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Structural Integrity Monitoring and Damage Detection by Using Pattern Recognition and Expert Systems

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ABSTRACT

In this paper, the computer pattern recognization technique is used for identification of the damage states of jacket platforms, which are considered as fluid-structure-soil interaction systems with time-varying factors. The training samples of each damage class of the jacket platform can be obtained by a series of model tests in the ocean simulation laboratory or by computer simulation taking into account the modification of the mathematical model and environment condition according to the monitoring measurements on the field site. In order to limit the number of possible damage states and avoid the data explosion,the knoledge-based expert system is proposed to make use of the related knowledge available for damage detection of jacket platforms including the human expert experience. The system consists a knowledge base and inference engine implemented in Prolog-i and Turbo prolog and links up with a Fortran environment for signal processing and numerical analysis via the data base.

INTRODUCTION

Structural integrity monitoring and damage detection are getting important for jacket platforms to prevent pollution of environment and loss of life and also to protect investment. Up to the present, the structural integrity monitoring and damage detection are still based on the underwater survey, mainly by visual inspection and the decision making for maintenance mostly upon the experience. It is not only very expensive but also not reliable. In order to improve the structural integrity inspection, make cost decision regarding maintenance, update residual fatigue life prediction, modify math. model and design codes, a lot of research work have been done in recent years on the structural integrity monitoring and damage detection of jacket platforms [1-11]. There are two kinds of structural damages to be detected. One is local crack, the other is the failure of functional structure members for the whole structure. Of course, the methods used for detecting different kinds of structural damages are different. For instance, the MPI (Magnetic Particle Ispection), ACFM(Alternate Current Field Measurement) and acoustic emittance method are usually used for crack detection. The structural vibration or elastic wave signals are taken to identify the dynamic behaviour of the structures for detecting the integrity of the whole structure, such as the natural frequency shift method, random decrement method, Rubin's flexibility method, the echomechanical method etc. Other kinds of physical or chemical signals reflecting the damage state of the structure also can be used for damage detection, for instance, the pressio-detection method. However, it seems no single of such methods is suitable enough to meet all the demands above mentioned. In this paper, a knowledge-based expert system is proposed to do planning, diagnosis and decision making for structural damage detection. It can make use of all the advantages from different methods and the experience accumulated by different experts.

The task of damage detection is to find out if the structure damage has happened, how serious it is and where it is located. As the jacket platform structures are highly redundant, severe damage to a single or a limited number

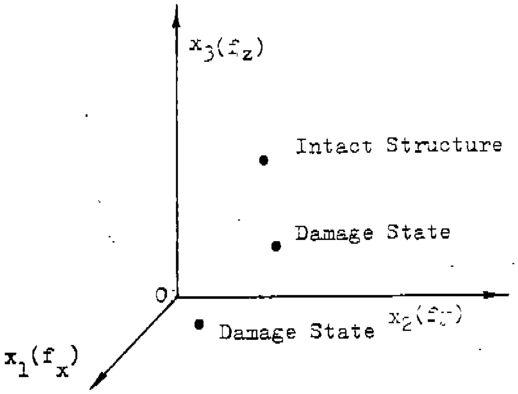


Fig.1 Damage State Space

of structural members will not necessarily constitute a significant loss of the integrity of the structure. Sufficient data which contain the information of damage state should be acquired for damage detection. It depends on the severeness of the damage to be detected and the effectiveness of the identification method used.

According to the severeness of the structural damages, the damage states can be cataloged into [12,13]

1. Total damage --- complete collapse of the struture,
2. Severe damage --- serious damage to the structure,
3. Significant damage --- significant damage to local area or minor damage to the structure,
4. Unsignificant damage --- no or unsignificant damage to the structure.

The system is designed for detecting the significant and severe damage states so that warning of disasters can be given in advance to prevent loss of life and valuable equipment and decision can be made for maintenance during the operating life of the structure.

The pattern recognition technique is used to make use of all the useful information from different identification methods effectively and efficiently. The jacket platform system is a fluid-structure-soil interaction system with time-varying factors such as mass and its distribution; sea still water level; corrosion and marine growth to the scantlings and configuration of the structure and the soil foundation etc. These time-varying factors should be measured or monitored simultaneously with the input(excitation) and output (response). Accordingly, a time-varying math. model is established for pattern training of damage states by using computer simulation.

