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Unsupervised statistical damage diagnosis for structural health monitoring of existing civil structures

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Abstract
Structural health monitoring is an important technology for ageing aerospace and civil structures. For this structural health monitoring, fiber optic sensors are increasing in popularity; however, several kinds of sensors are usually required, including sensors other than fiber optic sensors. Thus, a new technology for transforming conventional sensors into distributed sensors is required. The present study proposes Ethernet LAN technologies for the sensor integration required for structural health monitoring, and discusses the advantages of adopting this technology. Moreover, the paper describes an Ethernet-based health monitoring system and a statistical unsupervised damage detecting method for automatic damage diagnosis. Then, we create a system for monitoring the damage to an expressway tunnel jet-fan using system identification and statistical tools. Damage was detected from changes in a set of data measuring loads on the turnbuckles of the jet-fan. The resulting automatic diagnosis of damage to the jet-fan was successful.

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Structural health monitoring (SHM) systems are equipped with numerous sensors and are used to evaluate the state of an entire structure or its structural components in real time. Recently, in order to prevent serious failures of critical civil structures such as bridges and gas pipes, structural health monitoring systems have been put into place. In Japan, minimizing seismic disaster is especially important. Therefore, the development of a system that diagnoses the condition of existing civil structures at low cost is an urgent matter.

The sensors used in SHM systems are generally optical fiber strain sensors. However, multiple kinds of sensors, including speed counters, leakage sensors, gas sensors, intensity-based non-distributed fiber optic sensors and CCD cameras, are required for practical SHM systems. In some cases, actuators may be necessary for closing safety valves or activating vibration exciters. If these sensors and actuators were mounted on the system structures using wires, it would require many bundles of analog lead wires, and become too cumbersome to handle efficiently. The bundles of lead wire would also cause significant increase of weight. In some cases, the bundles would make it impractical to replace some structural components when the structure requires repairs or arrangements.

The Internet is generally adopted to transfer digital data packets through computer networks such as e-mail, multimedia information or Web data. The transfer of analog data from sensors via the Internet has already been attempted (Tate and Williams 1993, Ballard and Chen 1996). Conventional cases employ PCs for data acquisition and transfer. The present paper proposes new tools for SHM via the Internet. The main such tool is a diminutive 'smart' terminal that has a network socket, a CPU, memory, a large capacity silicon disk tip, A/D and D/A converters, and digital I/O ports. It adopts the Linux operating system, and it has a Web-server, mail-server and diagnostic methods for structural damage monitoring.

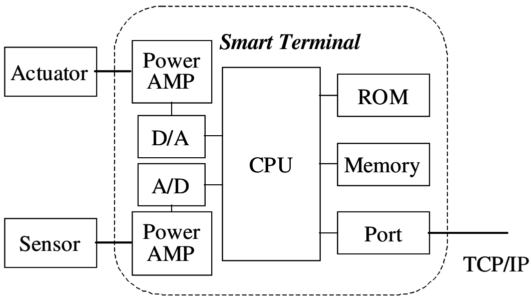
As a sample application, the present study attempted structural health monitoring of a jet-fan installed on an

Table 1. Hardware specifications for the smart terminal.

OS	RedHat 7.3	
CPU	Intel Pentium MMX 266 MHz	
Memory	On board 32 MB memory (MAX160 MB)	
Storage	IDE (Max60 GB HDD)	
LAN	Intel 82559 10/100 BaseTX ×2	
Interface	USB1.1 ×2, PCMCIA Slot ×1, Serial Port ×1	
Analog input (0–5 V, 16 bit)	CH	With amp (gain: 1–999) ×8
		Without amp ×2
	Sampling frequency	Up to 2 kHz
	Resolution	12 bit
	Memory for data	Storage to main memory
Analog output (0–5 V, 16 bit)	2 ports	
Digital output	2 ports	
Size	121.3 mm × 175.3 mm × 46.0 mm	

expressway tunnel as a ventilator fan. Damage to the jet-fan was detected from changes in the set of measured load data on the turnbuckles of the jet-fan. Damage was diagnosed using statistical similarity tests of the response surfaces at different points in time (Myers and Montgomery 2001), showing the relationships between the output of sensors. This diagnostic method requires only data sets for the non-damaged state, and does not require complicated modeling or numerous data sets after the generation of damage, thereby considerably lowering its cost. The resulting automatic diagnosis of damage to the jet-fan was successful.

