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Identification Technology of Offshore Platform Modal Parameters Based on Principal Component Analysis

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Abstract: Compared with the ground method, the offshore platform (OP) has the characteristics of complex structure and large volume. It has been used in harsh marine environments for a long time and is often affected by wind, wave, tide and ice loads; at the same time, adverse factors such as ship strikes, hurricanes, fires and explosions make the system vulnerable to damage. The destruction of the marine environment will not only cause serious safety accidents and economic losses, but also cause serious pollution to the marine environment, which makes people pay more attention to the safety of large-scale projects. The main purpose of this paper is to study the identification technology of modal parameter (MPs) of OPs based on PCA. Aiming at the shortcomings of the existing linear PCA technology to remove the influence of environmental factors, this paper adopts the nonlinear PCA (kernel PCA) technology to remove the influence of environmental factors. Experiments show that, except for working condition C1, the damage indexes of all other working conditions (C2~C6) exceed the control limit, and the identification is correct, but for working condition C2, it can be seen from the figure that most of the samples have damage index critical control limit edges. , it will also cause some disturbance to the recognition results. The results of the test model show that the PCA technique can effectively remove the influence of environmental factors on the damage identification of OP structures.

1. Introduction

Principal component analysis (PCA), also known as "PCA", "principal component regression analysis", is a data compression technology proposed in the 1980s [1-2]. In essence, the PCA method is to map high-dimensional data into a small size, and the spatial dimension is linearly transformed, so that each first component is a linear combination of the original variables, and the first components are independent of each other, so that the first component can be Keeping the first information of the original variable so that the information is contained without overlapping each other can also simplify the problem while reducing the dimension of the original variable. It is widely used in structural damage detection research.

In a related study, Raheem et al. mentioned that in-situ analysis of OPs basically requires proper design of new structures and real evaluation of existing structures [3]. A nonlinear finite element analysis of the platform structure and pile-soil interaction above the seabed is used to estimate the in situ behavior of a typical fixed OP. The analysis includes interpretation of dynamic design parameters based on available site-specific data, as well as foundational design recommendations for in-situ loading conditions. According to Tronci et al., MP estimation usually requires some degree of user interaction, mainly when using parametric system identification methods [4]. Such procedures typically depend on the selection of a set of parameters that are defined according to heuristic criteria and that remain constant over long periods of monitoring activity. The main purpose of this paper is to demonstrate the necessity of abandoning identification methods based on a single parameter set in long-term monitoring campaigns, and to propose a semi-automatic modal identification tool in which user-defined parameters vary in value within a given range, which can be independent of the user's Professional knowledge to set up.

The change of environmental factors has a great influence on the characteristic parameters of the OP. In order to ensure the reliability of the structural damage identification results, the interference caused by environmental factors should be eliminated [5-6]. In this paper, PCA technology and nuclear PCA technology are used to remove the influence of environmental factors on the damage identification of OP structures, and the three-dimensional finite element model and experimental model of the five-layer OP are used to verify and analyze the two methods. When using the PCA technique, the influence of the selection of different principal component orders on the damage identification results of the OP structure is studied, and it is found that the peak value of the damage identification rate of the structure usually appears in the interval [m/2, m-1] (m means number of variables) on certain order principal components within the range. Aiming at the shortcomings of the existing linear PCA technology to remove the influence of environmental factors, this paper adopts the nonlinear PCA (kernel PCA) technology to remove the influence of environmental factors.

2. Design Research

2.1. Identification of Traditional MPs

The traditional parameter identification is called the Input-Output method [7-8]. It depends on the output and input signals of the system. If it is in the time domain, it needs to obtain the time domain impulse response function, and if it is in the frequency domain, it needs to obtain the frequency response function, so it is divided into time domain and frequency domain methods [9-10].