PATTERN RECOGNITION

Damage State Space

A pattern or damage state D can be characterized with a feature vector X comprising the values of a finite set of parameters considered relevant to the pattern,

$$X=(x_1,x_2,\ldots,x_n) \quad , \tag{1}$$

where x_i, $i=1,2,\ldots,n$ represents the particular value associated with the i-th dimension of the damage state D. The damage state D is presented by pattern feature vector X,

$$X=f(D) \quad , \tag{2}$$

or

$$x_i=f_i(D) \quad , \tag{3}$$

where f_i is the measurement procedure associated with feature i. Using n independent feature parameters x_i, $i=1, 2,\ldots,n$ as a frame system of the damage state space, each possible damage state can be expressed as a point in the space. For instance, if the fundamental eigenfrequencies of lateral vibrations of the jacket platform in x direction and y direction f_x, f_y and the fundamental eigenfrequency of the torsion vibration of the jacket platform f_z are selected as the feature parameters x_1,x_2,x_3, any point in the space $O\text{-}x_1x_2x_3$ represents a damage state of the jacket platform, Fig.1. Variety of frame systems with different feature parameters can be taken to describe the damage states. It should be so selected that all the measured samples can be partitioned into homogeneous and well- separated subsets. It means all the samples for the same class of damage

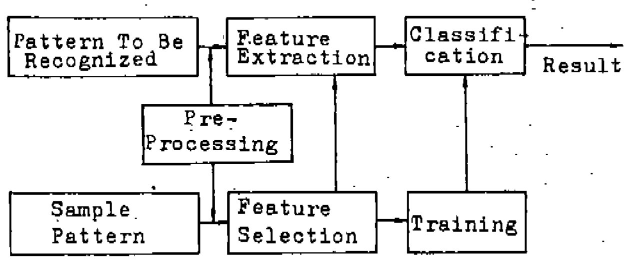


Fig. 2 Pattern Recognition System

states are similar to each other and dissimilar to the samples belonging to other class of damage states, according to some predefined measure of similarity[14].

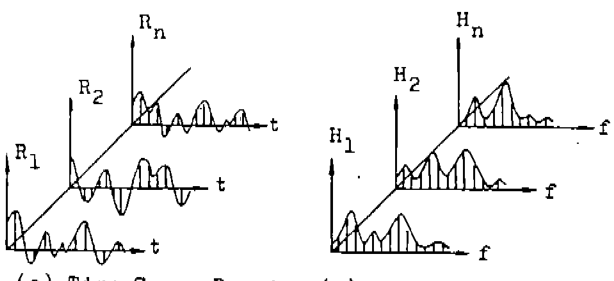
Classification Of Damage States

The discriminant system for pattern recognition is shown in Fig.2. It comprises two stages: analysis stage and implementation stage. The preprocessing should be taken to delete the noise, correct system error in the measurements and normalize the signals. The features are selected and an effective classifier is designed for training pattern in the analysis stage. Then, any pattern to be recognized can be easily classified to one of the classes of damage states in the implementation stage.

For damage detection of jacket platforms, the dynamic response at finite points of the structure to a given excitation or environment are measureed. A set of the discreted signals in time domain, frequency domain or space domain can be selected as the feature variables, for instance, the transfer functions $H(f_j,s_i)$, the power spectrum density functions $Psd(f_j,s_i)$ or the Randec signatures $R(t_j,s_i)$, $i=1,2,\ldots,m$, $j=1, 2,\ldots,n$, see Fig.3.

Assume there are M different classes of damage states $W_1,W_2,\ldots,W_M$, including the intact state class, considered as a special class of damage states, then the state space can be considered as consisting of M regions, each of which encloses the pattern points of a class of damage states, Fig.4.

The problem of recognition is to generate the decision boundaries which seperate the M classes of damage states



(a) Time-Space Domain (b) Freq.-Space Domain

Fig. 3 Feature Vectors From Vibration Signals

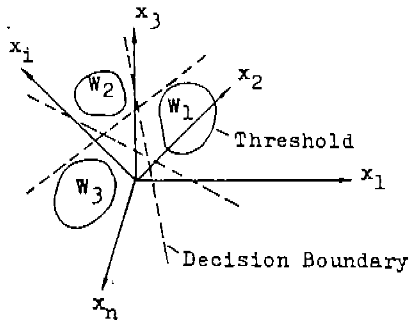


Fig.4 Space of Damage States (Pattern Classes)

on the basis of the feature vectors extracted from the observed measurements. Let the decision boundaries be defined by decision or discriminant functions which are scalar and single value functions of the pattern vector X, $d_i(X)$, $i=1,2,\ldots,M$. If $d_i(X)>d_j(X)$, for all $i\neq j$, then X belongs to class W_i. Since the damage states of jacket platforms are normally generated under randomness, Bayes decision function is chosen for classification.

