and locate damage. Here the sample sets from State 1 (health state), State 2 (damage state 1), State 3 (damage state 2), and State 4 (damage state 3), totally 200 samples, are used for damage identification. These samples are divided into two parts. One is the first 25 samples of State 1 as the training sample set. Another is the test sample set composed of the later 25 samples of State 1 and the remaining three damage states, totally 175 samples. The identification results of the channel 19, 26, 27, and 28 are shown in Fig. 4, in which the blue bar indicates that no damage occurred, the red bar means the damage, and the green horizontal line is the threshold which is calculated assuming that the distribution of the square of the Mahalanobis distance is chi-square distribution with the DOFs equal to the AR model order.

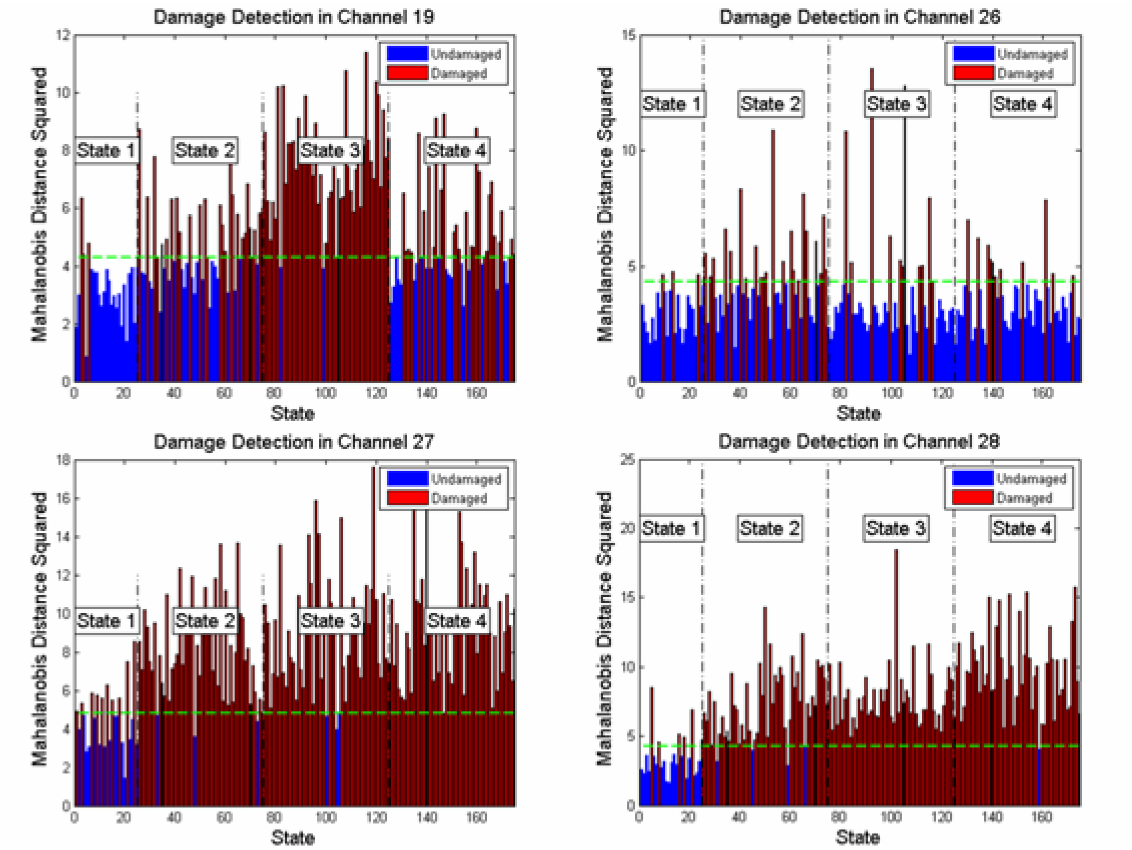

Figure 4. Results of damage detection and location in channel 19, 26, 27 and 28

There is no damage occurred when the number of blue-bar is larger than the red-bar in each state, otherwise, the damage appears. Observing the amount of the red bars, the number of the red bars in the channel 19, 27, and 28 is large, so the conclusion is that the approximate location of the damage is near the position of the channel 19, 27, and 28, but lacking more detailed information, such as the direction, size and severity about the damage. So next the Bayesian model updating method is used to identify the specific parameters of the damage.

