Diagnostic Monitoring and Sensitivity Analysis of Contact Dynamics in Jointed Structures

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The operation and performance of elastically jointed structures can be degraded by dynamic contacts arising from a number of factors including excessive levels of vibration, inadequate lubrication, and improper joint clearance. In many applications, such as a space structure, periodic disassembly and inspection are impractical; thus, a monitoring and diagnosis system is desired to automatically detect and diagnose significant changes in the dynamic contact state of jointed structures. A time-series-based monitoring and diagnosis system has been formulated to address this need. The system incorporates a cross-entropy minimization method, based on the nearest neighbor classification rule, and a cross-entropy dissimilarity measure to classify a new observation of vibration states into one of a set of prestudied "standard" vibration patterns. The approach is applied to a unit truss cell, representative of space structures, and laboratory experiments are conducted to evaluate its performance and assess its sensitivities. The experimental results indicate that the system can satisfactorily detect and classify changes in the vibration states of such structures.

Introduction

PERFORMANCES of elastic joints can strongly affect the dynamics of an elastically jointed space structure.[1] The presence of joint clearances may cause chaotic vibration,[2,3] affect system characteristics,[4] introduce a great contact force,[5,6] and in turn, result in accelerated fatigue, wear, and finally, system failure.[7] The performances of jointed structures may change during the operation of the space structure.[8,9] Therefore, it is necessary to monitor and diagnose any possible change of system characteristics to avoid the excessive vibration and make control decisions for improving performance.

The purpose of a diagnostic monitoring system is to detect any change of system state from the normal working condition, and diagnose and predict any possible failure in operations. When a measuring system is set up, the diagnostic monitoring is a decision-making process; i.e., given some labeled (or "standard") state types determined by a prestudy of system behaviors, these state types are used to classify a new observation into one of the alternative state types in an optimal way. The pattern classification technique has been widely applied to detect changes of the system state of a dynamic system.[10] When this technique is used, a main task is to find a proper measure for detecting the "dissimilarity" between a new observed pattern and a labeled system state. Bayes decision theory is a theoretical basis of pattern classification[11] that has become more practical and useful since the nearest neighbor (NN) classification rule was first studied.[12] Euclidean distance is a basic dissimilarity measure used in early exploration. Some improvements have been made to enhance its capability.[13] Cross-entropy minimization (CEM) was introduced quite early by Kullback[14] and is used successfully as a dissimilarity measure in pattern recognition. Shore et al.[15-17] reviewed two basic classification methods and their properties, which have been named the Jaynes principle of maximum entropy and the Kullback principle of minimum cross entropy. Furthermore, it is proved that the maximum entropy method is equivalent to the CEM method.[18] For engineering applications, Benveiste et al.[19] developed a monitoring system for detection of abrupt system state changes. Gersch et al.[20,21] used the NN time-series approach in the classification of engine faults and medical signal processing. Sata et al.[22] and Hardy et al.[23] used automatic diagnosis and monitoring techniques in manufacturing operations. These works are obviously valuable for developing a new diagnostic monitoring system for the operation of jointed structures.

In the diagnosis and monitoring of a jointed-structure operation, the vibration mechanism is difficult to identify, due to the dynamic contacts in elastic joints. Based on previous studies, the vibration of an elastically jointed structure can be represented by a high-order stochastic model,[1,5] which gives a possibility to apply the pattern classification technique to automatically diagnose and monitor the contact vibration processes. The problems to be considered are as follows: to develop a diagnostic monitoring system with a satisfactory sensitivity, and to carry out this process in real time. Herein a time-series-based diagnostic monitoring system is developed with an application to a unit space structure: a truss-cell unit structure model. In the following sections, the diagnosis model for pattern classification is first introduced. A real-time diagnostic monitoring system for vibration identification of jointed structures is then presented. Finally, diagnosis and monitoring sensitivities are defined and analyzed in an application to the truss-cell unit structure.

Diagnosis Model

When a vibration signal is measured, a diagnostic model (i.e., CEM model) is applied to classify the vibration state to one of the prestudied system states, which is based on the NN classification rule and cross-entropy (CE) dissimilarity measure. In this section, the diagnosis model is introduced theoretically. Its application to the analysis of a truss-cell unit structure follows in the next section.

