Damage monitoring framework based on probability modeling under varying structural boundary conditions

Fang Fang, Lei Qiu*, Shenfang Yuan, Yuanqiang Ren

Research Center of Structural Health Monitoring and Prognosis, State Key Lab of Mechanics and Control of Mechanical Structures, Nanjing University of Aeronautics and Astronautics
29 Yudao Street, Nanjing 210016, PR China
*Corresponding author, Professor, Ph.D. Lei Qiu, E-mail: lei.qiu@nuaa.edu.cn

Abstract

A key challenge for the practical application of aircraft structural health monitoring (SHM) is to realize reliable damage monitoring under time-varying conditions. To deal with this challenge, a damage monitoring framework based on probability modeling is proposed to provide a modular architecture with high generalization capability. In this framework, double probability models combining short term and long term SHM information are updated dynamically and an improved probability modelling method is proposed to construct models in a stable, adaptive and efficient way. Finally, the probability similarity of models is measured to realize normalized and reliable damage detection under time-varying conditions.

Keywords: Structural Health Monitoring, time-varying condition, probability modeling, dynamic update, Guided Wave, aircraft structures

1. Introduction

Structural Health Monitoring (SHM) system is an important technology to achieve Condition Based Maintenance (CBM) [1-2] to ensure safety and reduce maintenance cost of engineering systems such as aerospace vehicles. However, for the application of SHM to in-service aircrafts, a key challenge is to realize reliable damage monitoring under time-varying conditions (TVCs), such as time-dependent environmental temperature, random flight load and varying structural boundary conditions [3-4]. The TVCs lead almost all the Damage Monitoring Features (DMFs) to be random and uncertain, which greatly reduce the reliability and stability of damage monitoring [4-6]. To achieve reliable damage detection under TVCs, several methods are proposed, such as parameter compensation [7], low baseline dependency [8] and data normalization [9], but these methods have their own limitations and the reliable damage detection of aircraft structures is still difficult to be achieved.

A SHM technique must be developed and validated under a rigorous specification to reach an accepted technical maturity [10]. SAE international published ARP6461 [10], which indicates that a detailed aircraft SHM framework under TVCs needs to be developed which can be a guidance to SHM system designers to explore different kinds of strategies to address the TVC problem so as to maximize the reliability of the corresponding SHM techniques comprehensively. However, the relevant research on aircraft SHM framework which considers the TVC problem is barely reported [11-12]. As a result, it is important to develop an aircraft SHM framework under TVCs for the application of aircraft SHM technology.

Considering that the DMF is uncertain and random under TVCs, SHM methods combined with probability and statistics modeling are gradually studied recently [12-14]. For example, Avendaño-Valencia et al. [12] proposed a stochastic framework based on Gaussian Mixture Model...
(GMM) for reliable damage monitoring under the uncertain influence of TVCs. Rogers et al. [14] proposed a semi-supervised SHM method based on the Dirichlet process GMM to realize structural crack monitoring under varying system mass and stiffness introduced by TVCs. Though these studies realized dynamic probability modeling of DMFs accompanying the damage propagation, they are still at the preliminary research stage. Further studies are needed to establish a common standardized framework to develop more applicable aircraft SHM methods under TVCs by integrating effective DMF extraction methods, stable and adaptive probability modeling methods and applicable updating strategies.

In this paper, a probability modeling-based damage monitoring framework is proposed. In the framework, an adaptive GMM constructing method is proposed to realize stable and adaptive probability modeling of the DMFs under TVCs. Then, the probability similarity between dynamically updated models is measured for normalized damage detection. Finally, the framework is validated by the hole-edge cracks monitoring of an aircraft wing spar under varying structural boundary conditions.