(1) Frequency domain method. The frequency domain method is to use a scientific method to fit the scale with the smallest error, also known as the curve fitting method. According to the obtained frequency response function or actual measurement, relevant parameters can be obtained through the modal expansion of the frequency response function. Commonly used methods include partial derivative method, sub-least square method, global identification method, distribution method, least square method, etc. In addition, according to input and output, it can be divided into SISO (input and output is single), SIMO (input is single and output is multiple) and MIMO (input and output is multiple). With the frequency domain averaging technique, noise reduction is the biggest advantage, so the position order problem can be easily solved. However, the frequency domain method has

some disadvantages such as aliasing frequency and power leakage [11-12].

(2) Time domain method. The time-domain method uses the structural vibration response signal, and the parameters can be obtained by processing the output response. The acquired processed signals are generally free or forced signals. Commonly used techniques include ITD, feature system implementation, etc. The time-domain method does not need time-frequency conversion, which can avoid Fourier transform, that is, without considering the interference problem caused by frequency-domain transform, only the measured signal can be analyzed online, and there will be no problems of energy leakage and low resolution. The accuracy and noise immunity are very good. At the same time, the time-domain method also has limitations: the time-domain signal is greatly affected by noise, false modes, and it is difficult to determine the order of the model. Noise reduction processing such as averaging technology is required [13-14].

2.2. Existing Problems and Cross-Model Approach

The marine platform system has been used in harsh marine environments for a long time, and its safety and strength are very important. Once an accident occurs, it will not only cause huge economic losses and casualties, but also cause adverse consequences such as environmental pollution and environmental disasters. In order to ensure the safe operation of the external platform system and avoid serious fatal accidents, it is necessary to conduct safety and life evaluation of the external platform system during the work [15-16].

Evaluation models showing actual structures are the basis for safety evaluations of external structures, but there are often errors between models created from original design data and systems in use. A common approach to this problem is model correction techniques. However, the traditional model correction methods have some shortcomings (such as the matrix method cannot maintain the asymmetry, sparseness and positive definition of the system matrix, so that the correction model is not physically important; while the sensitivity-based design parameter method requires. Iterative solution, calculation large volume), it is difficult to apply to large external base units. The Cross-Model Method (CMCM) can not only make up for the shortcomings of traditional methods, but also has many other advantages, so it is more promising to be applied to model modification of external infrastructures [17-18].

The marine engineering process is complex and the model uncertainty is large, but limited by the experimental conditions, the measurement information is often very limited and disturbed by noise, which makes the technical application of the model correction method one of the highlights. But the problems to be solved are: 1) selection of correction parameters, 2) solution of bad model correction system, 3) correction of nodes and boundary conditions, etc. If the CMCM method is to be applied to practical applications, it also solves the above problems.

2.3. Algorithm Research

(1) PCA

For a vector xj∈Rp×1(j=1,2,…,n) with p variables, denoted X=[x1,x2,…,xn], the first step of PCA is to find a linear algorithm Sub u1, the variance of the linear transformation uT1X is maximized, and then a linear operator u2 is found to maximize the variance of uT2X and has nothing to do with uT1X, and so on, and finally p such operators can be found. The k-th transformation uTkX is called the k-th principal component, also called scores. Denote U=[u1,u2,…,un] as the principal component coefficient matrix, also known as loadings.

For the first-order principal component uT1X, to maximize its variance, that is:

$$\max J(u_1) = u_1^T XX^T u_1 and u_1^T u_1 = 1 \tag{1}$$

Denote $\Sigma = \sum_{j=1}^{n} x_j x_j^T = XX^T$ as the covariance matrix of xj, according to the Lagrange multiplier method, formula (1) is denoted as:

$$\max J(u_1, \lambda) = u_1^T \Sigma u_1 - \lambda(u_1^T u_1 - 1) \tag{2}$$

If the maximum value of formula (2) is taken, the first-order partial derivative with respect to u1 is required to be equal to 0, that is:

$$\frac{\partial J(u_1, \lambda)}{\partial u_1} = \sum u_1 - \lambda u_1 = 0 \tag{3}$$

or

$$(\Sigma - I_p \lambda) u_1 = 0 \tag{4}$$

In the formula, Ip is the identity matrix of pxp, λ is the eigenvalue of the covariance matrix Σ, and u1 represents the corresponding eigenvector.

