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Damage and Fault Diagnosis of In-service Structure via Statistical Comparison of Relation between Sensor measurements

(Damage Diagnosis of in-service Structure under High Noise Environment using Multiple Reference Data)*

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Abstract

The present study is about an automatic diagnostic method for the structural health monitoring. In this study, a new diagnostic method applicable to existing structures from the present moment is proposed. In the proposed method, structural condition is diagnosed without information about damaged condition. The proposed method statistically diagnoses structural condition by means of investigating the change of a response surface. The response surface is calculated as a regression model of relationship between multiple sensors. The shape of the response surface is changed reflecting the change of the structural condition. In this method, the change of the response surface is statistically investigated with the F-test. In the F-test, the threshold of normal or damaged condition is decided with only theoretical F-probability distribution. This theoretical F-distribution is easily calculated using the response surface parameters. Therefore, diagnosis is conducted by means of only intact data used for the reference data. This means the proposed method doesn't require information about the damaged condition. In this study, the health monitoring system of the jet fan was developed to investigate the effectiveness of the proposed method. In this study, field test was conducted using an actual jet fan in a tunnel. In the field test, robustness of the proposed method was investigated. As a result, the structural condition of the jet fan was successfully diagnosed and effectiveness of proposed method was confirmed.

Key words: Smart Structure, Structural Health Monitoring, Response Surface, Unsupervised, Probabilistic Method, Structural Reliability, Nondestructive Inspection

1. Introduction

This study is concerned with the application of our damage and fault diagnosis method based on the statistical comparison of the correlation between sensor measurements to civil structures operated in changing environments. Our group proposed a non-destructive statistical method of damage and fault diagnosis that is applicable to existing aging structures. In our previous paper, we conducted experiments on its application to a

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ventilation jet fan in a laboratory environment that allowed sensors to be highly sensitive to delamination damage of composite materials(1) in order to test the effectiveness of our method for in-service structures of complex form(2). The method we proposed makes diagnosis of damage and faults by analyzing variations in the correlation between measurements rather than variations in measurements or measurement parameters themselves. Therefore, if measurements are performed at a normal condition over an extended period of one or two years, a massive amount of data is recorded, and making a diagnosis using all measurements recorded during the period as normal-condition data would require a diagnosis device with an enormous capacity for calculation and data storage. Diagnosis made under these conditions, while still possible, would lose its real-time nature. However, since the enormous amount of normal-condition data accumulated includes repetitions of similar patterns through most of the period (including environmental elements such as temperature and humidity, and operation conditions such as number of revolutions and pressure in piping systems), using all data for diagnosis would be unnecessary. Therefore, in this paper we will examine a method of grouping normal-condition data into a number of data sets in order to make a diagnosis based on effective data sets selected for the purpose in question. We will examine the effectiveness of this method by applying it to long-term data in a field experiment with a jet fan used for a road tunnel.

2. Field Experiments Using an In-service Jet Fan

We conducted field experiments with a jet fan used in an operating environment in order to examine the effectiveness of our method of making a diagnosis based on a limited number of normal-condition data sets. The field experiments were conducted using an in-service jet fan installed in a tunnel (of 746 meters in total length). Figure 1 shows a schematic diagram of the jet fan, and Figure 2 the appearance of the jet fan with sensors installed. Maintenance of the jet fan involves the construction of scaffolding for jobs at the tunnel ceiling, requiring large-scale preparation work such as traffic regulation as well as high economic and social costs. The fact that damage to the jet fan is most often caused by accidental factors, such as collisions with vehicles, leads us to believe that structural monitoring based on damage measurements will provide an effective means of maintenance.

As shown in Figure 1, the jet fan used for the experiments is supported by two turnbuckles at both ends and four turnbuckles at the middle, and these turnbuckles are all fixed to the tunnel ceiling. Since the two turnbuckles at both ends are used to reduce vibrations, the bulk of the weight of the fan is supported by the four turnbuckles in the middle. We therefore affixed load cells to the four turnbuckles in the middle in order to measure the axis force. To avoid accidents caused by damage to the load cells, we used washer type load cells shown in Figure 3 for the measurement. The load cells were affixed to the turnbuckles and the joints of the jet fan. Figure 4 shows load cell numbers and the top view of the configuration. Load cells were numbered 1 through 4. The jet fan measures 1,200 mm in diameter, with a total length of 4,900 mm. Installed at a point about 100 meters from the tunnel entrance, it starts to rotate when the dust density measured by an exhaust transmission indicator exceeds a certain level. The jet fan rotates at a rotation frequency of 30 Hz.