2. Probability modeling-based damage monitoring framework

2.1. Architecture of the framework

A framework is required to realize reliable damage monitoring under TVCs for the aircraft application. When applying damage monitoring to an aircraft structure, a large amount of SHM data can be acquired in the healthy state and damage monitoring state of the structure, respectively. Then, the DMF of SHM data in the two states can be extracted. Though TVCs and damage all have an impact on the DMFs, but the TVC influence is random and uncertain and the damage influence is fixed and certain. If the probability structure of DMFs under the random TVC influence can be modeled, some certain variation trends of the DMFs’ probability structure, such as local concentration and migration, can be caused by the damage. Therefore, the basic damage monitoring principle of the framework is to compare the DMF probability structures of the two states.

A damage monitoring framework should also be of high generalization to be applied to most of the SHM techniques, since many SHM techniques based on different kinds of SHM sensors have been developed [15] such as GW SHM technique [16], electromechanical impedance SHM technique [17] and vibration monitoring technique [18]. Therefore, the framework should be compatible for different SHM data from the output of different SHM techniques. This compatibility can be realized by the generalized definitions of software interfaces [19]. In addition, the damage monitoring result output from the framework should be normalized to maximize the generalization capability of the framework because such results can be fused with other SHM information without obstacles and can also be easily understood by SHM system users.

Figure 1. Probability modeling-based damage monitoring framework.

The damage monitoring framework as shown in Figure 1 is designed to be a modular hierarchical architecture which contains three blocks. Block 1 is the baseline probability modeling corresponding to the healthy state. Block 2 is the monitoring probability model corresponding to the damage monitoring state. The two blocks are established by a data evolutionary process including the SHM data, the DMFs, the feature spaces and the probability models. Block 3 corresponds to the damage monitoring including damage detection and evaluation based on the difference between the two probability models. The three blocks are driven by the four strategies including the feature extraction, the feature space update, the probability modeling, the probability difference measuring. They are referred to the corresponding methods. Specifically, the feature space
update strategy includes the short term update strategy for updating monitoring feature space and the long term update strategy for updating baseline feature space.

The input of the framework is the original data generated by SHM sensors and the data input interface is to convert the original data to be the SHM data required by blocks 1 and 2. The output of the framework is damage monitoring result and the data output interface is to convert the damage monitoring result to be a required data format for further processing [19].

2.2. Realization of damage monitoring framework

To date, nearly an infinite number of DMF extraction methods have been proposed for different SHM techniques. The feature extraction strategy and feature space update strategy highly depend on a specific SHM technique. Among the four strategies, the probability modeling strategy and the probability difference measuring strategy are relative independent. Therefore, to achieve the SHM capability of the framework, the probability modeling strategy and the probability difference measuring strategy are proposed as follows.

The feature extraction strategy and the feature space update strategy are briefly given in Section 3 combining with the GW SHM technique.

2.2.1. Probability modeling strategy

The probability modeling strategy is based on the GMM. In this paper, GMM is constructed by the proposed adaptive constructing method in a stable and efficient way with no initial parameters. The GMM and adaptive constructing method is illustrated as following.

Let \( Z = [z_1, z_2, \ldots, z_N] \) denote a feature space, \( i=1,2,\ldots,N \). \( z_i=[z_{i1}, z_{i2}, \ldots, z_{iD}] \) denote a DMF with \( D \) dimensionality. GMM is a weighted sum of a finite number of Gaussian Components (GCs). The probability density functions of GMM and GC are expressed as Eq. (1) and Eq. (2).

\[
\Phi(z|\Theta) = \sum_{k=1}^{K} \alpha_k \phi_k(z|\mu_k, \Sigma_k) \\
\phi_k(z|\mu_k, \Sigma_k) = \left(\frac{1}{2\pi} \right)^{D/2} \left|\Sigma_k\right|^{-1/2} e^{-\frac{1}{2}(z-\mu_k)^T \Sigma_k^{-1} (z-\mu_k)}
\]

where \( \Theta \) is the parameter set of GMM and \( \Theta = \{ (\alpha_1, \mu_1, \Sigma_1), \ldots, (\alpha_K, \mu_K, \Sigma_K) \} \). \( K \) is the number of GCs. For the \( k \)-th GC, \( \alpha_k \) is the mixture weight, \( \mu_k \) is the mean and \( \Sigma_k \) is the covariance matrix. \( |.| \) is the determinant value. \( T \) is the transpose.