Nearest Neighbor Classification Rule

If a system state (denoted by an index i) is defined by a vector of model parameters $\{\xi\}_i$ that is estimated from a set of data $[X_t]_i$, the NN classification rule says that a new observa-

Received April 2, 1990; revision received Oct. 25, 1990; accepted for publication Oct. 25, 1990.

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tion $\{\xi\}_0$ should be classified to one of the reference system state $\{\xi\}_r$, if the distance (d) between $\{\xi\}_0$ and $\{\xi\}_r$ is the smallest compared with other samples.[13,21] That is,

$$\text{If } d(\{\xi\}_0, \{\xi\}_r) < d(\{\xi\}_0, \{\xi\}_i)$$

$$\text{for } i = 1,2,\ldots,n, \quad \text{and } i \neq r$$

$$\text{then classify } \{\xi\}_0 \text{ to } \{\xi\}_r \tag{1}$$

The NN rule is a widely used method in pattern classification application because of its convenience and clear physical meaning. A proper distance measure needs to be defined for a successful application of the NN rule.

Cross Entropy: A Dissimilarity Measure

Cross entropy is a nonparametric measure of the dissimilarity between two stochastic processes (with the probability density functions P_i and P_j). The CE distance is defined as

$$d(\{\xi\}_i, \{\xi\}_j) = \int P_i(\{\xi\}) \ln \frac{P_i(\{\xi\})}{P_j(\{\xi\})} d\{\xi\} \tag{2}$$

When the probability density functions (P_i and P_j) of the stochastic processes are given, Eq. (2) can be simplified and calculated.

Time-Series Model

In this study, an autoregressive moving average (ARMA) model is used to represent the stochastic vibration process of elastically jointed structures. It has been proved that an ARMA model can be expressed as a finite autoregressive (AR) model with a desired accuracy.[24,25] If real-time monitoring and diagnosis are concerned, the AR model is more important because of its linear feature. An nth-order AR model, AR(n), is expressed as follows[24]:

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_n x_{t-n} + a_t \tag{3a}$$

or in a matrix form as

$$[X_t]\{\Psi\} = \{A_t\} \tag{3b}$$

where $\{\Psi\} = \{1, -\varphi_1, \varphi_2, \ldots, \varphi_n\}^T$ is the AR model parameter vector; $\{A_t\} = \{a_{n+1}, a_{n+2}, \ldots, a_N\}^T$ is the model residual vector, which is a white noise time series;

$$[X_t] = \begin{bmatrix} x_{n+1} & x_n & \cdots & x_1 \\ x_{n+2} & x_{n+1} & \cdots & x_2 \\ \cdots & & & \\ x_N & x_{N-1} & \cdots & x_{N-n} \end{bmatrix}$$

is the vibration data matrix; and the squared standard deviation (σ_t^2) of the model residuals is

$$\sigma_t^2 = \frac{1}{n-1}\{A_t\}^T \qquad \{A_t\} = \frac{1}{n-1}\{\Psi\}^T[X_t]^T[X_t]\{\Psi\} \tag{4}$$

Note that $\{\ \}^T$ and $[\ ]^T$ denote either a vector or matrix transposed.

Cross-Entropy Minimization

If two vibration processes represented by the time series are independent, and with zero-mean normal distribution, the CE distance between them is expressed as[26]

$$d_{ce}(\{\xi\}_i, \{\xi\}_j) = \ln\left[\frac{\sigma_i^2}{\sigma_j^2}\right] + \frac{\sigma_{j,i}^2}{\sigma_i^2} - 1 \tag{5}$$

where $\{\xi\}_i = \{\{\Psi\}_i, \sigma_i^2\}$ are AR(n) model parameters, which represent a system state and are estimated from the data set $[X_t]_i$; σ_i and σ_j are the standard deviations of AR(n) model residuals, which are estimated from the models $\{\xi\}_i$ and $\{\xi\}_j$ and data sets $[X_t]_i$ and $[X_t]_j$, respectively; and $\sigma_{j,i}$ is the standard deviation of residuals obtained by using data set $[X_t]_i$ and AR(n) model $\{\xi\}_j$ estimated by the data set $[X_t]_j$, which is defined as

$$\sigma_{j,i} = \frac{1}{n-1}\{\Psi\}_j^T[X_t]_i^T[X_t]_i\{\Psi\}_j \tag{6}$$

The classification rule of the CEM method can be expressed as follows: When a new data set $[X_t]_0$ is measured and the AR model parameters $\{\xi\}_0$ are estimated, the CE distances are calculated by using Eq. (5) between $\{\xi\}_0$ and each prestudied system-state type $\{\xi\}_i$. The new observation $\{\xi\}_0$ should be