(a) Appearance



(b) Schema

Figure 1. Smart terminal.

2. Health monitoring system via the Internet

2.1. Smart terminal for structural health monitoring system

For conventional applications adopting Ethernet for data transfer, PCs, A/D converters and Ethernet cards have been required. This requirement has made the structural monitoring via Ethernet cumbersome. As a solution for this problem, the present paper proposes a new tool, called a 'smart terminal', for structural health monitoring via the Internet.

The smart terminal is a small Linux computer which has as its hardware a network socket, a CPU, memory, a large capacity silicon disk tip, A/D and D/A converters, and digital I/O ports. For software, it has a Web-server, mail-server and diagnostic methods for structural damage monitoring. In our structural monitoring system, sensors are connected to the terminal and the terminal is connected to the Internet. The monitoring of the structure is automatically performed by the built-in CPU, and a remote user confirms the results using a Web browser.

The smart terminal, which we are developing now, is a lunch-box size small computer that has several A/D and D/A converter channels. Figure 1 shows the appearance and schema of the smart terminal. Detailed hardware specifications are shown in table 1. Since this new smart terminal has a D/A converter, users can react to the structures on the basis of sensor information. For example, when a gas pipeline fracture is detected, the pipeline valves can be closed remotely. Using smart terminals, users are also able to build distributed sensor systems using conventional sensors.

2.2. Health monitoring system using a smart terminal

Using the smart terminal described above, it is possible to construct a structural health monitoring system via the Internet. The monitoring system proposed in the present study is shown in figure 2. The example shown here is a structural health monitoring system for a jet-fan installed in an expressway tunnel as a ventilator fan.

Multiple kinds of conventional sensors such as optical sensors, thermometers, vibration sensors and speed counters are required for the structural health monitoring. If these sensors are mounted using conventional analog lead wires, the system expands into bundles and bundles of analog lead wires, the weight and volume of which lead to numerous difficulties. Using a smart terminal, these troubles are avoided. Analog lead wires are required only for the connection of sensors and the smart terminal, and data is transferred by Ethernet, either wired or wireless. Since the smart terminal has a CPU, quasi-real-time measurements can be performed by installing a data transfer control program to avoid data collision. The smart