The Expectation-Maximization (EM) algorithm can be used to construct the GMM with a certain number of GCs [20]. However, the EM is sensitive to the initialization values of \( \Theta \), which results in reduced stability of GMM and damage monitoring results. Besides, the number of GCs should be pre-defined for GMM constructed by EM algorithm. In this paper, an adaptive density peaks-based clustering (ADPC) algorithm is proposed to obtain the initialized \( \Theta \) to achieve stable, reasonable and adaptive initialized parameters for EM algorithm.

In ADPC, cluster centers are first identified by the finding of density peaks in the DMF space, which are characterized by a higher density than their neighbors and a relatively large minimum-distance from the other DMFs with higher density [21]. The probability density of a DMF \( z_i \) defined as the probability that a DMF will fall in a small region centered on \( z_i \) can be estimated by the kernel density [22]. A commonly used kernel density is based on Gaussian kernel function expressed as Eq. (3) [22].

\[
p_i = \frac{1}{N} \sum_{j=1}^{N} \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{1}{2} \frac{d_j^2}{\sigma^2}}
\]

where \( d_j \) is the distance between DMF \( z_i \) and DMF \( z_j \). \( \sigma \) is the radius of the small region and can be selected so that the average number of DMFs in the region is around 1% to 2% of the total number of DMFs in the DMF set [22].

The minimum-distance between \( z_i \) and any other DMF with higher density, denoted as \( v_i \), can be calculated by Eq. (4). For the DMF with highest density, \( v_i \) is taken as following.

\[
v_i = \begin{cases} 
\min_{j, r_j > r_i} (d_j) & \text{others} \\
\max_{j} (d_j) & \text{if } p_i \text{ is largest}
\end{cases}
\]

The product of \( p_i \) and \( v_i \), denoted as \( \tau = p_i \times v_i \), defined and is the larger \( \tau \) is, the more likely a DMF is to be a density peak. Besides, the product of minimum \( p_i \) and minimum \( v_i \) that density peaks may have is set as the threshold of \( \tau \) to select density peaks. First, the minimum \( p \) of density peaks can be set as the mean density since \( p \) of density peaks is much larger than that of common DMFs. Second, \( \sigma \) can be used to estimate the minimum \( \tau \) because \( \tau \) of density peaks is usually larger than the span of clusters which is typically larger than \( \sigma \). Hence, the threshold of \( \tau \), denoted as \( \tau_{\min} \), is expressed as Eq. (5).
The damage monitoring index can be calculated by Eq. (1) and Eq. (2). The damage monitoring index used to measure the probability model is calculated by Eq. (6), denoted as $PD = \frac{P(Z_{MC} | \Theta_B) \cdot P(Z_{MC} | \Theta_M)}{P(Z_{MC} | \Theta_B) \cdot P(Z_{MC} | \Theta_M)}$, in the probability model can be calculated by Eq. (6), where $\Theta_B$ and $\Theta_M$ are the parameters of baseline and monitoring probability models, respectively.

2.3.2. Probability difference measuring strategy

In this paper, the probability similarity measuring method based on Monte Carlo simulation is adopted to estimate the damage monitoring index. Firstly, a large number of random samples can be obtained by the Monte Carlo sampling and the set of these random samples is denoted as $Z_{MC} = \{z_1, z_2, ..., z_R\}$, where $R$ is the number of samples. Secondly, the posterior probability of $Z_{MC}$, denoted as $P(Z_{MC} | \Theta) = \{\Phi(z_1 | \Theta), \ Phi(z_2 | \Theta), ..., \Phi(z_R | \Theta)\}^T$, in the probability model can be calculated by Eq. (1) and Eq. (2). The damage monitoring index used to measure the difference between the baseline probability model and the monitoring probability model is calculated by Eq. (6), where $\Theta_B$ and $\Theta_M$ are the parameters of baseline and monitoring probability models, respectively.