The maximum variance of the first-order principal components is:

$$u_1^T \Sigma u_1 = u_1^T \lambda u_1 = \lambda \tag{5}$$

Therefore, λ must be large enough, and u1 is the eigenvector corresponding to the largest eigenvalue of the covariance matrix Σ.

(2) MP identification

Perform eigenvalue decomposition on the discrete state matrix A, then:

$$A = \psi \Lambda \psi^{-1} \tag{6}$$

Among them, Λ=diag(λ)∈Rn×n, is a diagonal matrix; ψ is a matrix composed of discrete-time eigenvectors.

In the same way, the eigenvalue decomposition of the continuous state matrix Ac, then:

$$A_c = \psi_c \Lambda_c \psi_c^{-1} \tag{7}$$

In the system state matrix, the relationship between A and Ac is as follows:

$$A = \exp(A_c \Delta t) = \psi \Lambda \psi^{-1} = \psi_c \exp(\Lambda_c \Delta t) \psi_c^{-1} \tag{8}$$

In addition, the relationship between the corresponding eigenvalues of A and Ac is:

$$\lambda = \exp(\lambda_c \Delta t) \Leftrightarrow \lambda_c = \frac{\ln \lambda}{\Delta t} \tag{9}$$

The relationship between the complex eigenvalue λc of the system and the natural frequency and damping ratio is as follows:

$$\lambda_c = -\xi\omega \pm \mathrm{j}\omega\sqrt{1 - \xi^2} \tag{10}$$

In summary, the MPs of the system can be obtained as:

$$
\begin{aligned}
&\omega = \sqrt{(\lambda_c^R)^2 + (\lambda_c^I)^2} \\
&\xi = \frac{\lambda_c^R}{\omega} \\
&\Phi = \mathrm{C}\Psi
\end{aligned}
\tag{11}
$$

where ξ is the damping ratio, ω is the circular frequency, Φ is the mode shape, and Δt is the sampling time interval.

3. Experimental Study

3.1. Modal Test Equipment

The equipment currently used in the laboratory for modal testing includes: several sensors, 1 PCB hammer, data acquisition front-end, modal testing and analysis software, as shown in the following table:

Table 1. Sensor parameters

Serial Number	Voltage sensitivity mv/g	Acceleration range g peak	Frequency response function Hz	weight g
J0149	959.76	±50	0.6-1000	160
J0150	952.22	±50	0.6-1000	160
J0151	958.07	±50	0.6-1000	160
J0152	955.93	±50	0.6-1000	160
PCB352A	1000	±500	5-5000	35
PCB353A33	100	±1000	1-3000	40

Table 2. PCB hammer

Serial Number	086C20
Hammer sensitivity mv/N	0.16
range lb	0-5000
Put some time constant s	2000
output impedance ohms	100
Output bias volts	9.70

3.2. Steps of Modal Testing

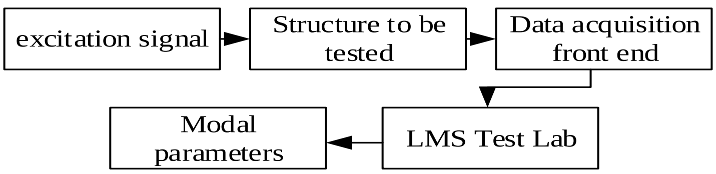

Figure 1. Modal test flow chart

First, the measuring points are arranged and the geometric model is established according to the structure to be tested, and then the excitation signal is applied to the structure to be tested. The LMS Test Lab modal testing and analysis software controls the SCADAS Mobile data acquisition front-end to collect the excitation signal or response signal, and analyze it. The window processing is performed, and then the MPs such as the modal frequency and the modal mode shape of the structure to be measured are obtained by using the parameter identification method, so as to carry out the damage detection of the structure.