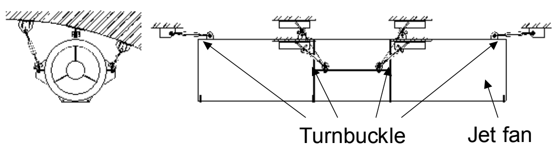


Fig. 1 Schematic diagram of a jet fan

Fig. 2 Installation of the sensors to the jet fan

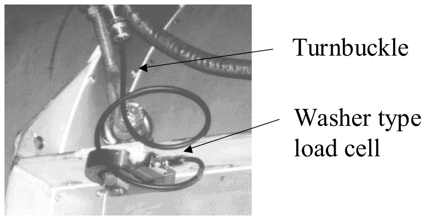


Fig.3 Image of the washer type load cell

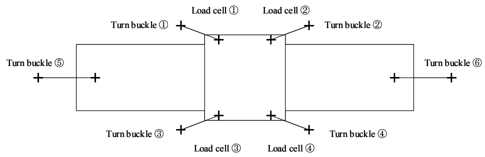
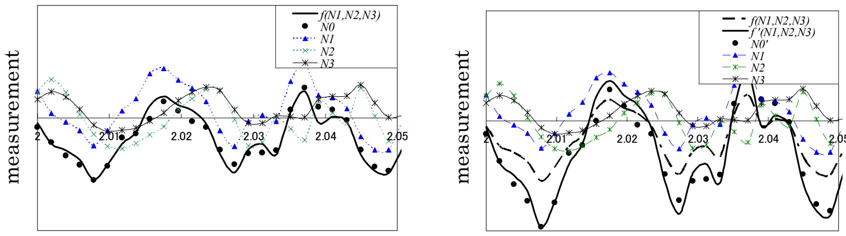


Fig. 4 Test configuration of the jet fan



(a) Intact (b) Damaged

Fig. 5 Fluctuation of correlation between the sensors resulting from the generation of damage

3. Fault Diagnosis of the Jet Fan Based on the Statistical Comparison of Correlation between Sensor Measurements

3.1 Outline of the Statistical Comparison of the Correlation between Sensor Measurements

The statistical comparison of the correlation between sensor measurements(1)(2) provides a means of detecting faults from variations in the correlation between a number of parameters rather than variations in any one of the parameters. Given four measurement parameters, N_0, N_1, N_2, and N_3, whether or not a structure is intact is ordinarily evaluated by whether any one of the parameters N_0 through N_3 exceeds a certain threshold value. Therefore, since vibrations and noises within the structure are affected by drifts and changes in the environment, there is a need to set the threshold at a relatively conservative value in order to ensure the accuracy of diagnosis. The method proposed in this paper provides a means of diagnosing a structure by the statistical analysis of changes in the following correlation function *f* between a given parameter N_0 and the other three:

$$N_o = f(N_1, N_2, N_3) \quad (1)$$

ex. $$N_0 = \beta_0 + \sum_{j=1}^{3} \beta_j x_j \quad (2)$$

In other words, this method diagnoses damage by the system identification of the parameters and by statistical analysis of its changes. The response surface methodology is used for the identification of correlations(3). If a structure is intact, the correlation between measurement parameters shows no change despite changes in the parameters themselves caused by factors such as noises, changes in the environment, and operating vibrations of the structure (see Figure 5 (a)). Meanwhile, a fault in the structure causes only those parameters that are subjected to its influence to change (*e.g.*, only N_0), thereby causing the correlation between the parameters to change from $f\,(N_i)$ to $f\,'\,(N_i)$ (Figure 5 (b)). The method proposed in this paper, which diagnoses the health of a structure through the analysis of variations in the correlation $f\,(N_i)$ between a number of parameters rather than variations in the parameters themselves, thus provides a means of making an accurate automatic diagnosis in an environment that involves constant changes in parameters. Since the method detects faults from variations in correlation, all it requires as pre-diagnosis information is normal-condition measurement data. In this paper, we will call data recorded at normal times "reference data," and data recorded at the time of diagnosis "diagnostic data."

3.2 Fault Diagnosis Based on Turnbuckle Axis Force Measurements

We measured four weighted time-series data sets n_i (i = 1 - 4) using load cells 1 through 4 to make diagnosis of faults based on changes in the load. Load measurements are standardized according to the following formula in order to remove the effects of bolt tightening load:

$$N_i = n_i - \overline{n_i} \quad (i = 1,2,3,4) \qquad (3)$$

where $\overline{n_i}$ represents the mean of load measurements for the i-th load cell.