3. Experimental validation

3.1 Validation set-up

The proposed damage monitoring framework is realized by combining with the guided wave (GW) SHM technique and validated by the hole-edge cracks monitoring of an aircraft wing spar. The aircraft wing spar shown in Figure 2 was supplied by Beijing Aeronautical Technology Research Center of China. It is made of the alloy steel 30CrMnSi. The bolts on the wing spar edge as shown in Figure 2 are used to connect the wing spar with the wing skin. They suffer from a high in-service fatigue load. The holes of these bolts are most likely to generate hole-edge cracks due to fatigue. Therefore, the hole-edge crack detection under varying structural boundary conditions is performed to validate the method.

The SHM system shown in Figure 2 is used to control the two PZTs to excite and receive GW signals. The excitation signal is a five-cycle sine burst modulated by a Hanning window with the central frequency of 200 kHz. The sampling rate and excitation amplitude are set to 10 MSamples/s and ±70 V respectively. The hole-edge crack is introduced at the bolt hole 3 to simulate the fatigue crack which generates GW reflections to GW signals.

Figure 2. Validation system on the aircraft wing spar.

Totally 400 GW signals numbered from No. 1 to No. 400 are acquired. The basic operation is acquiring a GW signal after loosen and re-fasten random one of bolts 1 to 6. When the wing spar is in the healthy state, repeat the basic operation for 40 times. Thus, 40 healthy signals are acquired and numbered as Signal No. 1 to No. 40. When in the damage monitoring state, repeat the basic operation for 40 times firstly. Second, remove the bolt 3 and produce a crack of 1 mm at the bolt hole-edge, re-fasten the bolt 3 and repeat the basic operation for 80 times. Then extend the crack length to 4 mm with an increasing step of 1 mm, and repeat the basic operation for 80 times at each crack length. Thus, 360 monitoring signals are acquired and numbered as Signal No. 41 to No. 400. Three typical GW signals, two acquired in the healthy state (Signal No. 20 and Signal No. 60) and one in the damage monitoring state (Signal No. 180, crack length 2 mm) are shown in Figure 3. It can be seen that the variation of the GW signals introduced by the varying structural boundary conditions is larger than that
introduced by the crack.

Figure 3. Typical GW signals acquired under varying structural boundary conditions.

### 3.2 Feature extraction and feature space update strategies

The feature extraction strategy includes two steps. Firstly, signal features can be extracted by using Damage Indexes (DIs). Then, the Principal Component analysis (PCA) is used to construct a two-dimensional DMF ($D = 2$). In this paper, the DIs shown in Table 1 are adopted. GW No.1 is set to be $f_s(t)$ and $f_c(t)$ is GW No.1 to 400. $F_s(\omega)$ and $F_c(\omega)$ are the frequency spectrum of $f_s(t)$ and $f_c(t)$ respectively.

The results of DIs are shown in Figure 4. Usually, damage can be detected when the values of DIs exceeds a pre-defined threshold. However, due to the random variation of the DIs, no thresholds can be defined for reliable damage detection.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name</th>
<th>Expression</th>
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<tbody>
<tr>
<td>DI$_1$</td>
<td>Frequency spectrum difference</td>
<td>$D_{I_1} = \int_0^\infty [F_s(\omega) - F_c(\omega)] d\omega / \int_0^\infty F_s(\omega) d\omega$</td>
</tr>
<tr>
<td>DI$_2$</td>
<td>Normalized correlation moment</td>
<td>$r_c(\tau) = \int_0^\infty f_s(t) f_c(t - \tau) dt / \int_0^\infty f_s(t) dt$</td>
</tr>
<tr>
<td>DI$_3$</td>
<td>Frequency spectrum amplitude difference</td>
<td>$D_{I_3} = \int_0^\infty [F_s(\omega) - F_c(\omega)]^2 d\omega / \int_0^\infty F_s(\omega)^2 d\omega$</td>
</tr>
<tr>
<td>DI$_4$</td>
<td>Phase difference</td>
<td>$\tilde{\alpha}(t) = \sqrt{\int_0^\infty f_s(t)^2 dt}, \quad \alpha(t) = \frac{\int_0^\infty \tilde{f}_s(t) \tilde{f}_c(t) dt}{\sqrt{\int_0^\infty f_s(t)^2 dt}}$</td>
</tr>
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</table>

