Research on Structural Damage Identification Method for Aircraft Full Scale Fatigue Test

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Abstract: Structural fatigue cracks in aircraft full scale fatigue test were traditionally found by regular non-destructive Inspection (NDI), and it tend to be larger in size due to the high complexity of structure and the limitation of detection space, which is very unfavourable for the structural repair. In order to identify the crack timely and improve the probability of detection for short crack, a strain monitoring based method on fatigue damage identification for aircraft structure in full scale fatigue test was established. Firstly, an approach used to distinguish failed strain sensors was presented to avoid false damage warning. Secondly, a data cleaning method combined K-means clustering algorithm with 3σ rule was developed and used to detect and eliminate outliers in strain data. Lastly, a new fatigue damage identification method based on the statistical characteristics of strain data was established. In aircraft full scale fatigue test, it was proved that fatigue cracks in critical parts can be identified and located timely and successfully by the established method owning higher accuracy and sensitivity, compared with existing methods, which would be helpful for structural modification and reducing crack repair cost in the practical engineering application.

Keywords: Full scale fatigue test, damage identification, data cleaning, failure sensor detection

INTRODUCTION

One of the purposes of aircraft full scale fatigue test (FSFT) is to expose the weak regions of aircraft structure and improve the structure design in time, so as to avoid the structural failure caused by the fatigue cracks exceeding the critical repairable size [1]. In the past, structural fatigue cracks in the full scale fatigue test were mainly discovered by periodic non-destructive inspection (NDI), which was usually too late, and its effect was affected by NDI method, equipment ability, personnel capacity. Therefore, mature and reliable strain gauges were widely used for auxiliary monitoring of critical parts in the test [2-8]. With the development of damage monitoring sensor technology, intelligent coating, acoustic emission and piezoelectric sensors are gradually used in a few parts for direct monitoring [9-12], but the effect for complex aircraft structure is not ideal. Strain gauge is still the preferred auxiliary monitoring method for the full scale fatigue test.

In the past, limited by structural strength simulation analytical technique, the hot points of critical parts were difficult to determine accurately, and the arrangement of strain gauges was not optimized enough. With the improvement of the accuracy of aircraft structural stress analysis [13], the problem about the accurate recognition of hot points was resolved gradually and the arrangement of strain gauges became more targeted. Besides, several methods for damage detection and identification based on measured strain data were presented. Y Z Lu, et al. [14-15] analysed the relation-ship between strain change and fatigue crack formation and propagation in the fatigue test of automobile rear axle. P F Song [16] proposed a probability distribution method to detect structural damage based on the measured strain data. G An, et al. [17] used the relative error of strain data to guide crack detection. G Y Zhong [18] proposed threshold method and linear regression method to achieve automatic monitoring of aircraft structure damage based on the measured strain data. P W Zhang, et al. [19] calculated the difference of the relative strain variation before and after the crack initiation, obtained the effective zero point and extreme point of the difference curve, and studied the location of the prefabricated 25 mm long crack. Z T Liu, et al. [20] presented a method to diagnose the fatigue crack by using the variance of the residual error of the time series model. For aircraft full scale fatigue test, probability distribution method [16] and time series model method [20] were very sensitive to data acquisition quality; Relative error method [17], relative error difference method [19], threshold value method and linear regression method [18] were suitable for the identification of longer cracks, while the sensitivity of strain variation caused by shorter cracks was low, and the damage criteria were empirical to some extent. Therefore, there was a risk of missing reporting or lagging in the structural damage identification in the fatigue test.

On the basis of improving the data quality through data cleaning method, an approach for structural damage identification which takes the mean value, standard deviation and coefficient of variation of strain data into account was presented in this paper, and a dynamic self-adaptive damage criterion was adopted to improve the universality, sensitivity and accuracy.

AUTOMATIC DETECTION METHOD OF STRAIN GAUGE FAILURE

The fatigue test lasts for several years, and the strain gauge will inevitably fail with the increase of the service time, resulting in the distortion of the strain response. If failed gauge is not identified in time, the reliability of the structural damage identification would be reduced. Hence, the response characteristics of failure strain gages in fatigue tests are studied in this paper. The failed response characteristics were extracted: a) over-range; b) the strain response is constant and does not vary with external load; c) the strain response shows an increase/decrease phenomenon independent of the external load. According to these features, the automatic detection method of the failed strain gauge was proposed using the statistical theory.