We regress these N_i 's to obtain a quadratic response surface represented by the following equation to be used for diagnosis:

$$N_4 = \beta_0 + \sum_{i=1}^{3} \beta_i N_i + \sum_{i=1}^{3}\sum_{j=i}^{3} \beta_{ij} N_i N_j \qquad (4)$$

where β_i and β_{ij} are regression coefficients. Although the dependent variable N_4 is regressed on N_1, N_2, and N_3 in the above equation, we also construct response surfaces using N_1, N_2, and N_3 respectively as dependent variables in order to make diagnosis of measurements for each one of the load cells. In the experiment, the measurement frequency was set to 512 Hz, with measurements of 16 seconds grouped into one data set (one data set comprising 8,192 elements). We made continuous measurements for short-term data presented in Section 4, and discontinuous measurements of 16 seconds every five minutes for long-term data presented in Section 5. The response surface represented by the above equation is estimated by choosing data at 60 points chosen at random for each set of measurements and by calculating the regression coefficients using the least squares method.

3.3 Damage Diagnosis Using Mean F_0

Similarity between correlations is tested by F-tests. Assuming that error terms ε in two samples are mutually independent and that they have the same variance, the similarity of the two response surfaces is tested using the test statistic F_0 defined by the following equation [4]:

$$F_0 = \frac{SSE_0 - \left(SSE_1 + SSE_2\right)}{\left(SSE_1 + SSE_2\right)} \times \frac{n - 2p}{p} \qquad (5)$$

where p is the degrees of freedom and n is the number of data points used for the regression analysis of response surfaces. SSE_1, SSE_2, and SSE_0 represent, respectively, sums of squares error for the reference response surface, diagnostic response surface, and response surface obtained by regressing reference and diagnostic data together. If two response surfaces are similar, the probability distribution of F_0 follows an F-distribution (p, n-2p) that depends on the degrees of freedom of response surfaces and the number of data points. Therefore, by the central-limit theorem, the mean F_0 value obtained from r repetitions will follow a normal distribution, $N(E(F_0), \sigma^2(F_0)/r)$, with mean $E(F_0)$ and variance $\sigma^2(F_0)/r$, which are defined by the following equations[5]:

$$E(F_0) = \frac{n-2p}{n-2p-2} \quad (6)$$

$$\sigma^2(F_0) = \frac{2(n-2p)^2(n-p-2)}{p(n-2p-2)^2(n-2p-4)} \quad (7)$$

Hence, the confidence interval for the similarity hypothesis is given by the following inequality, which varies depending on the significance level α:

$$E(F_0) - z\frac{\sigma(F_0)}{\sqrt{r}} < \overline{F}_0 < E(F_0) + z\frac{\sigma(F_0)}{\sqrt{r}} \quad (8)$$

where $\overline{F}_0$ is the mean of F_0's and z is a value determined by the significance level. A diagnosis of damage or a fault is given if the similarity hypothesis is rejected by an F-test using the mean F_0 value. We will set the significance level at 5% for diagnosis in this paper. As equation (4) indicates, response surfaces used for diagnosis in this paper have ten degrees of freedom, and given the number of data elements n = 60 and the number of repetitions r = 100, the interval defined by inequality (8), within which the similarity hypothesis will be accepted, is given as follows:

$$0.935 < \overline{F}_0 < 1.13 \quad (9)$$

3.4 Diagnosis by Multiple References

The jet fan diagnosed by our method, which is greatly affected by the surrounding environment, does not have a single structural configuration that can be used as a reference. For this reason, we use multiple reference data sets to make a structural health diagnosis. Using multiple reference data sets for diagnosis requires selecting reference data that are closest to diagnostic data in terms of measurement conditions. Sohn *et al.* select their reference data based on differences between regression coefficients, which they assume to represent differences between measurement conditions[6]. Given response surfaces A and B represented by equations in (10) for two sets of data A and B recorded under different conditions, we assume in this paper that the difference in measurement conditions for data sets A and B is represented by the sum of squares of differences between regression coefficients D defined by equation (11), and choose appropriate reference data sets based on this assumption. For a data set used for diagnosis, we calculate the value of D with regard to each one of the reference data sets and make a structural health diagnosis using a reference data set with the minimum D value.