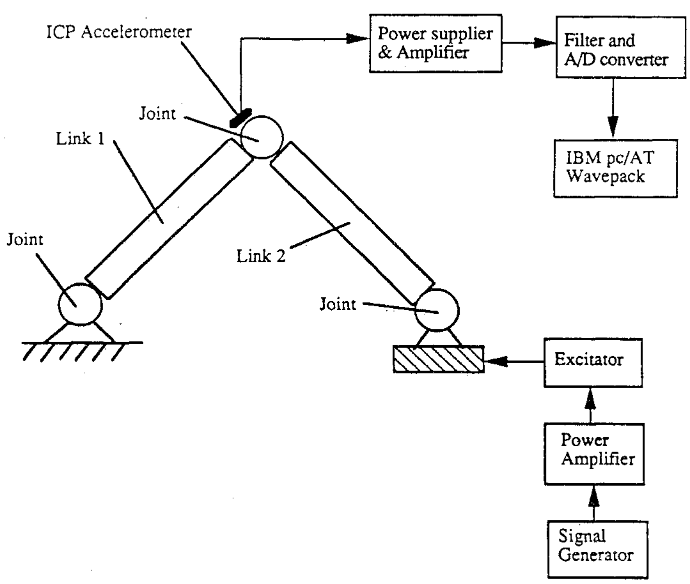

Fig. 1 Experiment system: truss-cell unit structure.

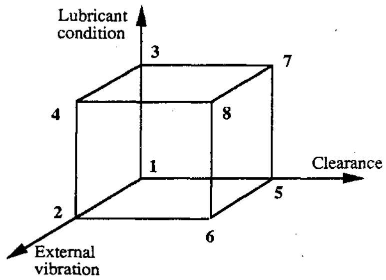

Fig. 2 Diagnosis reference coordinate system.

Table 1 Standard vibration condition parameters

Vibration condition	Clearance, mm	Lubricated	Vibration, g
1	0.013	Yes	1.5
2	0.013	Yes	2.8
3	0.013	No	1.5
4	0.013	No	2.8
5	0.038	Yes	1.5
6	0.038	Yes	2.8
7	0.038	No	1.5
8	0.038	No	2.8

classified into a system state $\{\xi\}_r$, if the distance measured by CE between them is the smallest compared with others. That is,

$$\text{if } d_{ce}(\{\xi\}_0, \{\xi\}_r) < d_{ce}(\{\xi\}_0, \{\xi\}_i), \quad \text{for } i = 1,2, \ldots, n \text{ and } i \neq r$$

$$\text{then classify the system state } \{\xi\}_0 \text{ to the system state } \{\xi\}_r \tag{7}$$

Diagnostic Monitoring of a Jointed Structure

The vibration of a truss-cell unit structure is studied in this research. Three factors affecting vibration state are considered: joint clearances, lubricant conditions, and levels of external vibration. Development of the diagnostic monitoring system includes a prestudy of structure vibration, i.e., diagnosis reference establishment, and the development of a monitoring and diagnosis scheme. In this section, the experiment device, a truss-cell unit structure model, is first introduced, which includes a discussion of system-state variations and experiment conditions. The procedure of establishing diagnosis references and a diagnosis monitoring scheme is then presented in detail.

Jointed Truss-Cell Unit Structure Model

The truss-cell unit structure is considered as a basic configuration of large, jointed flexible space structures. Figure 1 shows a schematic diagram of the truss-cell experimental system, which includes a two-dimensional truss-cell structure with joints, vibration sensors, and a signal processing system. There are three joints in the truss cell, in which the mechanical clearance in the joint can be adjusted by changing its individual pin size. The vibration signals of the central joint are measured when the truss cell is excited at one end of a link (the other link is fixed to the ground). Therefore, the vibration pattern can be studied by considering different vibration conditions.