Firstly, the mean value $\bar{y}$ of the strain gauge within full sequence strain response, the sample standard deviation s, and the slope k are calculated by the formula (1) ~ (3) respectively.

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1}$$

$$s = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}{n-1}} \tag{2}$$

$$k = \frac{n\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \tag{3}$$

Where x is an one-dimensional variable representing time, y is the strain response data, and n is the sample number of y. Slope k was obtained by linear regression of x and y.

Secondly, according to the response characteristics of the failed strain gauge, the following failure criteria are established:

1) If $|k| \leq 10^{-6}$, the strain gauge have failed, corresponding to feature b);
2) If $|k|>10^{-6}$and $|\bar{y}| \leq \varepsilon_{th}$, $s>s_{th1}$, the strain gauge have failed , corresponding to feature c);
3) If $|k|>10^{-6}$and $|\bar{y}|>\varepsilon_{th}$,$s>s_{th2}$, the strain gauge have failed , corresponding to feature a);

The values of ε_{th}, s_{th1} and s_{th2} are related to the performance of data acquisition system and the amplitude of structural strain response, which can be determined according to the measured results in the debugging phase of the full scale fatigue test. ε_{th}= 1000, s_{th1}=1000 and s_{th2}=2000 were used in a full scale fatigue test, and the accuracy for the failure strain gauge detection was greater than 95%. The method was used to detect the failure strain gauge and eliminate the influence of the failure strain gauge on the structure damage identification, thus to reduce false alarm rate effectively.

DATA CLEANING

Due to the system error of test loading system and data acquisition system and the influence of test environment and noise, some outliers exist in strain gauge data under same load condition. These outliers would reduce the accuracy of damage identification, and thus it’s necessary to eliminate the outliers before damage identification.

It should be noted that the phenomenon of nonlinear increment or decrement of strain data under the same load condition is the key feature of damage identification. However, using traditional data cleaning methods such as 3σ rule, Romanovsky's rule, and etc., the strain change caused by damage would be judged as outlier and eliminated, resulting in feature loss, which is not suitable for damage identification. In order to avoid this problem, the data were segmented by clustering and then cleaned by 3σ rule in this paper. The effect is remarkable except some strain gauges with lower data quality. Therefore, the likelihood filtering method was further proposed, and a large scale experimental data cleaning algorithm combined with k-means clustering and 3σ rule was formed. This algorithm includes three steps as follow.

Step 1: Macro outlier eliminate
The likelihood function between strain data and its mean value under the same condition is defined as follow:

$$L_i = \exp\left\{ \frac{|y_i - \bar{y}|}{s^{m(\delta)}} \right\} \tag{4}$$

Where δ represents the coefficient of variation that can be calculated by formula (5).

$$\delta = \frac{s}{|\bar{y}|} \tag{5}$$

In formula (4), the distance between strain data and its mean value was quantized by the likelihood Li. The closer y_i is to $\bar{y}$, the closer Li is to 1. Traditionally, $m(\delta)$=1, when the data dispersion is large, s is large, resulting in a small value of Li, which is unfavourable to the identification of outlier. In order to address this issue, m was defined as a function of δ, and the following expression was constructed.

$$m(\delta) = 1 - \exp\left[\frac{-1}{\delta^{\frac{1}{\exp(\delta)}}} \right] \tag{6}$$

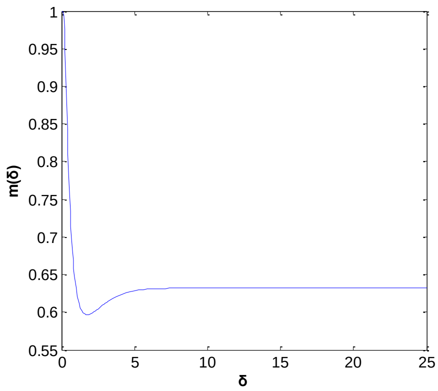

Figure 1:The curve where $m(\delta)$ changes with δ

The relationship between δ and m is shown in the figure 1, when δ =1.76, m(δ) takes the minimum value 0.596396. Few obvious centralized outliers would always be eliminated for data with different scatter though introducing m(δ). In order to ensure the universality of the method, the threshold function $delta(s)$ was proposed through derivation and analysis, as showed in formula (7).

$$delta(s) = \exp(\frac{s}{s^{\min[m(\sigma)]}}) \tag{7}$$

When the formula (8) was satisfied, y_i is judged as outlier and eliminated.

$$L_i \geq delta(s) \tag{8}$$

It was found that according to formula (8), only macro outliers were eliminated without accidentally losing the characteristics of normal data, which avoid the data clustering produce unreasonable results in next step.