$$y^{\mathrm{A}} = \beta_0^{\ \mathrm{A}} + \sum_{i=1}^{p-1} \beta_i^{\ \mathrm{A}} x_i^{\ \mathrm{A}}$$
$$y^{\mathrm{B}} = \beta_0^{\ \mathrm{B}} + \sum_{i=1}^{p-1} \beta_i^{\ \mathrm{B}} x_i^{\ \mathrm{B}} \quad (10)$$

$$D = \sum_{i=1}^{p-1} (\beta_i^{\ \mathrm{A}} - \beta_i^{\ \mathrm{B}})^2 \quad (11)$$

In order to choose a reference data set with characteristics similar to those of the diagnostic data set based on the value of D, we calculate D using all measurements (8,192) contained in a data set for the regression analysis of the response surface.

3.5 Flow of the Health Monitoring of the Jet Fan

Figure 6 shows a flow chart of the diagnosis of the jet fan using multiple reference data sets. In this method, we estimate response surfaces using N_1 through N_4 respectively, as dependent variables in order to make a diagnosis. Thus, four response surfaces are constructed for one set of measurements to make four different diagnoses. We choose a reference data set used for diagnosis for each one of the four response surfaces. Reference data sets to be compared against diagnostic data sets are chosen according to the procedure shown in Section 3.4. After choosing reference data for diagnosis, we ① choose 60 data points from each data set and ② perform regression analysis to estimate response surfaces. The response surface estimated from data chosen from the reference data set with the smallest D value with regard to the diagnostic data set is used as the reference response surface, and a response surface constructed from the diagnostic data is used as the diagnostic response surface. ③ We then calculate the test statistic F_0 according to the equation (5) to test the similarity between the reference and diagnostic response surfaces. We repeat procedures ① through ③ r times to obtain the mean F_0 value, which will be used as the evaluation value for diagnosis. If the structure is intact, the mean F_0 value follows the theoretical distribution shown in Section 3.3. A total of four diagnoses of the output of each load cell are obtained by these procedures. We conduct the health monitoring of the jet fan by applying this flow of diagnosis to each new measurement of data.

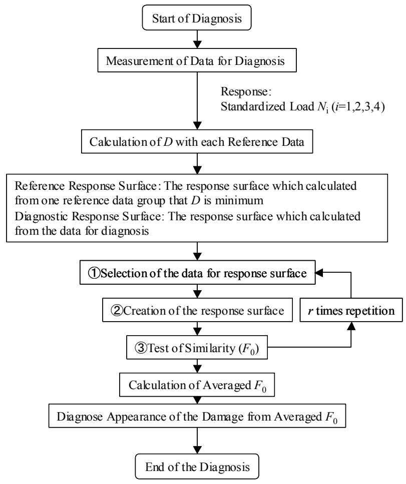


Fig.6 Procedure of the damage diagnosis using multiple reference data and averaged F_0

4. Test of the Effectiveness of Multiple Reference Data Sets Based on Short-term Measurements of the In-service Jet Fan

4.1 Outline of Short-term Measurements of the Jet Fan

We conducted a field experiment on short-term measurements using the jet fan installed in the tunnel. The jet fan used in our experiment is a structure operated in actual operating conditions, and since we are not allowed to simulate structural faults using the jet fan, our experiment was designed to examine the accuracy of normal-condition diagnosis only. It was confirmed by visual inspection that the jet fan was operated under normal conditions during the experiment period.

The experiment was conducted with the jet fan in operation. The sequence of 8 minutes and 16 seconds of measurements followed by 1 minute and 44 seconds of pause was repeated four times to perform measurements of load data for a total of 40 minutes due to restriction of the measurement device. No damage was observed in the jet fan during the experiment. Meanwhile, considerable changes were observed in the loading condition of the turnbuckles due to large vibrations of the jet fan caused by the wind pressure from large-size vehicles. We obtained a total of 128 sets of normal-condition load measurements during this 40-minute test.