Bayes decision functions

$$d_i(X)=p(X/W_i)P(W_i),\quad i=1,2,\ldots,M \qquad (4)$$

minimize the average cost of misclassification with the lowest probability of error. Where $p(X/W_i)$ is the likelihood function of class W_i, $P(W_i)$ is the a priori probability of occurrence of damage class W_i. X is assigned to class W_i if and only if

$$d_i(X)>d_j(X)$$

or

$$[p(X/W_i)/p(X/W_j)]>[P(W_j)/P(W_i)]. \qquad (5)$$

For damage detection of jacket platforms, it is reasonable to assume that $p(X/W_i)$ is multivariate Gaussian,

$$p(X/W_i)=(2\pi)^{-\frac{1}{2}}|C_i|^{-\frac{1}{2}}\exp[-\tfrac{1}{2}(X-m_i)^T C_i^{-1}(X-m_i)],$$

$$i=1,2,\ldots,M. \qquad (6)$$

Where m_i and C_i are the mean vector and the covariance matrix respectively. In view of the exponential form of the probability density functions the decision functions can be simplified by taking the natural logarithm of the likelihood ratio, u_{ij}. X is assigned to the class W_i, if and only if

$$u_{ij} > a \ , \qquad (7)$$

where

$$a = \ln[P(W_j)/P(W_i)] = \ln P(W_j) - \ln P(W_i) \ , \qquad (8)$$

$$u_{ij}(X) = \ln[p(X/W_i)/p(X/W_j)]$$

$$= \ln p(X/W_i) - \ln p(X/W_j) \ . \qquad (9)$$

Assume $C_i = C_j = C$, i.e. the likelihood functions of class W_i and class W_j have same covariance matrix,

$$u_{ij}(X) = X^T C^{-1}(m_i - m_j)$$

$$-\tfrac{1}{2}(m_i - m_j)^T C^{-1}(m_i - m_j) \ . \qquad (10)$$

Since $u_{ij}(X)$ is a linear combination of the components of X which is Gaussian, u_{ij} is also Gaussian. The mean value and variance of u_{ij} are $\frac{1}{2}r_{ij}$ and r_{ij} respectively. Where

$$r_{ij} = (m_i - m_j)^T C^{-1}(m_i - m_j) \qquad (11)$$

referred to as the Mahalanobis distance between $p(X/W_i)$ and $p(X/W_j)$. The probability of misclassifying a pattern when it comes from class W_j is $p(u_{ij} > a/W_j)$ and the probability of misclassifying a pattern when it comes from class W_i is $p(u_{ij} < a/W_i)$. Therefore, the probability of error is given by

$$P(e) = P(W_i)p(u_{ij} < a/W_i) + P(W_j)p(u_{ij} > a/W_j)$$

$$= P(W_i)\phi(ar_{ij}^{-\frac{1}{2}} - \tfrac{1}{2}r_{ij}^{\frac{1}{2}}) + P(W_j)$$

$$[1 - \phi[ar_{ij}^{-\frac{1}{2}} + \tfrac{1}{2}r_{ij}^{\frac{1}{2}}) \ ] \qquad (12)$$

where ϕ is the standard normal distribution function. P(e) can be used as a reference of certainty factor in inexact reasoning.

Reject Class Of Damage States

In order to limit the number of the class of damage states in the classifier, it is wise to put all less possible damage states in a "reject class" which is the complement set of the union of all the M classes of damage states in the universe of damage states. The Mahalanobis distance

$$r_{xm_i} = (X - m_i)^T C^{-1}(X - m_i) \qquad (13)$$

can be used as a measure of similarity between the pattern vector X and the mean vector m_i of class W_i. According to the demand for the level of significance or the confidence limits, a criterion can be set as the threshold G of the reject class. If Bayes classifier assigns X into class W_i but $r_{xm_i} > G$, then X belongs to the reject class.