3.3. Detection Results of Step 2

In order to identify the damage parameters, the plate structure is divided into the 100 rectangular elements of 10 by 10. Then the non-dimensional parameter, representing the contributions of the element stiffness to the system stiffness matrix, is introduced to model the damage. Based on the detection results of Step 1, only the six parameters near the damage approximate area, θ_i (i = 1, 2, …, 6), are updated in Bayesian model updating method of Step 2.

3.3.1. FE Model Refinement

A precise model is required before applying Bayesian model updating method for damage identification, so the FE model is refined to minimize the model error by conducting a series of parametric analysis.

The experimental modal frequency is firstly identified by the LMS modal analysis software using the acceleration signal. Here the results of State 1 (health state), State 2 (damage state 1), State 3 (damage state 2), and State 4 (damage state 3) are shown in Table 2.

Table 2. Modal frequency of the healthy and damage states

Mode	State 1 (Hz)	State 2 (Hz)	State 3 (Hz)	State 4 (Hz)
1	40.9330	42.4120	42.3030	41.9960
2	137.4630	135.9660	135.6860	134.9330
3	307.7550	304.8220	305.3790	301.6580
4	436.2560	436.2100	432.7160	430.4220
5	690.2900	683.8950	674.1470	679.2060
6	806.7520	803.8900	802.2440	808.0970

The geometric parameters of the plate are accurately measured as 515 mm by 515 mm and 2.95 mm thick. The density of the 304 stainless steel is 8150 kg/m^3, the Modulus of Elasticity is 189 GPa, and the Poissons ratio is 0.285. The four-node rectangular element is used in the FE model, and the size of the grid element is 51.5 mm by 51.5 mm. The nodes of the elements located in four corners are fully constrained to simulate the bolt constraint. The comparison of the modal frequency between the FE model and the actual undamaged plate is shown in Table 3.

Table 3. Comparison of the modal frequency between FE model and actual plate

Mode	Test(Hz)	FEM(Hz)	Diff(%)
1	40.9330	40.9361	0.0076
2	137.4630	140.5776	2.2658
3	307.7550	315.8144	2.6188
4	436.2560	427.5859	-1.9874
5	690.2900	703.1238	1.8592
6	806.7520	809.1443	0.2965

Although the refined FE model is close to the actual structure, the model error is modelled a Gaussian process. Then the post PDF is constructed according to the Bayesian theorem. The posterior samples of the damage parameters θ_i are generated using the stochastic simulation method based on TMCMC-slice sampling.

3.3.2. Damage Identification

The damage identification results of the TMCMC-slice algorithm are checked. The statistics of the sample are shown in Table 4, where column 1 is the actual values of the parameters, column 2 shows the identified sample mean, column 3 shows the sample standard deviation (s.d.), and column 4 displays the coefficient of variance (c.o.v.).

Table 4. Results of damage identification for plate structure based on TMCMC-slice

	Actual	Identified	s.d.	c.o.v.
θ_1	1.0000	0.9950	0.7742	0.7781
θ_2	0.5000	0.5181	0.2100	0.4053
θ_3	1.0000	2.6051	1.5647	0.6006

θ_4	1.0000	0.9500	0.8905	0.9374
θ_5	1.0000	0.6889	1.4918	2.1655
θ_6	1.0000	0.9771	0.9996	1.0231

The result of the TMCMC-slice method is satisfactory, only the identified values of θ_3 and θ_5 are deviate from the actual values, but the corresponding standard deviation (s.d.) and coefficient of variance (c.o.v.) are also large, which denote that the results have lower credibility.
Then the sample updated trajectory and probability density distribution are respectively used to further analysis the performance of TMCMC-slice, as shown in Fig. 5 and Fig. 6.