4.2 Results and Considerations

An example of a load cell output recorded during the experiment is shown in Figure 7. The horizontal axis in the figure

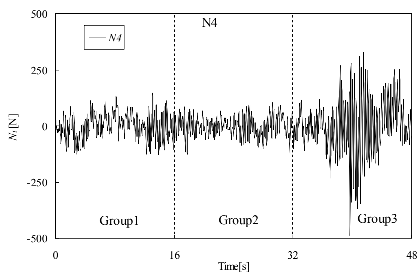


Fig.7 Loading condition of turnbuckle(0 to 48 sec.)

represents the time from the start of the experiment, and the vertical axis represents the load measured using load cell 4. Data for the first 48 seconds from the start of the experiment, comprising a total of three measurement sets, is shown in the figure. The figure indicates that although the loading condition remained relatively stable from the start until 32 seconds later, there were considerable variations in the load data between 32 seconds and 48 seconds. Figure 8 shows what was happening in the tunnel 41 seconds into the experiment, when the load data showed a marked change. As the picture shows, the jet fan, installed in an actual operating environment, was exposed to strong effects of outside factors such as wind pressure from large-size vehicles, which caused its conditions to change constantly.

Fig.8 Condition of the jet fan (41 sec.)

Figure 9 shows the probability distribution of F_0 (before being averaged) used for the tests of similarity between the measurements from 0 to 16 seconds and measurements ① from 0 to 16 seconds, ② from 16 to 32 seconds, and ③ from 32 to 48 seconds. The horizontal axis represents the value of F_0, and the vertical axis the probability of F_0. The continuous curve in the figure represents the theoretical distribution F (10, 100). As the figure shows, the mean F_0 value increases from ① to ③ in accordance with the change in the condition, demonstrating the need to select appropriate reference data that represent conditions of the external environment at the time of diagnosis.

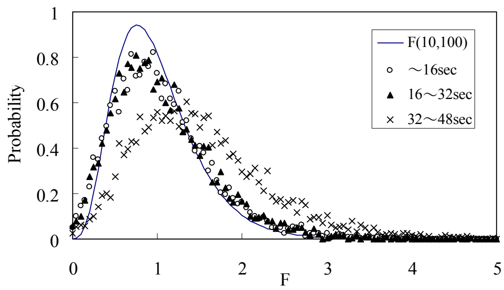
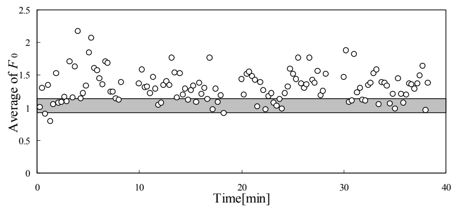
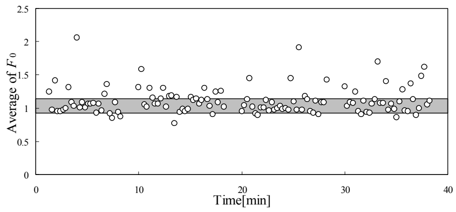


Fig. 9 Probability distribution of F0

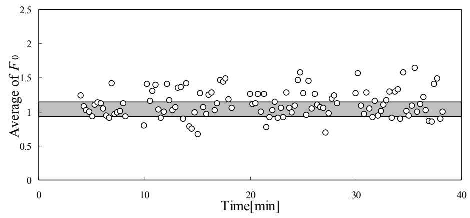
Figure 10 shows mean F_0 values calculated according to the procedure shown in Section 3.5 by using as reference data the first data set measured in the experiment, the first five data sets, and the first fifteen data sets. The horizontal axis in each figure represents the time from the start, and the vertical axis the mean F_0 value. Results obtained using only one reference data set is shown in (a), results for five data sets in (b), and results for fifteen data sets in (c). These are results concerning the response of load cell 4. The mean F_0 values shown in the figure were calculated using 100 repetitions. The figures show acceptance intervals of the similarity hypothesis at a 5% significance level. As these figures indicate, using a larger number of reference data sets results in an increase in the probability of choosing reference



(a) Number of reference data = 1



(b) Number of reference data = 5



(c) Number of reference data = 15

Fig. 10 Average of F0 of intact condition jet fan using multiple reference data (40 min.)

data close to the current conditions, causing mean F_0 values to concentrate around the acceptance interval defined by the theoretical distribution. These results lead us to conclude that the sum of squares of differences of regression coefficients D defined in (11) provides an efficient means of choosing reference data that match diagnostic data in terms of external conditions, thereby reducing the probability of diagnostic errors.