Failure Discussion and Experiment Conditions

Failures in space truss structure operation might be caused by excessive vibrations due to the dynamic contacts in joints,[27] which could result from a poor lubricant condition (small contact damping), worn out components (large mechanical clearance), poor operation environment (large external vibration amplitude), and other factors. In this study, three factors are considered: clearance size, lubricant condition, and the amplitude of external vibration (which is simulated by an external excitation in the laboratory experiments). These factors are defined as three state variables. They change along three axes and form a three-dimensional space, as shown in Fig. 2. The linear relationship of these three factor effects is assumed; i.e., two levels of vibration condition variables are considered. Thus, eight (2^3) standard system states are determined according to the results of theoretical analysis and simulation study,[27] which are presented in Table 1. The range of clearance variation is from 0.013 to 0.038 mm. The well-lubricated condition means that the clearance is fully filled with grease; otherwise, there is no lubricant. Random excitation is used to excite the truss-cell unit structure. The amplitude of external excitation is from 1.5 to 2.8 g. The normal vibration condition is defined as small clearance (0.013 mm), well-lubricated, small external vibration (1.5 g), which is shown as vibration condition 1 in Table 1 and as origin point 1 in Fig. 2.

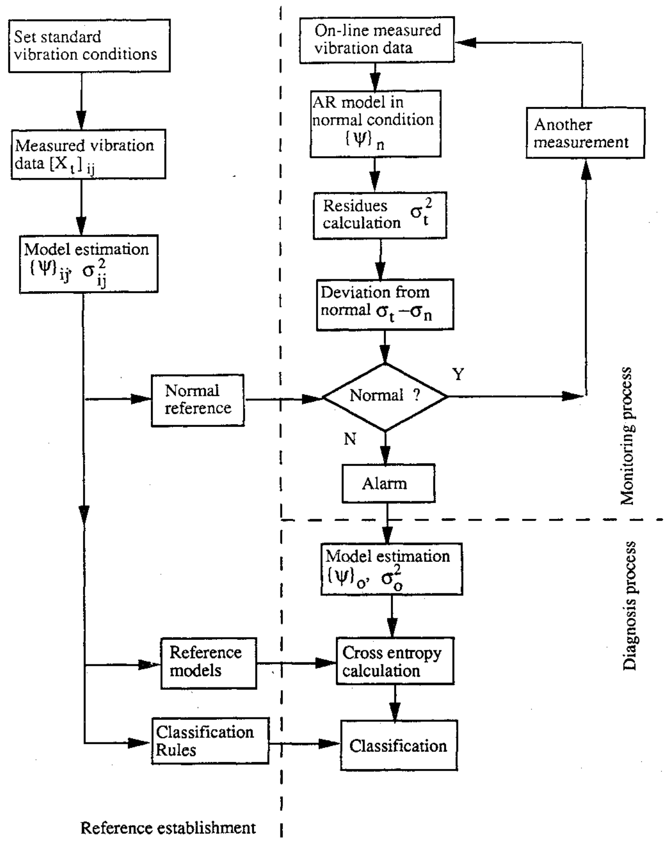

Fig. 3 Diagnostic monitoring system.

Establishment of Diagnosis References

When a vibration process is monitored diagnostically, a criterion for the normal vibration condition should be established in advance. Once an abnormal vibration condition is detected, it needs to be classified into a standard vibration reference, which is also established at the reference study stage. Figure 3 is a schematic diagram of such a diagnostic monitoring system.

The establishment of diagnosis references is to determine the model parameters in each standard vibration condition. The procedure of establishing diagnosis references involves four steps:

1) The standard vibration conditions of the truss-cell unit structure are predetermined, as shown in the last section.

2) Vibration data sets $[X_t]_{ij}$ are collected, where subscript $j(=1,2, \ldots, 8)$ refers to the different vibration conditions and subscript $i(=1,2, \ldots, 10)$ refers to the repetitions of the

tests under each specific vibration condition (indexed by j). As a result of the uncertainties of joint friction and other random factors, especially for the use of random excitation, these data are in random feature.