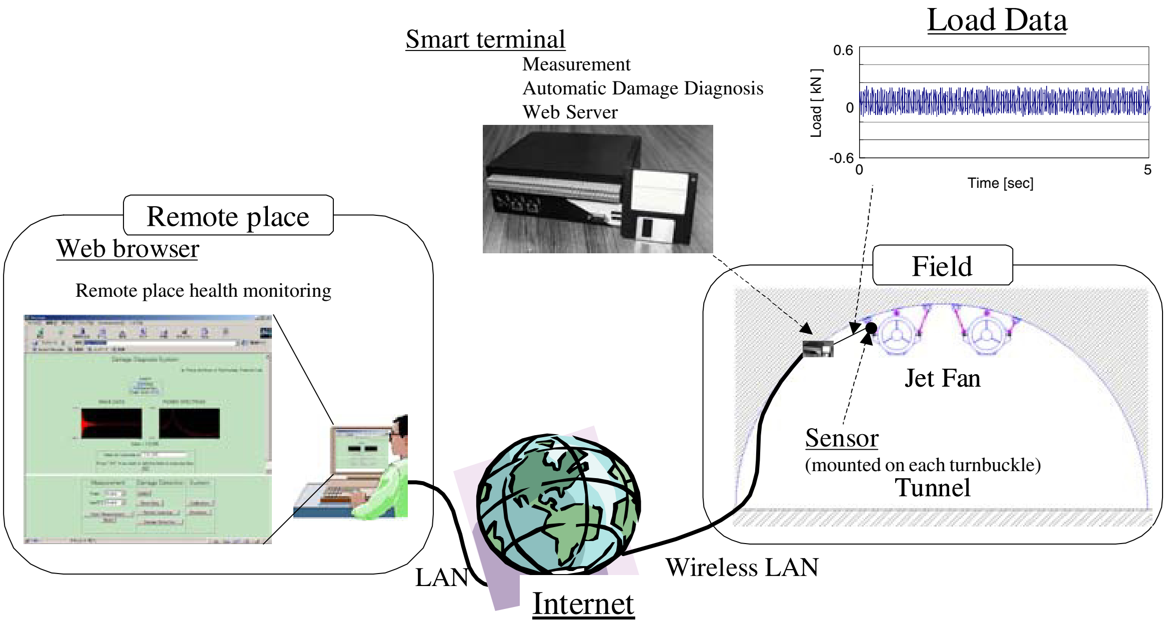


Figure 2. Schema of the system for health monitoring via the Internet.

terminal includes a Web server; thus, a remote user can confirm the diagnoses that the smart terminal sends via Web services.

Using the smart terminal and Ethernet for structural health monitoring has the following advantages:

(1) Since the Ethernet is a digital technology, it is resistant to noise.
(2) With Linux as the operating system, the network has high security.
(3) Replacement of sensors and actuators is very easy.
(4) Multiple kinds of conventional sensors and actuators can be used for remote monitoring and actuating.
(5) Any troubles with the sensors or actuators do not affect the network system.
(6) Network topology can be changed simply by changing plugs.
(7) Using dynamic routing and multiple network cables, network troubles can be automatically avoided.

3. Damage diagnostic method

This section addresses a statistical unsupervised damage diagnostic method for the structural health monitoring of existing structures at minimal cost. Numerous damage diagnostic methods for structures have been proposed; most employ either a parametric method based on structure modeling, or a non-parametric method such as an artificial neural network (ANN). Proposed parametric methods include a substructural flexibility method (Felippa *et al* 1998) and a residual force method (Kameyama *et al* 1999), while proposed non-parametric methods include ANNs (Chang *et al* 2000, Kawiecki and Xu 1999, Zapico *et al* 2001) and response surface methods (RSMs) (Todoroki and Tanaka 2002). Parametric methods require modeling of each structure, and non-parametric methods require numerous data sets for training. Both structural modeling and data sets for training are very costly. In the health monitoring of existing structures, obtaining post-damage data sets for programming the ANN or RSM is almost impossible. This raises the demand for a low-cost diagnostic method that does not require the training data. Therefore, generally damage is diagnosed by judgment from the threshold values of arbitrary parameters. When judging the damage from the threshold value, the threshold value is experimentally determined from the relation for the probability distributions of the parameter for the structure for the normal condition and the non-normal condition. Therefore, high-level experimental skill or data is required for determining the threshold value for high diagnostic accuracy. And application to a structure with a usually fluctuating parameter (like in rotation apparatus) is difficult. Moreover, in a real environment, the average of the measurements changes dynamically with temperature drifts etc, and the average of the distribution at the structure for normal conditions also changes. Therefore, deciding on the threshold value with high accuracy for a structure in a real environment is difficult and the diagnosis could be very unstable. In order to perform stable diagnosis using the threshold value, it is necessary to search for a parameter which can clearly provide a distinction between the structure for the normal condition and that for the non-normal condition from experiment or analysis. Since an experiment or analysis is required for the method, it is difficult to construct a structural health monitoring system for the existing structure which requires a breakdown experiment or model construction for the analysis. Therefore methods for damage diagnosis by detecting changes of the time relations (Shon and Farrar 2001) or the spatial relations (Iwasaki *et al* 2001, 2002a, 2002b) of sensor outputs are proposed. The latter study proposes a low-cost statistical diagnostic method for structural damage detection. The statistical diagnostic method proposed in the present paper is a low-cost, simple system. The diagnostic

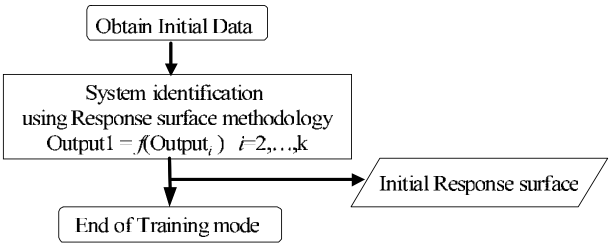


Figure 3. Flow of training process.

method employs system identification using a response surface (RS), and the damage is automatically diagnosed by testing changes in the identified system by means of a statistical F.