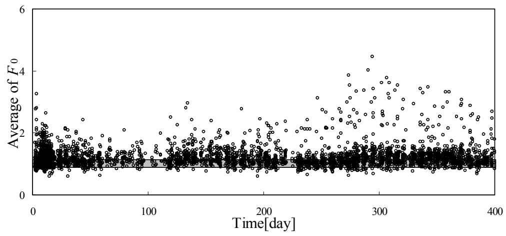
5. Long-term Diagnosis of the Jet Fan Using Multiple Reference Data Sets

5.1 Outline of the Field Experiment

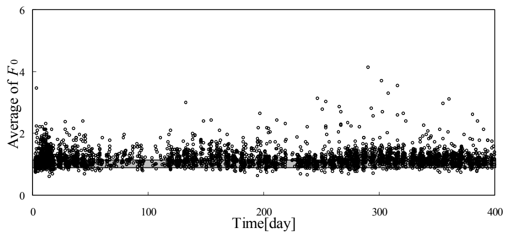
We conducted a long-term diagnosis field experiment using a jet fan installed in a tunnel in order to test the accuracy of structural diagnosis using multiple reference data sets. Since the experiment was conducted using a jet fan used in actual operations, measurements were all made under normal operating conditions. The performance of the jet fan was examined once every month by visual inspection, and an inspection was also made after the experiment to check that the fan was running normally. The field experiment was conducted between September 22, 2003 and November 30, 2004. When the experiment was started, nine months had passed since the load cells were affixed, and the jet fan was running in stable condition. Diagnosis was made using the jet fan in actual operation, and a total of 3,737 diagnostic data sets were diagnosed. Measurement conditions were the same as those discussed in Section 4, and measurements were made for 16 seconds every five minutes, as explained in Section 3.2. Ten, fifteen, and thirty reference data sets were used for the tests. These reference data sets were chosen in the early stages of the experiment, and these same sets of reference data were used for diagnosis throughout the experiment.

5.2 Long-term Diagnosis Using Multiple Reference Data Sets

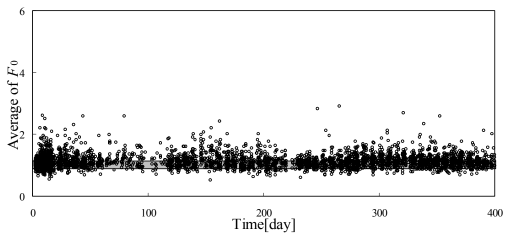
Results of the experiment are shown in Figure 11. The figures show the results obtained using (a) 10 sets of reference data, (b) 15 sets of reference data, and (c) 30 sets of reference data, respectively. The horizontal axis in each figure represents the time from the start of the experiment, and the vertical axis the mean F_0 value. The figures show results about the response of load cell 4. Mean F_0 values were calculated using 100 repetitions. The acceptance intervals of the similarity hypothesis at a 5% significance level are shown in the figures. The figures show greater variations in diagnosis compared to jet fans diagnosed in a laboratory environment due to greater changes in the surrounding environment. Although some changes were observed in the mean F_0 value after the 250th day, these changes were temporary, with the mean falling to the previous level after the 350th day. The method used in the experiment was measuring changes from normal conditions in the early stages of the



(a) Number of reference data = 10



(b) Number of reference data = 15



(c) Number of reference data = 30

Fig. 11 Average of F0 of intact condition jet fan using multiple reference data (400 days) experiment, and changes in the mean F_0 value are likely to have been caused by the condition of the sensors, which were greatly affected by the expansion of the jet fan during summer. Changes observed around the 120th day were caused by measurement deficiencies, which will be discussed in the following section. Sudden increases in the mean F_0 value caused by strong effects of the surrounding environment, such as the effects of large-size vehicles, were temporary phenomena, as seen from the fact that the value fell back to the previous level soon after the increases.

Percentages of similarity hypotheses concerning response surfaces that were accepted at a significance level of 0.05 are shown in Figure 12. The figure indicates that increase in the number of reference data sets used for diagnosis improves diagnostic accuracy. Although increase in the number of reference data sets thus leads to improvement in diagnostic accuracy, it also increases the cost of calculation, which demonstrates the need to make a careful examination of the relationship between diagnostic accuracy and calculation cost when determining the number of reference data sets.