3) The parameters ($\{\Psi\}_{ij}$ and σ_{ij}^2) of the stochastic models are estimated from each set of data. The 12th-order AR model, AR(12), is considered as a suitable model of the jointed-structure vibration system according to an adequacy analysis.[24]

4) Finally, the reference model parameters $\{\Psi\}_{rj}$ and σ_{rj}^2, are determined in each vibration condition (j) by averaging the 10 groups of AR(12) parameters $\{\Psi\}_{ij}$ and σ_{ij}^2, i.e.,

$$\{\Psi\}_{rj} = \text{average} \quad (\{\Psi\}_{ij},\ i = 1,2,\ldots,10), \quad j = 1,2,\ldots,8$$

$$\sigma_{rj}^2 = \text{average} \quad (\sigma_{ij}^2,\ i = 1,2,\ldots,10), j = 1,2,\ldots,8$$

where the subscript r denotes reference, and the system-state vector of standard reference vibration conditions are obtained as $\{\xi\}_{rj} = (\{\Psi\}_{rj}, \sigma_{rj}^2)$.

Table 2 shows the results of reference model parameters for each vibration condition. When a new vibration signal of the truss-cell unit structure is measured, the parameters of the AR(12) models are estimated. The CE distance between the new observation and each reference model is calculated by using Eq. (5) (for details, see the diagnosis scheme in the next section). This new observation is then classified into one of these eight references according to the CEM rule, thereby determining the specific operation conditions of the truss-cell unit structure.

All of the information needed in the process of estimating the diagnosis references comes from the experiment data. Therefore, it is possible for the diagnostic monitoring system to have a self-learning capability; i.e., the knowledge of the dynamic properties of a jointed-truss structure can be acquired automatically through laboratory experiments and/or normal operations.

Diagnostic Monitoring Scheme

Diagnostic monitoring of a vibration process is detecting any change of vibration conditions from the normal vibration condition and finding sources that caused this change. In the diagnostic monitoring system, the vibration data $[X_t]_0$ are measured in real time and compared with the normal vibration state. Once a deviation of the vibration state is detected from the normal vibration state, a warning alarm is given and additional diagnosis is followed (see Fig. 3).

Monitoring Scheme

In the monitoring process, the measured vibration data $[X_t]_0$ are filtered by the normal reference model: first, the reference model parameters $\{\Psi\}_n$ are used to calculate the residues $\sigma_{n,0}^2$. (Here, the subscript n denotes the normal vibration condition.) Then $\sigma_{n,0}^2$ is compared with the reference σ_n^2 to evaluate the deviation from the normal vibration condition. If the difference between $\sigma_{n,0}^2$ and σ_n^2 is within a certain range, the vibration state is assumed normal. If not, it is abnormal, which means that the reference model for the normal vibration condition is no longer suitable for the current vibration state. Alarm and diagnosis will be followed. The boundary of the normal vibration condition is determined based on the monitoring sensitivity and the requirement of the space structure operations.

Diagnosis Scheme

When an abnormal vibration condition is detected in the monitoring stage, the parameters ($\{\xi\}_0 = \{\{\Psi\}_0, \sigma_0^2\}$) of the AR(12) model for the current vibration state are estimated from the measured vibration data $[X_t]_0$. The CE distances between the measured data and each reference are calculated using Eq. (5) where $\sigma_{rj,0}^2$ needs to be estimated using Eq. (6). Finally, the measured vibration condition is classified to one of the eight reference vibration conditions according to the CEM rule [Eq. (7)], i.e.,

$$\text{Classify } \{\xi\}_0 \text{ to } \{\xi\}_r$$

where

$$d_{ce}(\{\xi\}_0, \{\xi\}_r) = \min(d_{ce}(\{\xi\}_0, \{\xi\}_{rj}, j = 2,3,\ldots,8)$$

Illustrative Examples of Diagnosis Monitoring

The state change of jointed-structure vibrations could be a rather gradual, or slow, process. When it deviates from the normal vibration condition, the CE distance between the normal and current vibration conditions can be measured, which increases from zero. Once the CE distance reaches the boundary of the normal vibration condition, an abnormal vibration state is assumed and additional diagnosis is required. Figures 4–8 show some examples of the CE distance increases in different ways, which are obtained from the experiments on the truss-cell unit structure vibration. These results show the vibration state deviation process from the normal operation condition (Fig. 4, point 1) in different parameter-changing processes.