Reduction Of Feature Parameters

An optimization procedure is developed to reduce the feature parameters for classifying M classes of damage states. The function of separation among different classes in the damage state space is defined as

$$S = \sum_{i=1}^{M} P(W_i)(m_i - m_o)^T Q^{-1}(m_i - m_o) \ . \qquad (14)$$

Where M -- the number of damage classes to be recognized,

$P(W_i)$ -- the occurence probability of class W_i,

m_i -- the mean vector of the ith damage class W_i,

m_o -- the global mean vector of all M damage classes,

$$m_o = \sum_{i=1}^{M} P(W_i) m_i \ ,$$

Q -- the mean covariance matrix of all covariance matrices of the M damage classes,

$$Q = \sum_{i=1}^{M} P(W_i) C_i \ .$$

If M=2, $C_1 = C_2 = C$ and $P(W_1) = P(W_2)$, then the function of separation S will be the same as Mahalanobis distance, the measure of similarity.

By using the fact that

$$(m_i - m_o)^T Q^{-1}(m_i - m_o)$$

$$= tr[Q^{-1}(m_i - m_o)(m_i - m_o)^T] \ , \qquad (15)$$

and let

$$B = \sum_{i=1}^{M} P(W_i)(m_i - m_o)(m_i - m_o)^T \ , \qquad (16)$$

the separation function S can be expressed as

$$S = tr[D] \ , \qquad (17)$$

where $D = Q^{-1}B$, rankD=M-1, $(m_i - m_o)(m_i - m_o)^T$ is the matrix outer product and results in a symmetric matrix rank 1. Matrix B reflects the distribution of the damage classes in the damage space while matrix Q reflects the distribution of damage states within each class.

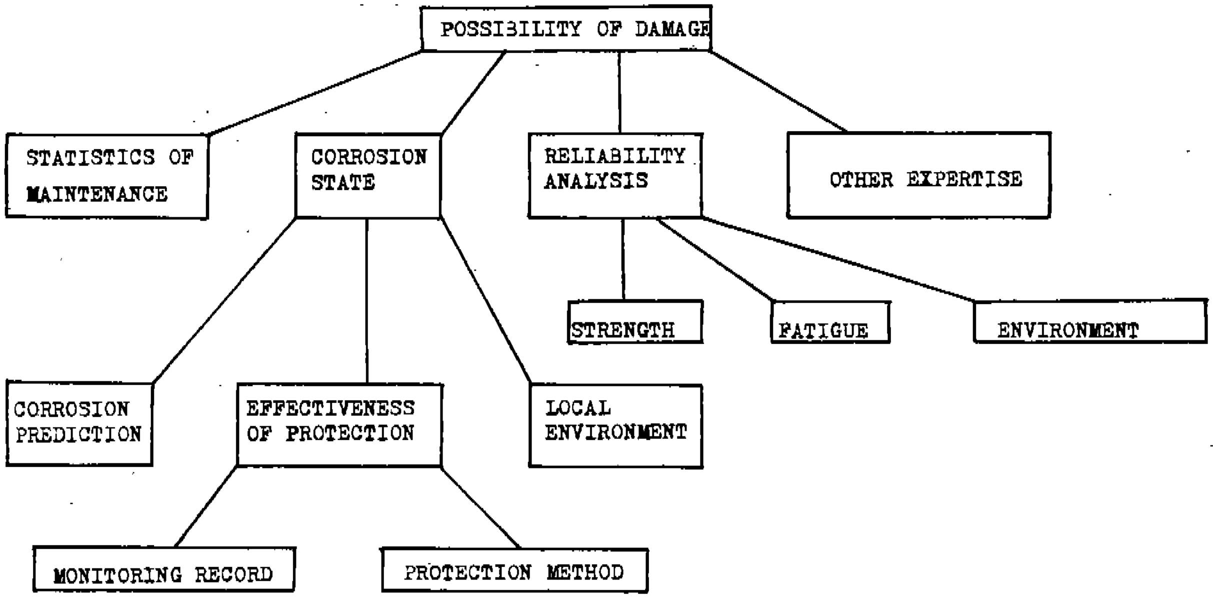


Fig.5 Inference Network for Assessment of Damage Possibility

Obviously, if the damage states spread loosely within each class and closely among different classes, the value of separation fuction S will be very low. In other words, separation fuction S depends on the spread of the damage states within each class and among different classes. In order to reduce the number of feature variables and get the optimal feature vector or the optimal frame system of the damage state space, separation function S is chosen as the objective function of optimization.