The system does not require programming for the relation between the measured sensor data and damage, nor does it require an FEM model of the entire structure. This method simply diagnoses slight changes in the relation between the measured sensor data.

3.1. Damage diagnostic using SI—F method

The basic procedure of the present diagnostic method for damage detection is shown in figures 3 and 4. First, we perform system identification of a structure in its intact state using a response surface (shown in section 3.2) and create a response surface from the measured sensor data obtained from this initial state (figure 3). The response surface is called the 'initial response surface'. For example, data from one sensor are selected as a response while data obtained from adjacent sensors are selected as predictors. Of course, we can select natural frequencies obtained from vibration data instead of using the measured data directly for the damage detection for the entire structure. After the training process, the damage monitoring process is started. During the monitoring process (figure 4), a set of every sensor's data is periodically obtained by cycling measurements several times. From the measured set of data, we perform system identification of the structure and a response surface is re-created. Such a response surface is called a 're-created response surface'. The two response surfaces are compared using a statistical similarity test with an F test (shown in section 3.3). When the re-created response surface is discriminated from the initial response surface, that means that the relation between the sensor data has changed, and it can be concluded that something has happened to the structure. Of course, this does not always means damage. Nevertheless, this method can provide a low-cost solution for diagnosing abnormality of a structure to determine the necessity for a more precise investigation.

3.2. System identification using response surface methodology

Response surface methodology (Myers and Montgomery 2001) is used for system identification in this method and is often employed for the process of optimization in the field of quality engineering. It consists of a series of experiments designed to select the most suitable points for fitting surfaces effectively using the least-squares method to regress response surfaces. The response surface is the approximation function that expresses the relationship between a response and predictors. Generally, a response surface is represented with the following formula:

$$y = f(x_1, x_2, \ldots, x_l) + \varepsilon, \tag{1}$$

where x variables are predictors, y is the response, ε is the regression error and l is the number of predictors. In general, polynomials are used.

For simplification, let us consider the case in which a response is approximated by quadratic polynomials of two predictors as follows:

$$y = \beta_0 + \sum_{j=1}^{l} \beta_j x_j + \sum_{j=1}^{l} \beta_{jj} x_j^2 + \sum_{i=1}^{l-1} \sum_{j=i+1}^{l} \beta_{ij} x_i x_j, \tag{2}$$

where β is the regression coefficient.

If squares or interactions of the predictors x_j^2 and $x_i x_j$ are replaced by new predictors x_j $(j > l)$, the formula (2) becomes

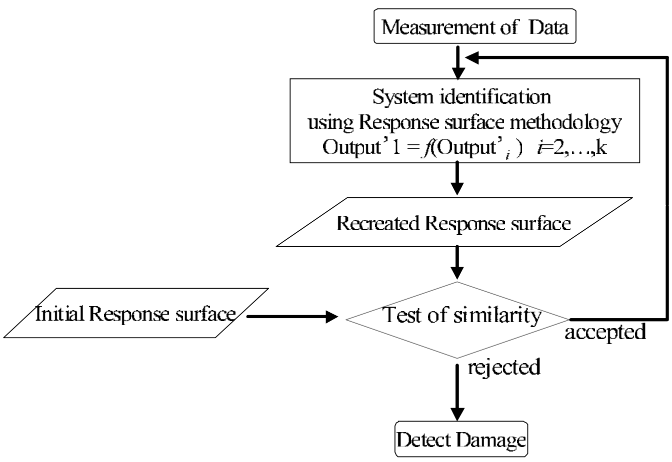
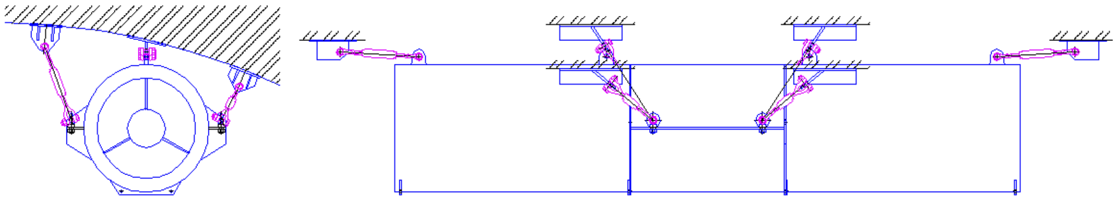


Figure 4. Flow of monitoring process.