In Fig. 5, only the clearance size is increased (Fig. 4, path 1-a-5). In Fig. 6, the clearance size and the amplitude of external vibration are increased simultaneously (along 1-b-6). In Fig. 7, only the external vibration amplitude is increased (along 1-7-2). Finally, in Fig. 8, the lubricant condition is first changed from well lubricated to poorly lubricated (without any lubricant), and then the clearance is enlarged (along 1-d-7). From these figures, it can be concluded that, if the vibration condition deviates from the normal working condition, the CE distance between the normal and current vibration conditions can be significantly, continuously measured, which indicates a feasibility proof of monitoring the jointed-structure vibration. The different patterns of CE distance increases

Table 2 AR(12) model parameters for diagnosis references

	j*: standard reference vibration conditions							
$\{\xi\}_{ri}$	1	2	3	4	5	6	7	8
φ_1	1.408	5.522	5.886	4.496	0.984	4.892	4.054	5.268
φ_2	1.366	1.533	− 2.132	− 2.725	1.790	2.948	− 0.868	− 2.738
φ_3	− 0.271	0.786	− 4.214	5.804	− 0.930	− 0.524	− 3.360	− 5.202
φ_4	2.208	0.482	− 2.272	− 3.166	0.234	− 2.256	0.018	2.198
φ_5	0.652	0.198	− 0.603	− 2.614	− 0.666	− 0.198	1.346	3.036
φ_6	− 0.338	− 0.308	1.224	− 1.346	− 0.400	− 1.096	2.133	− 0.066
φ_7	0.636	0.140	1.256	− 1.942	− 0.134	0.392	1.316	− 0.582
φ_8	− 0.624	0.384	− 0.240	− 0.822	0.302	0.144	− 0.324	2.064
φ_9	0.424	− 0.372	− 0.906	− 0.732	− 0.167	− 0.706	− 0.248	− 0.756
φ_{10}	− 0.188	0.063	− 0.184	− 0.244	− 0.435	− 0.738	− 1.650	− 1.048
φ_{11}	− 0.072	0.060	− 0.062	− 0.024	0.084	− 0.224	− 0.133	− 0.220
φ_{12}	− 0.056	0.088	0.084	− 0.087	0.035	− 0.044	0.068	0.081
σ_{rj}^2	0.0142	0.0293	0.0264	0.0142	0.0147	0.0235	0.0256	0.0298

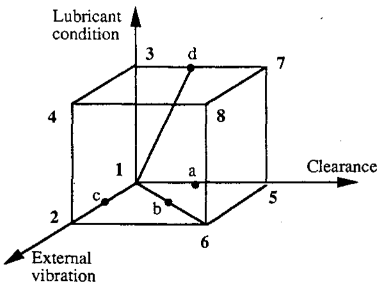

Fig. 4 Monitoring conditions.

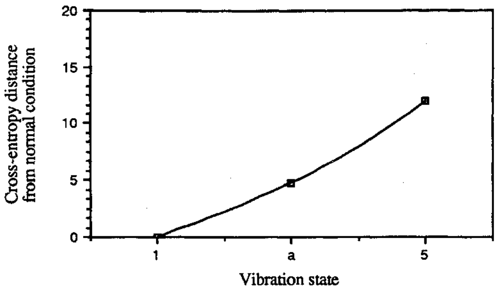

Fig. 5 Monitoring 1: increase clearance size.

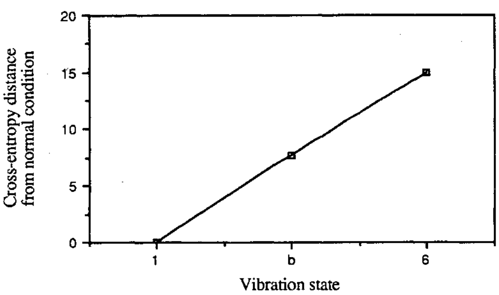

Fig. 6 Monitoring 2: increase clearance and external vibration amplitude.

reflect the sensitivities in different directions of system parameter effects, which will be discussed in a later section.

Discussion on Computation Time

The diagnosis reference establishment process is a prestudy of the structure vibration, which is an off-line process. Therefore, the computation time at this stage is not quite important, compared with the monitoring and diagnosis process. The monitoring is a real-time process. It is important to have a fast monitoring algorithm. In the monitoring process discussed earlier, only the residual, $\sigma_{n,0}^2$, is calculated and compared with the residual of the normal reference model, σ_n^2. In the diagnosis stage, fast computation is also required because the physical system is very likely linked with a real-time control system required to control the structure. Because of the use of the AR(n) model, which concerns a linear regression process, nonlinear regression and matrix calculation are not required. Therefore, the computation effort involved in the CEM method is rather efficient (e.g., compared with the improved Euclidean distance method).[27]