Firstly, the number of dimensions of the frame system of the damage state space can be reduced to the rank D =M-1. If

$$V=\begin{bmatrix} v_1 & & & \\ & v_2 & & \\ & & \cdot & \\ & & & v_{M-1} \end{bmatrix} \quad (18)$$

and

$$\phi=[\phi_1,\phi_2,\ldots,\phi_{M-1}] \quad (19)$$

are the eigenvalue and eigenvector matrix of matrix D, then by using ϕ as the transformation matrix of the frame system the feature vector X can be transformed to the principal coordinate system, expressed as feature vector Y,

$$Y=\phi^T X \ . \quad (20)$$

The number of feature parameters in the principal coordinate system can be further reduced according to its contribution to the separation function S,

$$S=tr[D]=\sum_{i=1}^{M-1} v_i . \quad (21)$$

Assume

$$v_1>v_2>\ldots>v_i>\ldots>v_{M-1} \ , \quad (22)$$

the coordinates corresponding to the lower eigenvalues can be truncated if their contribution to S is negligible.

DIAGNOSIS

Diagnosis Strategy

Diagnosis of structural damage can be considered as a sort of system identification or an inverse problem of structural dynamics. Principlely, by measuring the environment or artificial excitation(input) and the response of the structure system(output) the modal parameters i.e. eigenpairs and damping ratios or the physical parameters such as stiffness matrix, mass matrix and damping matrix can be identified or estimated. However, it is hardly to get the unique solution and very different to do differential diagnosis of variety of structure damage states, especially

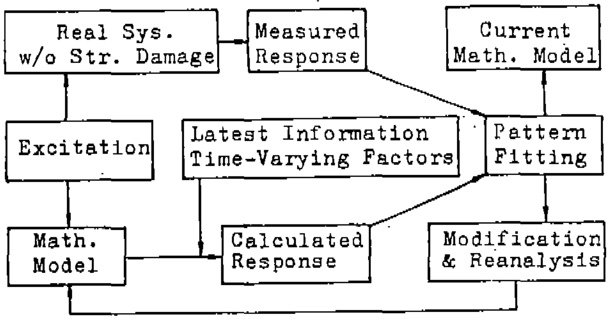


Fig.6 Establishing Current Math. Model

for the complex jacket platform structure system.

The diagnosis strategy we prefer is to estimate all the possible damage states of the jacket platform by making use of the available knowledge for assessment of structure damage such as reliability analysis, statistics of maintenance records of similar jacket platforms, the corrosion situation etc. and other human expert experience. The inference network for assessment of damage possibility is shown in Fig.5. In this way, the set of damage state classes to be recognized or diagnosed is determined. Then the pattern recognition technique is used to assign the state of structure system to one of the damage classes by the feature vector which is extracted from the monitoring signals and contains sufficient information for distinguishing different classes of damage.

Computer Simulation

The training samples of each damage class W_i can be obtained from the measurements on the jacket platform in damage state class W_i. Obviously, it is hardly realistic. However, it can be realized either by a series of model tests in the ocean simulation laboratory or by comupter simulation taking into account the modification of the time-varying math. model according to the monitoring measurements on the field site. The reanalysis technique for modification of the math. model can be used to make the large amount of computing more efficient. The scheme of system identification for establishing the current math. model is shown in Fig.6. The latest information from monitoring measurements and periodical inspection about the time-varying factors related to the behavior of the system should be considered in establishing the current math. model, such as mass and its distribution, soil foundation, corrosion, marine growth, sea level and others which make sense in the math. model. The block diagram of the diagnosis of structural damage is shown in Fig.7.

Although there are a lot of analysis work in the present method, the solutions of inverse problem of structural dynamics are avoided. Of course, the accurancy of the analysis or the uncertainties involved in the computation will affect the results of the diagnosis.

MODEL TEST

In order to verify the effectiveness of the present method, two model tests are carried out. One is a 2-D model tested in air and the other is a 3-D model tested in water with random wave excitation. In this paper only the 2-D model test is presented, as the test report of the 3-D model has not completed yet. It will come out in a few weeks.