(a) Front view

(b)Side view

Figure 5. Jet-fan for the experiment.

the linear regression model as follows:

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j, \tag{3}$$

where k is number of the predictors after the replacement.

In terms of n observations, the equation (3) can be written in matrix form as follows:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{4}$$

$$\mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}$$

$$\mathbf{Y} = \begin{Bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{Bmatrix}, \qquad \boldsymbol{\beta} = \begin{Bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{Bmatrix}, \qquad \boldsymbol{\varepsilon} = \begin{Bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{Bmatrix}.$$

An unbiased estimator of $\boldsymbol{\beta}$ ($\mathbf{b}$) is obtained using the least-squares method as follows:

$$\mathbf{b} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{Y}. \tag{5}$$

Lack of fit is evaluated with the adjusted coefficient of multiple determination R^2_{adj}. R^2_{adj} is defined as

$$R^2_{\mathrm{adj}} = 1 - \frac{\mathrm{SSE}/(n-k-1)}{S_{yy}/(k-1)} \tag{6}$$

where SSE is the square sum of errors, S_{yy} is the total sum of squares. Since the response surface was regressed by the least-squares method, the sum of square error (SSE) is defined as follows:

$$\mathrm{SSE} = \mathbf{Y}^{\mathrm{T}}\mathbf{Y} - \mathbf{b}^{\mathrm{T}}\mathbf{X}^{\mathrm{T}}\mathbf{Y}. \tag{7}$$

The value of R^2_{adj} is equal to or lower than 1.0. Higher values of R^2_{adj} imply a good fit. When the response surface shows a very good fit, R^2_{adj} approaches 1.0.

3.3. Similarity testing of response surfaces using an F test

Let us assume that we have two response surfaces that are created from two different sets of experiments:

$$\begin{aligned} \mathbf{Y}_1 &= \mathbf{X}_1\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_1 \\ \mathbf{Y}_2 &= \mathbf{X}_2\boldsymbol{\beta}_2 + \boldsymbol{\varepsilon}_2, \end{aligned} \tag{8}$$

where the number of experiments for regression are n_1 and n_2, respectively. In order to investigate the similarity of the two response surfaces, a null hypothesis is introduced. The hypothetical definition is shown as follows:

$$\mathrm{H}_0: \qquad \boldsymbol{\beta}_1 = \boldsymbol{\beta}_2, \tag{9}$$

assuming that each error term (ε) is independent and has the same distribution in two sets of experiments. In this case, the F statistic value F_0 is defined as follows:

$$\begin{gathered} F_0 = \frac{\mathrm{SSE}_0 - \mathrm{SSE}_{12}}{\mathrm{SSE}_{12}} \frac{n-2p}{p} \\ n = n_1 + n_2 \qquad \mathrm{SSE}_{12} = \mathrm{SSE}_1 + \mathrm{SSE}_2, \end{gathered} \tag{10}$$

where $p = k + 1$ and subscripts 1 and 2 show the SSEs of response surfaces 1 and 2, and 0 shows the SSE of the response surface which is regressed from the data for 1 and 2. This F statistic value F_0 follows an F distribution of degree of freedom $(p, n-2p)$ under the null hypothesis. When the two response surfaces are similar, F_0 becomes small. The critical limit for rejecting hypothesis H_0 is defined as follows:

$$F_0 > F^{\alpha}_{p,n-2p}, \tag{11}$$

where α is the significance level. The similarity of response surfaces is rejected when F_0 is larger than $F^{\alpha}_{p,n-2p}$.

4. Damage detection of jet-fan

4.1. Experimental set-up

The new diagnostic method was applied to the structural health monitoring of a jet-fan installed in an expressway tunnel as a ventilator fan, and the effectiveness of the method was investigated experimentally. The diameter of the jet-fan was 800 mm and the length, 3000 mm. The loading condition of the turnbuckles was employed as the parameter for diagnosis in the present study. A sample configuration is shown in figure 5.