Sensitivity Analysis

As a result of the random feature of measured vibration data as well as the model parameters, uncertainty of standard reference vibration states and CE distance calculations always exist to a certain degree. (The uncertainty in diagnosis and monitoring is also related to experiment noise.) Sensitivity is a performance evaluation of a diagnostic monitoring system. In

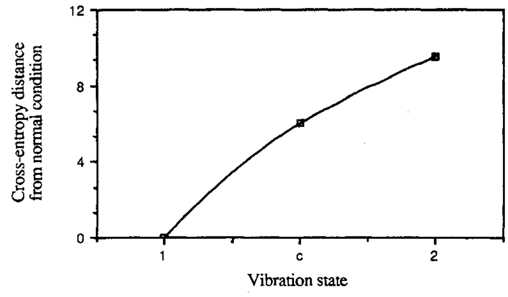

Fig. 7 Monitoring 3: increase external vibration amplitude.

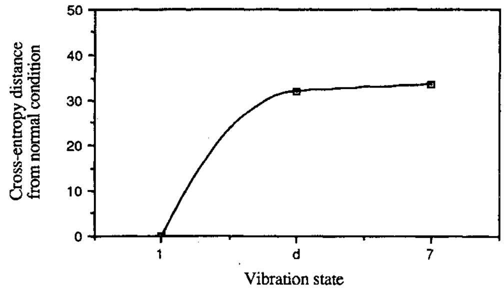

Fig. 8 Monitoring 4: change lubricant condition and clearance.

this section, the diagnosis and monitoring sensitivities are defined, and a sensitivity analysis is carried out for the diagnostic monitoring of jointed truss-cell unit structure vibration.

Definitions of Diagnosis and Monitoring Sensitivity

To reliably classify a new observation into one of the known system states, the distance between any two predetermined system states should be clearly distinguished compared with the uncertainty of the reference states. The diagnosis sensitivity E_{ij}^d (d refers to diagnosis) between two vibration states $\{\xi\}_{ri}$ and $\{\xi\}_{rj}$ is defined as a ratio of the reference uncertainty (inner-state distance) summation and the average distance between the two reference states (interstate distance), which is expressed as

$$E_{ij}^d = \frac{\text{uncertainty summation of two reference states}}{\text{average distance between two reference states}} \tag{8a}$$

or

$$E_{ij}^d = \frac{d_{ce}(\{\xi\}_{ri},\{\xi\}_{ri}) + d_{ce}(\{\xi\}_{rj},\{\xi\}_{rj})}{d_{ce}(\{\xi\}_{ri},\{\xi\}_{rj})} \tag{8b}$$

The monitoring sensitivity E_{ni}^m (m refers to monitoring) is defined as a ratio of the uncertainty of the normal vibration state over the distance between the normal state and any other reference (ith vibration condition), which is expressed as

$$E_{ni}^m = \frac{\text{uncertainty of normal state}}{\text{average distance between normal and reference states}} \tag{9a}$$

or

$$E_{ni}^m = \frac{d_{ce}(\{\xi\}_n,\{\xi\}_n)}{d_{ce}(\{\xi\}_n,\{\xi\}_{ri})} \tag{9b}$$

The expressions of the diagnosis and monitoring sensitivities statistically represent the minimum variation of a system state that can be detected by the diagnostic monitoring system. The values of E_{ij}^d and E_{ni}^m (note, by the definition, $E_{ni}^d > E_{ni}^m$) reflect the degree of confidence with which we classify the new observation to a reference or normal vibration condition. If

Table 3 Cross-entropy distances within and between references

Vibration condition	1	2	3	4	5	6	7	8
1	0.166	9.25	28.66	32.03	12.78	14.78	34.65	39.68
2		0.920	31.69	30.51	15.00	13.02	37.75	36.74
3			0.589	9.48	36.04	38.34	15.35	17.93
4				1.198	39.06	36.16	18.07	16.21
5					0.388	8.01	33.84	36.56
6						0.702	37.05	35.21
7							0.322	8.25
8								1.380

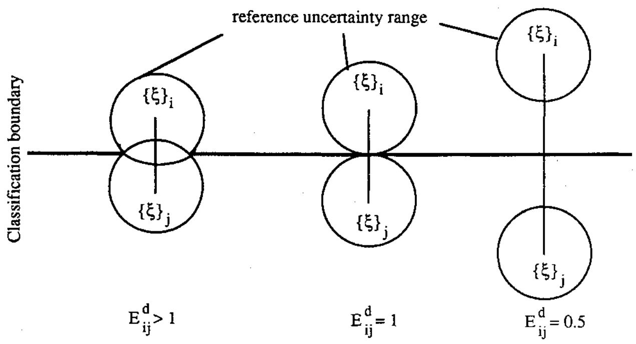

Fig. 9 Classification boundary.