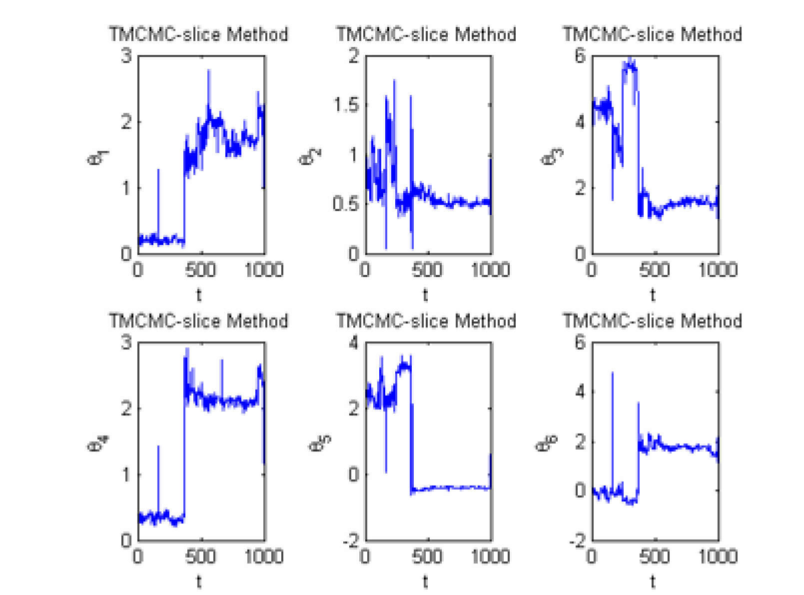

Figure 5. Sample path of the damage identification results based on TMCMC-slice

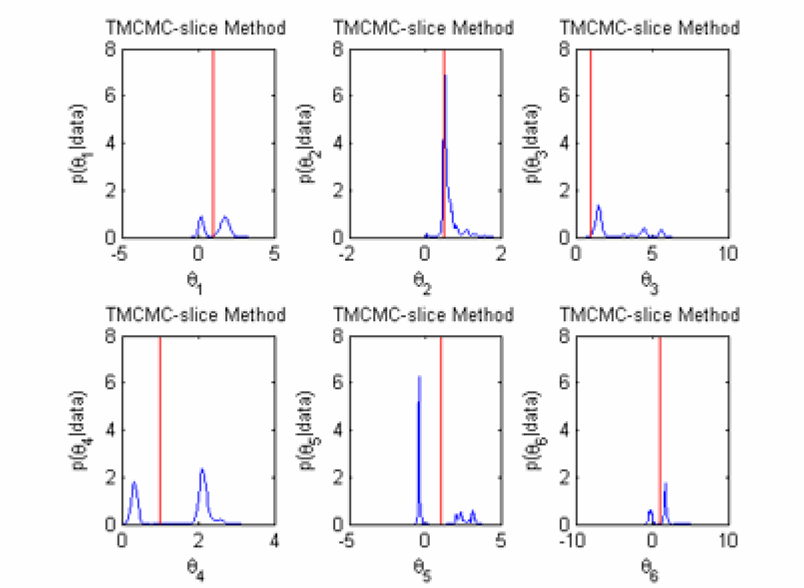

Figure 6. Probability density of the damage identification results based on TMCM-slice

4. Conclusions

This paper proposes a new damage detection strategy which can successfully identify the damage of the plate structure. Inheriting the results of Step 1, the non-dimensional stiffness parameters, only from the suspicious damage region, are updated using the Bayesian model updating method in Step 2. The significances of the method are that: when the identification of the detailed damage parameters focuses on the suspicious damage area, the number of the parameters needs to be identified has been greatly reduced, which can improve the convergence performance of the stochastic simulation method. The uncertainty of identification parameters will be reduced. More important, the nonuniqueness issue of the results of damage identification could be effectively relieved.

The finite element model which introduces local stiffness reductions representing damage may be the simplest method among these damage modelling methods for SHM. But different from the traditional usage way as [1, 9, 10] in which a damage threshold must be pre-assumed, this paper uses the stochastic simulation method to obtain the samples of the stiffness parameters. The sample means are the identified values of the parameters, which represent actual severity of damage. The value of the θ_i is closer to 1, the more health structure; closer to 0, the more serious structure damage. The sample variance gives the credibility of the recognition results. The size and orientation of the damage can be observed by the combination of the different damage elements. The accuracy of damage identification depends on the sizes of the finite elements, which can be controlled artificially but usually on the cost of the computation effort.

Although the experiment result has obtained encouraging results, how to improve the accuracy of the damage identification is the focus of the future work.

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