The experimental set-up of the jet-fan is shown in figure 6. Usually, such a jet-fan is hung on the ceiling of a tunnel by six turnbuckles, but four turnbuckles at the central part support almost all the jet-fan's load. For that reason, damage detection of the jet-fan could be based on changes in the loading condition of the turnbuckles of the four central parts (turnbuckles 1–4). The jet-fan used in the experiments and the load cell for measuring the loading condition of the turnbuckles are shown in figures 7 and 8, respectively. As shown in figure 8, washer-type load cells are mounted between the body of the

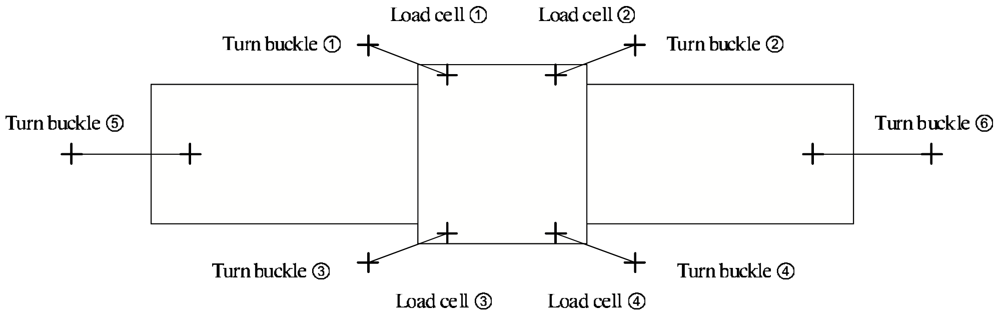


Figure 6. Experimental set-up of the jet-fan.

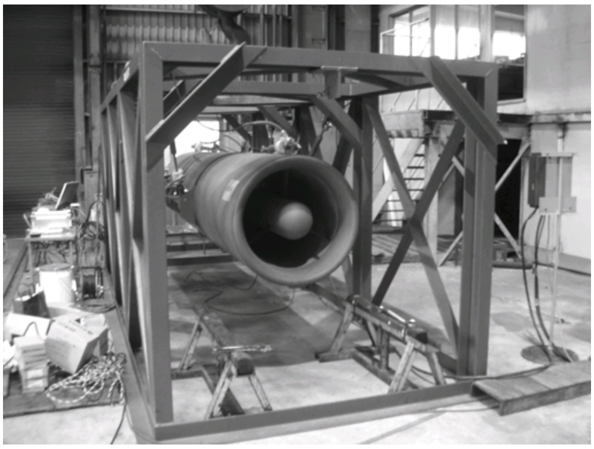


Figure 7. Jet-fan for the experiment.

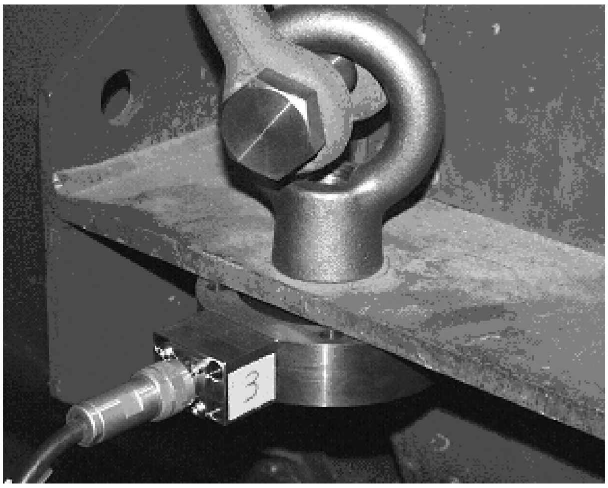


Figure 8. Load cell.

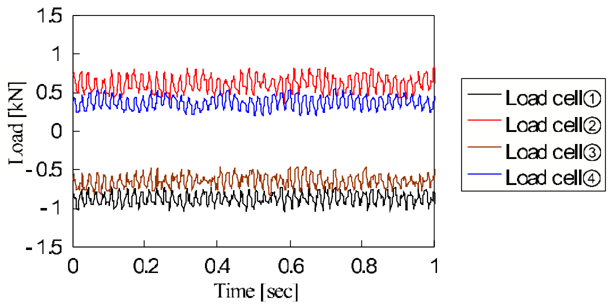


Figure 9. Loading condition of the turnbuckles.

jet-fan and the heads of the fastening bolts of the turnbuckles. Data was measured at 500 Hz. The rotation frequency of the fan of the jet-fan was 50 Hz. An example of measured data is shown in figure 9. Damage to the jet-fan was defined as looseness of a turnbuckle.