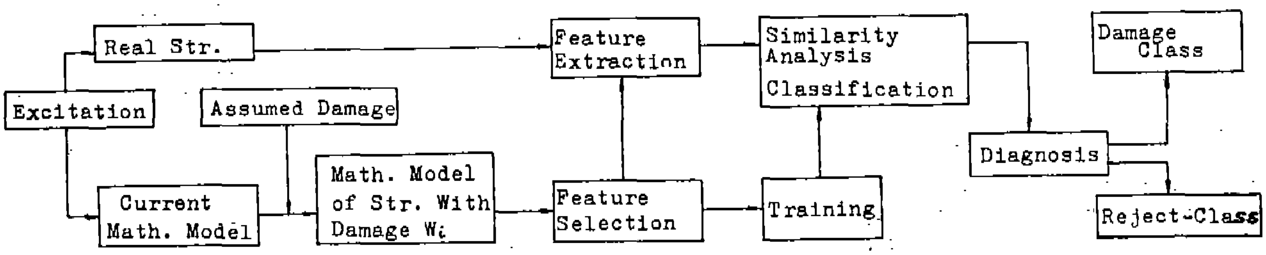


Fig.7 Block Diagram of The Diagnosis of Structural Damage

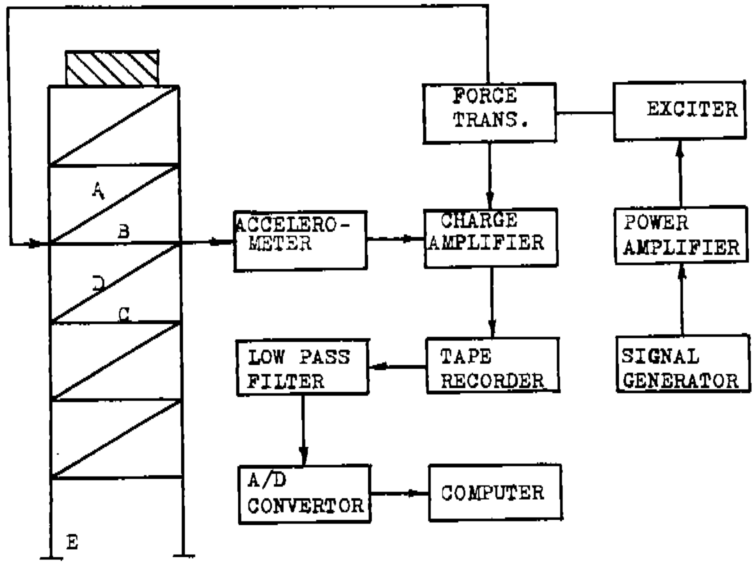


Fig.8 Scheme of the Model and Testing System

The 2-D frame structure model is made of plexiglass. The scheme of the model and the test system is shown in Fig.8. Five different classes of damage are designed to be tested:

1. intact structure,
2. severance of structural member A,
3. severance of structural member B,
4. severance of structural member C,
5. partly cut of the leg near the bottom at E.

All the damage states different from the above five classes are put in the reject class.

Single point random excitation and single point response measurement are taken for the test. The discrete transfer function and Randec signature are chosen as the feature vectors X_T and X_R. For each damage class a number of records are taken to get the mean feature vector m_i and the covarience matrix C_i $(i=1,2,3,4,5)$. The occurrence probability for different damage class is assumed same and the likelihood fuction $p(X/W_i)$ of each class is considered as normal distribution. Hence, the Bayes decision function can be expressed as $u_{ij}>0$ or

$$\ln d_i > \ln d_j \text{ , for all } i \neq j . \tag{23}$$

After training the samples from the five damage classes, the Bayes classifier is established. Then three record samples from three different classes of damage, i.e.

1. severance of member B,
2. partly cut of leg at E,
3. severance of member D,

are put in the classifier to see if the pattern recognition system works effectively.

The Bayes decision functions $\ln d_i$ for classifying the three record samples to one of the designed damage classes are given in table 1 and table 2 by using transfer function feature vector X_T and Randec signature feature vector X_R respectively. The classification result should be tested by using Mahalanobis distance r_{xm_i} to see if it is within the threshold G which is determined according to the given level of significance. Then the final diagnosis results are obtained and shown in the tables, see the last row.

The chi square distribution function at level of significance 0.01 is used for calculation of the threshold of each damage class. The threshold G=220 for the feature vector of transfer function, dimension number = 176 and the threshold G=44 for the feature vector of Randec method, dimension number = 25.

It seems the classifier works as well as designed.