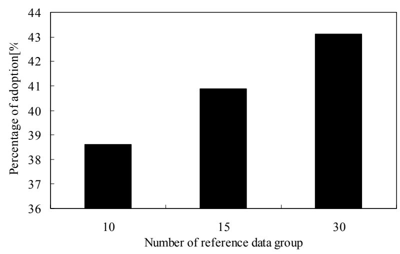


Fig. 12 Percentage of adoption of the similarity hypothesis

5.3 Fault Diagnosis Based on the Number of Consecutive Times of Rejection of Normality Evaluation

Since considerable variations are observed in the diagnosis of jet fans used in actual operations due to the effects of the surrounding environment, the percentage of diagnostic errors will increase if the critical value defined by the theoretical distribution is applied strictly, as shown in Figure 12. This is due to the fact that appropriate data that match the actual conditions are not always included in a finite number of reference data sets. There are various ways to overcome this difficulty, such as using all normal-condition measurements made over an extended period as reference data. However, since increase in the number of reference data sets involves increase in the time and capacity required for calculation, there is a need to examine how to perform a diagnosis using the minimum required number of reference data sets. To that end, we will examine in this section how to make diagnosis using the number of consecutive times of rejections of normality evaluation as a diagnostic parameter. The "number of consecutive times of rejection of normality evaluation" refers to the number of times the null hypothesis is consecutively rejected in the similarity test of response surfaces. If the structure of the jet fan is intact, the null hypothesis is likely to be accepted more than once in a series of tests, reducing the probability of consecutive rejection. In contrast, a structure with a fault will make it more likely for the similarity hypothesis to be consecutively rejected. Therefore, using the number of consecutive times the hypothesis is rejected as a diagnostic parameter will provide a means of detecting the fault.

Figure 13 shows the distribution of consecutive rejection of normality evaluation observed in tests using 30 sets of reference data. The horizontal axis represents the time from the start of the experiment, whereas the vertical axis shows the number of times normality evaluation was consecutively rejected in these tests. The figure shows that the number of consecutive times of rejection generally remained stable at low levels, except for the period around the 120th day of the experiment, when the number increased temporarily, displaying a sign of change in the structural configuration. As we can see from Figure 14, the increase in the number of consecutive times of rejection was due to temporary measurement trouble in load cell 3 caused by excessively low loading below the lower limit of the capacity of the measurement device. As the trouble was subsequently overcome, the number of consecutive times of rejection decreased to the previous level. These results make it clear that the number of consecutive times of rejection provided an accurate diagnostic parameter in this case. The histogram also shows that the number of consecutive times of rejection remained generally stable at low levels, exceeding 45 only twice around the 120th day, as shown in the figure.

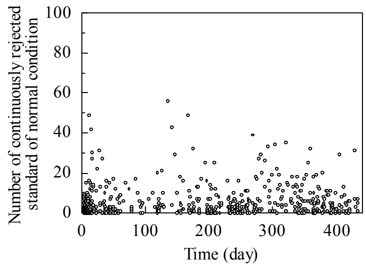
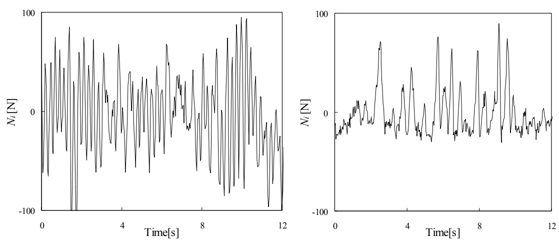


Fig. 13 Number of consecutive times of rejection using 30 reference data group

Distributions of consecutive rejections of normality evaluation observed in tests conducted with different numbers of reference data sets are shown in Table 1. The percentages of cases in which normality evaluation was rejected more than fifty consecutive times shown in the table were calculated relative to the total number of tests conducted. These results indicate that the number of consecutive times of rejection is likely to be small for tests conducted with a large number of reference data sets.

When using the number of consecutive times of rejection of normality evaluation as a diagnostic parameter, we need to note that major changes in the structural configuration are likely to cause the number of consecutive times of rejection to be larger with greater frequency. In the actual health monitoring of a jet fan, examining the distribution of consecutive rejection is an efficient way to analyze its structural configuration. It seems possible to create a system that issues a warning when the number of consecutive times of rejection exceeds a certain threshold, thereby liberating users of the jet fan health monitoring system from the task of constantly observing diagnostic results. It would be appropriate to choose 50 consecutive times of rejection as the threshold for issuing the warning in that case, considering that the percentage of cases in which normality evaluation is rejected more than fifty consecutive times is approximately 1% at the most and that these cases usually occur when some change is actually observed in the structural configuration. If the number of consecutive times of rejection exceeds 50, it would be advisable to issue a warning for users of the health monitoring system so that they can check the condition of jet fans and take appropriate measures, including inspection, depending on their condition.