When a turnbuckle rotates by about 720°, it stops holding the load of the jet-fan. Even if one turnbuckle does not hold load, the jet-fan operation is not affected, and fall of a turnbuckle does not occur either. This 720° rotation is defined as 100% of the damage level. The jet-fan health monitoring system aimed to detect this state.

4.2. Response surface for detection of damage of a jet-fan

In the present study, the loading condition of turnbuckle No 1 was the response, and the loading conditions of the other turnbuckles were predictors. In this case, average of R^2_{adj} of response surface using linear, quadratic and cubic polynomials are as follows:

Linear equation: 78.3

Quadratic polynomial: 96.2

Cubic polynomial: 99.3.

Since the quadratic polynomial shows good regression accuracy, the quadratic polynomials were employed for the creation of the response surface. The response surfaces were approximated as follows:

$$N_1 = \beta_0 + \sum_{i=2}^{4} \beta_i N_i + \sum_{i=2}^{4} \sum_{j=i}^{4} \beta_{ij} N_i N_j, \tag{12}$$

where N_i represents the load data for turnbuckle No i. The response surface of equation (12) is regressed from the data set of 60 measurements.

5. Results and discussion

5.1. Probability distribution of F_0 of a non-damaged jet-fan

The threshold value for the similarity testing of response surfaces first had to be defined; therefore, similarity tests of the

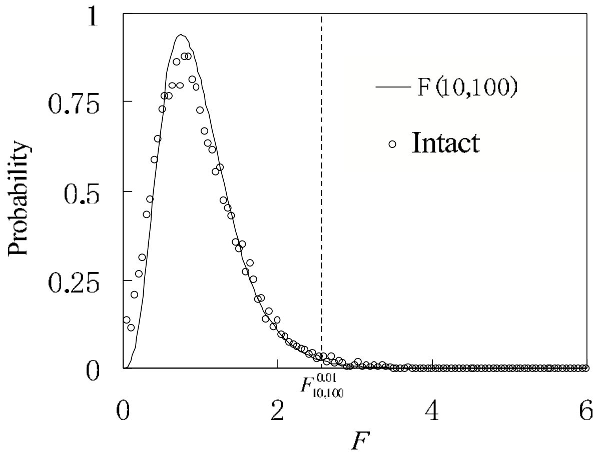


Figure 10. Probability distribution of F_0 for the intact state.

response surface for the initial state and the response surface for the same state were conducted. In order to obtain the probability distribution of the F_0 value for the intact state, 20 000 tests were conducted. The test value was calculated from the following process. (1) Select 60 data sets from 8192 data sets at random. (2) Regress the response surface from 60 data sets. (3) Calculate F_0. (4) Repeat 1–3. As shown in section 2.3, the probability distribution of the F_0 value in a similarity test of the same response surfaces follows $F(p, n-2p)$. In this case, the number of degrees of freedom p is 6, total the number of response surfaces is 120 and probability distribution of F_0 in the intact specimen may theoretically follow $F(6, 100)$. Figure 10 shows the theoretical value of an $F(6, 100)$ distribution and the experimental value of a probability distribution of F_0 in the intact state. In the experiment, both the initial response surface and the re-created response surface are created from measured data taken from the intact specimen.

As shown in figure 10, the experimental distribution and theoretical distribution exhibited good agreement. Therefore, the probability distribution of the F_0 value of the intact structure follows a distribution that depends on the model shape of the response surfaces. And the critical value of the F similarity test, which shows the threshold value between those for the intact state and the damaged state, is derived from only a number of data sets and freedom of response surfaces. This result signifies that the threshold value of the damage is decided only from the model of the response surface.

In this paper, the significance level α for the F similarity test was set to 1%. When $F^{0.01}_{6,100} = 2.50$ and F_0 exceeds this value, similarity of the identified systems is rejected and the structure is diagnosed as having been damaged.