The baseline feature space can be constructed directly by using the DMFs of the baseline data No. 1 to No. 40. When new monitoring data is acquired, the new data is input to the framework to update the feature space. The new monitoring data also can be divided into many groups and input to the framework one group by one group. In this paper, the monitoring data was input one by one. Let $Z(t)$ denotes the monitoring feature space and $t (t \geq 1)$ denote the update times of feature space. $Z(0)$ is the baseline feature space. When a new DMF is obtained, it is added into $Z(t-1)$ to be the newest DMF and the oldest DMF in $Z(t-1)$ is removed. In this experiment, the monitoring feature space is updated 400 times. Besides, the first 40 monitoring feature space are the same as baseline feature space.

### 3.3 The double probability models

The baseline probability model (Baseline GMM, BGMM) shown in Figure 5(a) is constructed by the probability modeling strategy. For comparison, EM initialized by the $k$-means clustering is also tried to construct GMM (EM-GMMs) on the baseline feature space and the number of GCs is set as 5 according to the baseline GMM shown in Figure 5(a). Three different EM-GMMs are given in Figure 5(b)-(d). It should be noted that the baseline GMM in Figure 5(a) is also obtained by the EM algorithm. Thus, four different GMMs are obtained by the EM based on the fixed baseline feature space, which will reduce the stability of crack detection.
For damage monitoring, monitoring probability models (Monitoring GMMs, MGMMs) can also be obtained by using the probability strategy based on the monitoring feature space at different crack propagation. The number of GCs of all the MGMMs is shown in Figure 6. The number of GCs recognized by the proposed adaptive GMM constructing method is changing adaptively to the changing monitoring feature space along with the crack propagation. Some typical monitoring probability models (MGMMs) are shown in Figure 7. It can be seen that the probability structure of the MGMMs are also changing adaptively accompanying the crack propagation.

3.4 Damage monitoring index results

The damage monitoring indexes are shown in Figure 8. In the probability difference measuring strategy, the number of Monte Carlo samples $R$ is set as 40000. As mentioned before, the first 100 GWs of the monitoring data are the same with the baseline data. Consequently, the corresponding damage monitoring indexes are zero, indicating that the probability modeling strategy is stable. Besides, the damage monitoring indexes increases gradually along with the crack propagation. A damage detection threshold 0.9 can be easily set to alarm the crack with high confidence. When the crack propagation length is longer than 3mm, the damage monitoring indexes is above the threshold. Therefore, the hole-edge crack longer than 3mm is detected effectively and reliably under varying structural boundary conditions.
5. Conclusion

A damage monitoring framework based on probability modeling is proposed to extend the relevant research which can truly benefit the application of aircraft SHM technology. It offers a modular hierarchical architecture for SHM system designers to explore different strategies to maximize the performance of the corresponding SHM techniques which can be applied to in-service aircraft structures under TVCs. Furthermore, the probability modeling strategy based on the adaptive GMM constructing method are proposed to realize the damage monitoring capability of the framework. Although the framework is validated and demonstrated in a hole-edge crack detection of a wing spar, the realization and validation of the framework for a long term real-world SHM is still a key problem.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (Grant No. 51921003, Grant No. 51635008 and Grant No. 51575263); the Fok Ying Tung Education Foundation of China (Grant No. 161048); the Program for Distinguished Talents of Six Domains in Jiangsu Province of China (Grant No. GDZB-035); the Priority Academic Program Development of Jiangsu Higher Education Institutions of China; the Funding for Outstanding Doctoral Dissertation in NUAA (Grant No. BCXJ19-01).

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