(a) normal (b) faulty

Fig. 14 Loading condition of the turnbuckle No. 3

Table 1 Number of consecutive times of rejection using multiple reference data group

Number of reference data	Number of continual rejection 0	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	over 50
10	65	153	74	46	33	10	8	3	8	0	1	4 (0.99%)
15	88	210	80	41	28	13	7	3	1	3	2	3 (0.63%)
30	101	265	87	42	24	6	8	7	1	2	2	1 (0.18%)

5.4 Accuracy in Detecting Faults

In this section, we will examine how structural faults are detected in our diagnosis algorithm. Since jet fans installed in actual operating environments are being used for practical purposes, we are not allowed to simulate structural faults. For this reason, we simulated data about structural faults from data on vibrations observed under abnormal conditions. See our previous paper for details of the diagnostic results about structural faults of jet fans tested in a laboratory environment(2).

In experiments conducted with test jet fans, loosening of load-supporting turnbuckles and unbalanced vibrations of rotating parts were observed to cause changes in the amplitude of vibration in load cell outputs. In this paper, we therefore created data about structural faults by causing changes in the amplitude of vibration in load cell outputs of a normal jet fan used in an operating environment. In actual conditions of structural faults, various changes are observed in factors other than amplitude, such as the number of vibrations. However, in our experiment, we changed only the amplitude for the sake of simplicity and performed analysis using results obtained when the looseness was 80%. Table 2 shows amplitude ratios between load cell outputs under normal conditions and those under abnormal conditions. Load cell numbers in the table are those of a jet fan used in an operating environment. We performed our analysis assuming that structural faults of the jet fan caused by the loosening of turnbuckles appeared in the long-term data presented in Section 5.1 after 278 days into the experiment.

Figure 15 shows the diagnostic results obtained from the simulation of faults caused by the loosening of load-supporting turnbuckles. The horizontal axis represents the time from the start of the experiment, and the vertical represents the F statistic. Mean F_0 values were calculated using the results of 100 tests. Fifteen measurement sets were used for reference data. A 0.05 significance level was adopted for the critical value for accepting the similarity hypothesis. The figure shows that the similarity hypothesis was rejected for 155 consecutive days from the 278th day through the 433rd day, and that the hypothesis continued to be rejected through to the end of the diagnostic period without allowing the structure to be diagnosed as normal after being diagnosed as abnormal due to the looseness of the turnbuckle.

Table 2 The oscillation ratio before and behind damage generating

	Loosening of turnbuckle
Load cell 1	0.69
Load cell 2	0.94
Load cell 3	0.64
Load cell 4	2.43

These results lead us to conclude that if the same changes in the load cell output caused in the test jet fans should occur in jet fans running under actual operating conditions, the consecutive number of rejections of normality evaluation will increase remarkably, allowing us

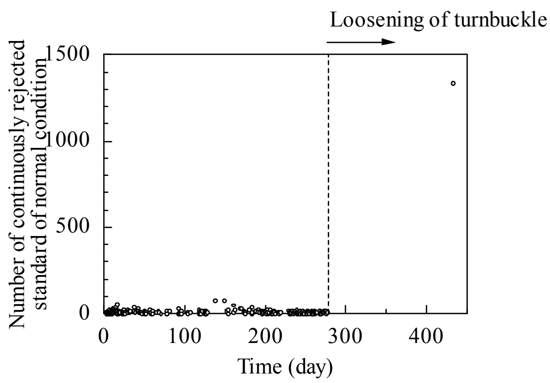


Fig. 15 Number of consecutive times of rejection of damaged condition

to detect faults using the diagnosis algorithm proposed in this paper.

6. Conclusion

In this paper, we examined the possibility of application of damage and fault diagnosis based on our method of statistical comparison of correlation between sensor measurements to structures operated in changing environments. In actual operating environments where these structures are operated, various factors cause changes in conditions, so that a large amount of normal-condition data on surrounding environments are needed for comparison. However, making a diagnosis using a large amount of data is unadvisable, since that would require diagnostic devices with an enormous capacity for calculation and data storage. In this paper, we proposed a method of grouping normal-condition data into a number of data sets in order to make diagnoses based on effective data selected for the purpose in question and examined the effectiveness of the method. Our examination led us to the following conclusions:

(1) Choosing normal-condition data sets by using the sum of squares of differences of regression coefficients D as the parameter of evaluation allows us to select normal-condition data sets that match the conditions of diagnostic data.

(2) Experiments conducted with a jet fan in an actual operating environment using the method proposed in this paper showed that our method provides an effective means of long-term diagnosis of jet fans operating in high-noise environment.

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