Step 2: Data clustering

After the macro outlier cleaning, the data are classified by the classical K-means clustering method. Theoretically, the clustering result can always reflect the data characteristics completely and correctly as long as the *k* was appropriate. Its essence is to find the central point for each class so that the sum of squares *J* of the distance from each point to the central point is minimized, and specifically, through the iterative method, solve the (r_{ik} , μ_k) that minimizes the value of *J*.

$$J = \sum_{i=1}^{N}\sum_{k=1}^{K} r_{ik} \left\| x_i - \mu_k \right\|^2 \tag{9}$$

Where: *N* represents the number of samples, *k* represents the number of classes, r_{ik} denotes whether the *i* th sample belongs to class *k*, and if so, r_{ik}=1, and vice versa r_{ik}=0, μ_k denotes the central coordinates of the *k* th class.

Step 3: Local Outlier elimination

In the *k* classes obtained by clustering, the data are cleaned again by 3σ rule. After clustering, each class reflected local features of the data, and the data in each class is less dispersed. Therefore, local outliers in every class would be eliminated effectively without losing data feature, and the features causing by structural damage can be presented perfectly (see Figure 2), thereby improving the accuracy of structural damage identification.

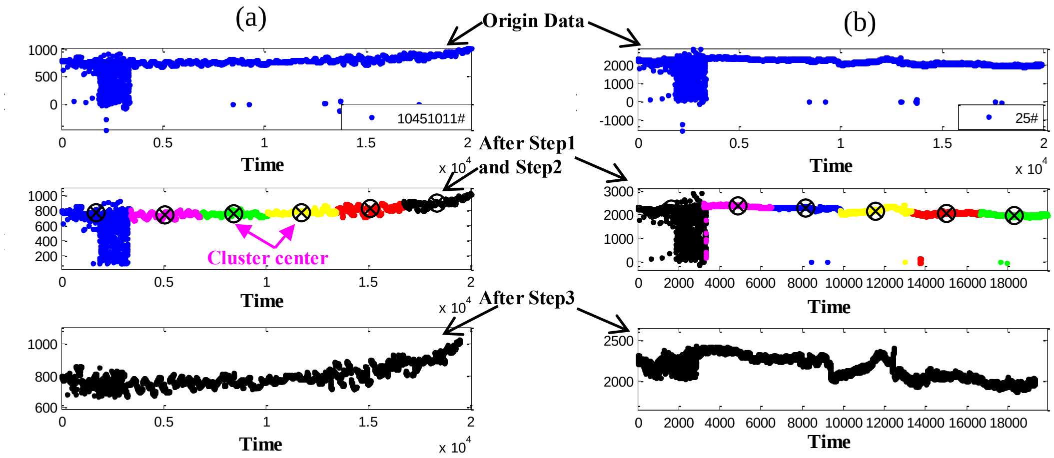

Figure 2: Two examples about data cleaning

RESEARCH ON DAMAGE IDENTIFICATION METHOD

In view of the existing methods' low sensitivity to short cracks and insufficient universality, the statistical characteristics of strain data were used in this paper, which took deviation degree and deviation rate as quantitative indexes and established an adaptive dynamic damage criterion. Hence a new strain data-driven structural damage identification method was proposed.

Firstly, the baseline data sequence y_b is selected, and its mean value $\bar{y}_b$, standard deviation s_b and coefficient of variation δ_b are calculated. Further, the deviation d_i and baseline deviation d_b are calculated by formula (11) ~ (12):

$$\delta_b = \frac{s_b}{|\bar{y}_b|} \tag{10}$$

$$d_i = e^{\frac{|y_{bi} - \bar{y}_b|}{s_b}} \tag{11}$$

$$d_b = \frac{1}{n}\sum d_i \tag{12}$$

Secondly, the mean value $\bar{y}$, standard deviation s and coefficient of variation δ of newly collected data after cleaning are calculated, $\bar{y}_b$ and s_b are taken as the basis to calculate the deviation degree of newly collected data.

$$d_{yi} = e^{\frac{|y_i - \bar{y}_b|}{s_b}} \tag{13}$$

if the structure is intact, d_{yi} is close to 1.0. If a crack occurs in the critical part of the structure, the response of the nearby strain gauge would change under same external loading. By formula (13), the small change of strain was magnified to ensure the sensitivity of damage identification.