Table 1. lnd_i and Diagnosis Results by Using X_T

lnd_i		Record Sample Damage B	 Damage E	 Damage D
Intact Str.	I	-7589	-2319	-49950
Severance	A	-1425	-480	-23790
Severance	B	217	-6948	-101600
Severance	C	-1649	-9065	-4919
Partly Cut	E	-4144	148	-39900
Classification Result		B	E	C
Threshold	G	220	220	220
r_{xmi}		145<G	205<G	1001>G
Diagnosis Result		B	E	reject

Table 2. lnd_i and Diagnosis Results by Using X_R

lnd_i		Record Sample Damage B	 Damage E	 Damage D
Intact Str.	I	-309	-188	-332
Severance	A	-218	-149	-236
Severance	B	-126	-181	-159
Severance	C	-172	-239	-138
Partly Cut	E	-241	-136	-261
Classification Result		B	E	C
Threshold	G	44	44	44
r_{xmi}		14<G	39<G	46>G
Diagnosis Result		B	E	reject

As mentioned before, the dimensions of feature vectors can be reduced or transformed to the principal vectors without decreasing the separation function S. The number of principal vectors for classifying five damage classes is 4. Therefore, the feature vector X_T and X_R can be transformed to the principal vector Y_T and Y_R with only four feature parameters in the vector. The threshold of the damage class now becomes G=13 for feature vector of 4 dimensions.

The diagnosis results are the same as from the original feature vectors X_T and X_R, see table 3 and table 4. However, the pattern training work in principal vector space is much more convenient than in the original feature vector space.

Table 3. lnd_i and Diagnosis Results by Using Y_T

lnd_i		Record Sample Damage B	 Damage E	 Damage D
Intact Str.	I	-1620	-356	-4691
Severance	A	-352	-124	-4477
Severance	B	3.7	-1583	-9632
Severance	C	-1455	-2990	-1576
Partly Cut	E	-1080	0.39	-7198
Classification Result		B	E	C
Threshold	G	13	13	13
r_{xmi}		3.2<G	8.2<G	3161>G
Diagnosis Result		B	E	reject

Table 4. lnd_i and Diagnosis Results by Using Y_R

lnd_i		Record Sample Damage B	 Damage E	 Damage D
Intact Str.	I	-138	-35.2	-172
Severance	A	-57.1	-22.9	-72.5
Severance	B	-17.8	-61.0	-31.6
Severance	C	-41.9	-47.9	-29.6
Partly Cut	E	-61.4	-17.0	-68.8
Classification Result		B	E	C
Threshold	G	13	13	13
r_{xmi}		3.0<G	8.9<G	27.6>G
Diagnosis Result		B	E	reject

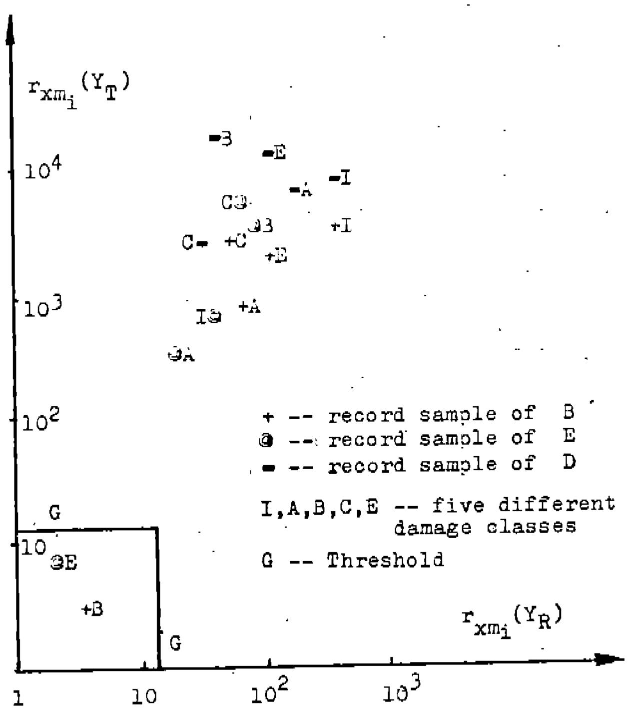


Fig.9 Mahalanobis Distance and Threshold

Fig.9 shows the Mahalanobis distances of the record samples to the mean vectors of the designed damage classes i.e. I, A, B, C and E, by using both transfer function method and Randec signature method. It can be seen from this figure the transfer function method is better than the Randec signature method as the difference of the Mahalanobis distances between assigned damage class and the other damage classes are larger in transfer function method for this specific example.