5.2. *Probability distribution of F_0 for a damaged turnbuckle*

After the threshold was defined, damage diagnosis of the jet-fan was conducted to investigate the method's effectiveness. Tests of various conditions of turnbuckle looseness were conducted. The looseness condition was quantized into four levels with 20% intervals.

Figure 11 shows the plot of the probability distribution for a looseness condition. Figure 11(a) shows the probability distribution when the looseness is 60% and figure 11(b) shows the distribution when the looseness is 100%. Each distribution differs from the probability distribution of the intact structure shown in figure 10. This result indicates that the F_0 value is an effective parameter for diagnosing the presence of damage.

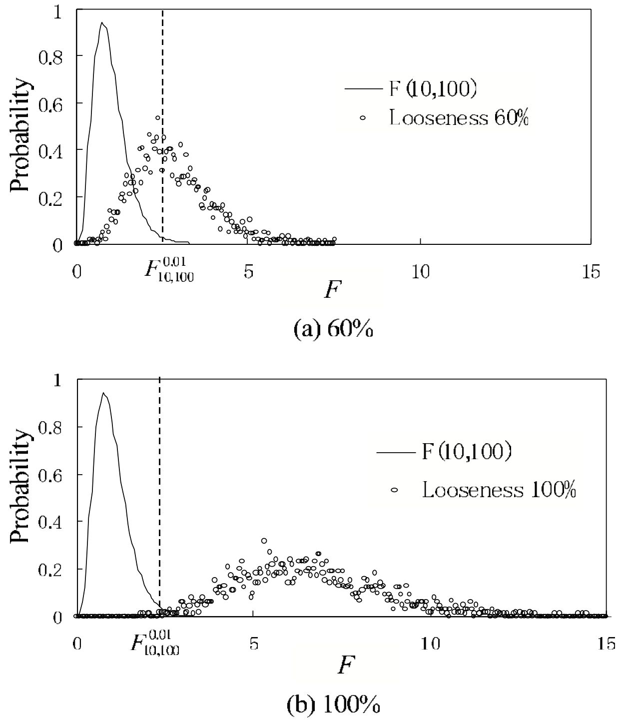


Figure 11. Probability distribution of F_0 for the damaged condition.

Table 2. Average of F_0 for each size region.

Looseness of turnbuckle 1 (%)	Average of F_0
Intact	0.982
40	1.51
60	2.83
80	4.79
100	6.88

Table 3. Diagnostic accuracy of detection of delamination.

Looseness of turnbuckle 1 (%)	Reliability of estimation (%)
Intact	99.2
40	18.4
60	54.7
80	97.4
100	100.0

Table 2 shows the average value of the F_0 statistics for each condition of looseness. F_0 increases uniformly according to the increase of the looseness.

Using the limit of 2.50 defined before, performance tests of the diagnostic method were conducted to investigate the effectiveness of the method. Table 3 shows the probability of diagnosis. For the intact case (the looseness of the turnbuckle is 0%), the similarity tests of the two response surfaces passed with a performance level of 99%. When the looseness of the turnbuckle was greater than 80%, the similarity of the two response surfaces was rejected with a performance level of

100%, which is a perfect diagnosis for the existence of damage. On the basis of the performance results, we concluded that the new diagnostic method provides high performance at low cost. For this method, data on the damaged state is not required to define the limit between the intact and damaged states.

6. Conclusions

The present paper describes the advantage of using the Internet for a structural health monitoring system, and demonstrates a statistical unsupervised damage diagnostic method using system identification and statistical tools. In the present paper we propose a new 'smart terminal' for a structural health monitoring system using the Internet. The smart terminal combines a CPU, A/D converter, memory, Ethernet and damage diagnostic method in a small package. Furthermore, it enables automatic structural health monitoring without the necessity of taking post-damage state measurements. The diagnostic method employs system identification using response surfaces: the damage is automatically diagnosed by testing the similarity of the RS to an initial RS by statistical methods. As an example of the type of monitoring that becomes possible with this method, we applied the technology to an expressway tunnel jet-fan. As a result, this method successfully detected damage to the jet-fan with a near-perfect performance.

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