Finally, the adaptive dynamic threshold f is introduced to calculate r which represents the probability of d_{yi} greater than f in newly acquired data, and the criterion of damage identification is established according to T and I which represents the flight hours of the load spectrum block and the new data respectively.

$$f = \frac{1}{d_b^2 \delta_b} \tag{14}$$

$$r = p(d_{yi} \geq f) \tag{15}$$

$$q = \frac{T - I}{T + I} + \frac{I}{10T} \tag{16}$$

$$r \geq q \tag{17}$$

If inequality (17) is satisfied, structural damage may have occurred near the strain gauge,and a damage warning is issued to trigger NDI for confirmation. In Eq.(14), if δ_b and d_b are large, it indicated that the dispersion of base strain data is large and the sensitivity of d_{yi} to the change of data is weak, so smaller f should be used to identify damage; otherwise, a larger f should be used to avoid high false alarm rate. In summary, f is related to data dispersity, it is adaptable to different quality of data, so it has higher sensitivity and accuracy for damage identification.

APPLICATION IN FULL SCALE FATIGUE TEST

According to the method presented in this paper, a structural damage identification procedure was developed and applied in the full scale fatigue test of an aircraft. The damage signals of several critical parts were captured in time, and short fatigue cracks were found by NDI. One example was showed in figure 3. Compared with the cracks, which usually greater than 10mm in length, found by regular NDI in the past, the crack detection guided by damage identification method was more timely and smaller in size, which greatly reduces the repair difficulty, cost and period, triggers the improvement design of aircraft structure more in time, and plays an important role in the full scale fatigue test.

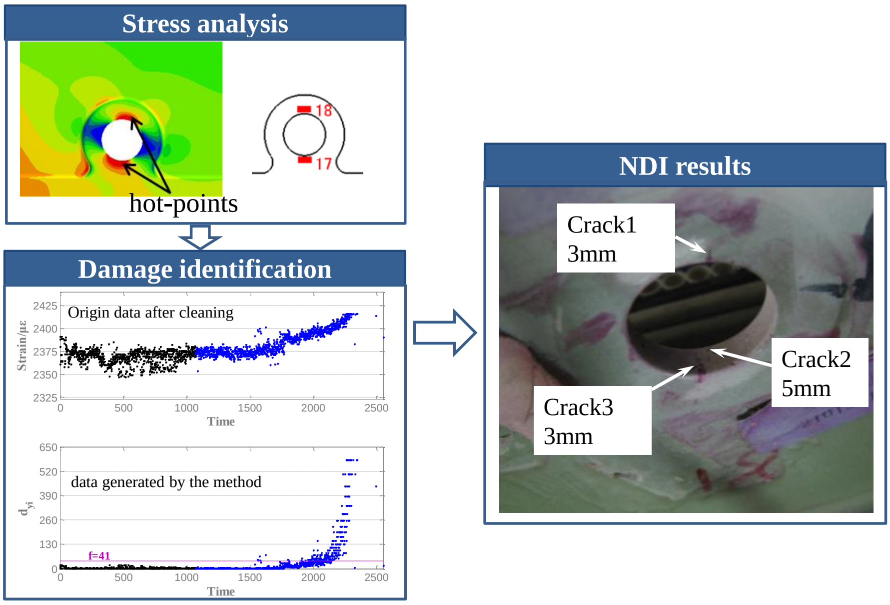

Figure 3: cracks found by damage identification.

CONCLUSION

A new fatigue damage identification method with high accuracy and sensitivity was presented in this paper. In order to improve the effectiveness and universal of this method, an approach used to distinguish failed strain sensors was presented to avoid or reduce false damage alarming, a data cleaning method which combined K-means clustering algorithm with 3σ rule was developed and used to detect and eliminate outliers in sensor data. These methods were applied in a full scale fatigue test, and several fatigue cracks were identified and located timely and successfully. It’s significant for structural modification and reducing repair cost and time of the structure including cracks.

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