EXPERT SYSTEM

Due to the complexity of structural damage detection, especially for such complicated Fluid-Structure-Soil system of jacket platform, the expert system is chosen to make use of all the knowledge accumulated in related fields, and take the advantages of different damage detection methods available, including hardwares, such as sensors, A/D converters, filters, anlysers etc. and softwares for preprocessing, feature selection, structural analysis, system identification, decision making and so on. For a lot of expertise are heuristic, an inference engine is needed for reasoning and a large amount of numerical process has to be done in preprocessing, structural analysis and pattern recognition, a hybrid knowledge-based expert system[15,16], implemented in Prolog-i, Turbo-prolog and Fortran is developed for dealing with both symbolic and numerical processes. The communication between Prolog and Fortran is realized throuth data base with data files. The structure of this expert system is shown in Fig.10.

The mixed search strategy of forward and backward chaining is adopted.

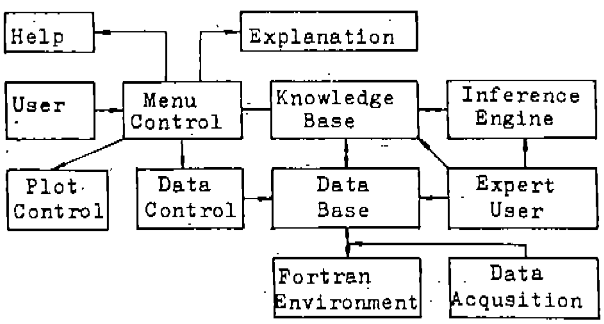


Fig.10 The Structure of Expert System For Damage Detection

Certainty factors are taken into account in the inexact reasoning. Certain factor CF is a real number in the interval [-1.0,1.0] indicates the certainty with which each fact or rule is believed, as it is used in the famous expert system for diagnosis and treatment of meningitis and bacteremia infections[17].

Due to a huge amount of possible damage states of jacket platforms, the reduction of searching area is extremely important to make the detection successful. The set of all functional structural members V can be patitioned into two subsets Vn and Vd. Vn consists of members never damaged or possibly damaged but easily to be inspected, such as the above water members. Vd is the complement of Vn. By using the initial information about the structure, the environment and the records of monitoring and inspection, the analysis of damageability of each element of Vd can be carried out and a limited number of classes of damage states due to the damage of one or some members of the most probably damaged members in Vd can be chosen as the damage class set U for pattern recognition. The intact structure state is considered as a special class in the set $\bar{U}$. All other damage states not belonging to U are put in the reject class U which is the complement of U in the universe of damage classes. In this way, the searching area can be reduced a lot. However, if the damage class set is not adequately selected or the number of class is too limited that the damage states of interest are calssified to the reject class, then the damage class set should be revised and the procedure of pattern recognition should be tried again.

The results of pattern recognition may be different for different feature vectors referring to different methods of identification. Each method gives an evidence for damage classification. The synthetic result can be obtained by using the inexact reasoning for more than one evidence[18].

CONCLUDING REMARKS

Combined with the idetification of the current math. model considering the time-varying factors in the structure and its environment, computer pattern recognition technique can be used to detect the damage of complicated structural system, such as the jacket platform. The feature vectors obtained by processing the measurements are different for different identification methods. It is possible to combine the features used in different identification methods in one feature vector. In this sense, pattern recognition technique can make use of the useful information from different identification methods. Obviously, correct detection will depend on the amount and completeness of discriminating information contained in the measurements and the effective utilization of this information.

In order to reduce the searching area of damage states and avoid data explosion, the knowledge-based expert system is proposed to make use of all the available domain knowledge related to the problem. The crucial problem is knowledge acquisition, i.e. collecting and utilizing the related knowledge and information. Seeking new identification methods which are sensitive, reliable and convenient for practical use is also an important issue for damage detection of jacket platforms.

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DISCUSSION

E. Nikolaidis

In your procedure to detect damage, obviously you minimize some quantity. What is this quantity that you minimize? I think you have used the term "Mahalanobis distance." Can you define this quantity?

X. Lu

I think you'll find in this paper a lot of mathematical expressions because we assume that distribution of a microcosm of the damage states is a multivariable Gaussian process. In this case we can point to the various logarithms of it and then we can get to this kind of distance which indicates how close two kinds of damage classes are in the space of damage states.