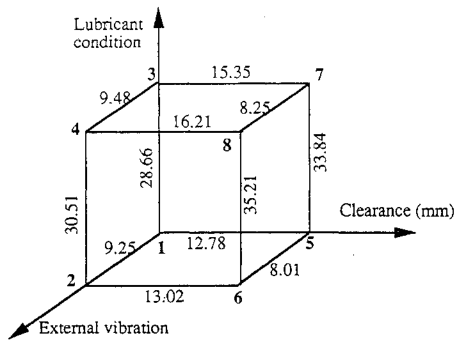

Fig. 10 Sensitivity analysis in different directions.

they are greater than 1, the regions of two reference conditions will overlap, and it is impossible to do the classification. If the value of E_{ij}^d approaches 1, we are not confident to do the classification because of the uncertainty of the classification boundary. Only when the value of E_{ij}^d is sufficiently smaller than 1 (say, ≤ 0.5) does the classification become dependable or trustworthy (see Fig. 9). Therefore, it is necessary that the maximum value of all of the sensitivities between any two references, as defined earlier, is less than a certain value (e.g., <0.5). Hence, the maximum value of E_{ij}^d or E_{ni}^m is defined as the diagnosis sensitivity (E^d) or monitoring sensitivity (E^m) of the diagnostic monitoring system, i.e.,

$$E^d = \max(E_{ij}^d,\ i = 1,2,\ldots,8;\ j = 1,2,\ldots,8;\ \text{and } i \neq j)$$

and

$$E^m = \max(E_{ni}^m,\ i = 2,3,\ldots,8)$$

Sensitivity Analysis of Diagnostic Monitoring of Jointed Structures

To analyze the sensitivities of monitoring and diagnosis, the reference uncertainties and average distances between references need to be calculated. Table 3 shows the calculation results from experimental data. In the table, the uncertainties of reference models, $d_{ce}(\{\xi\}_{ri}, \{\xi\}_{ri})$, are listed in diagonal positions. The other data represent CE distances between references, $d_{ce}(\{\xi\}_{ri}, \{\xi\}_{rj})$. It is observed that the reference uncertainties are much smaller than the distances between references, which indicates that the diagnosis sensitivity is high, according to Eqs. (8). Furthermore, the diagnosis sensitivity E^d of the diagnostic monitoring system for jointed-structure vibrations is found to be 0.20. This corresponds to the case of change from vibration condition 7 to vibration condition 8. It can also be seen that the diagnosis sensitivity is highly direction-dependent. For example, it is much more sensitive in detecting the change of lubricant condition than that of the external vibration amplitude, which can also be observed in Fig. 10. The lubricant condition is related to the value of joint contact damping, which strongly affects the dynamic contacts in the joint.[1]

The monitoring sensitivity can be found by comparing the uncertainties of normal vibration (vibration condition 1) and the average distances from the normal condition to any other reference condition (see first row of Table 3). Table 3 shows that the monitoring sensitivity E^m is 0.02, which corresponds to the change from vibration condition 1 to 2. The monitoring sensitivities are also direction-dependent.

Summary and Conclusions

A real-time-oriented diagnostic monitoring system was developed and applied to the vibration monitoring and diagnosis of an elastically jointed truss-cell unit structure. The nearest neighbor classification rule was applied, and the cross-entropy distance was used as a dissimilarity measure of vibration states. The newly observed vibration state was classified into one of the reference states, according to the cross-entropy minimization classification rule. Experiment results from the truss-cell unit structure model were analyzed and showed satisfactory sensitivities in both the monitoring and diagnosis processes. The cross-entropy distances were significantly detected when the vibration state deviated from the normal vibration condition, which indicated the feasibility of applying the methodology to practical problems.

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