3.3. Test System

The vibration monitoring of the platform structure is mainly composed of the following three parts: acceleration sensor, signal acquisition system and data processing system, as shown in Figure 2.

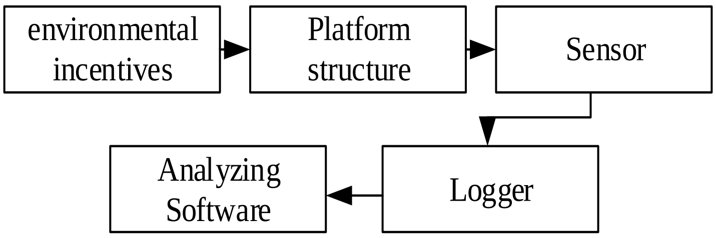

Figure 2. Platform structure vibration monitoring system

In Figure 2, the sensor is a balanced dual-axis accelerometer, which can measure vibration signals in two horizontal directions at the same time. The sensors are serially connected via Cat5E cables, which in turn are connected to the recorder, then to the computer via Ethernet, and finally real-time data analysis is done with the help of software. The sensor used in this experiment is an AC-7xD digital accelerometer and the transmitter is a GMplusD recorder.

3.4. Simulation Signal Analysis

Build a set of simulation signals and set initial VMD parameters. Based on the particle swarm algorithm, the [k,α] parameter combination when the envelope entropy of the reconstructed signal is the smallest is searched. The simulated signal is decomposed according to the parameter combination value, and the component signal containing characteristic information is reconstructed. Finally, the MPs of the signal are calculated by the SSI method. The specific process of signal analysis is shown in Figure 3.

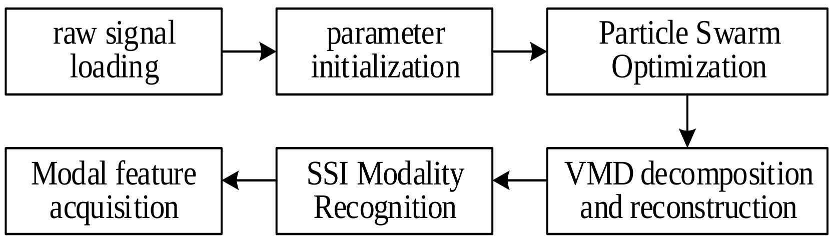

Figure 3. MP identification analysis flowchart

4. Experiment Analysis

4.1. Analysis of Contribution Rate

Using the PCA method to extract the features of variables 1, 2, 3, 4 and 5, the eigenvalues and variance contribution rates of the principal components of each order are shown in Table 3.

Table 3. Eigenvalues of covariance and their variance contribution rates under the influence of temperature alone

Eigenvalue serial number	Eigenvalues	Variance contribution rate (%)	Cumulative contribution rate (%)
1	4.35	86.97	86.97
2	0.49	9.70	96.68
3	0.11	2.18	98.86
4	0.04	0.72	99.58
5	0.02	0.42	100.00

The damage characteristic parameters (AR model coefficients) of the training samples and the test samples are projected on the principal component axes of each order, and then the projected load vector is determined by the training samples. Finally, the Q statistic combined with the control chart is used to identify the structural damage of the test samples.

It can be seen from the principal component score diagram that the influence of environmental factors (temperature) on the AR model coefficients is mainly concentrated in the first three principal components, which makes the principal component score data before and after structural damage overlap, so that the damage state cannot be correctly judged.

It can be seen that when the principal component order increases to 5, the damage index SPE value is equal to zero. At this time, no matter whether the structure is damaged or not, it cannot be read from the damage index. This also explains that the principal component order cannot be increased infinitely. s reason. In order to compare and analyze the influence of the principal component order on the damage index SPE, Figure 4 shows the correct rate of structural damage identification when n is 1, 2, 3, and 4.

Figure 4. Recognition rate of principal components of each order based on PCA method under the influence of temperature alone

Referring to Figure 4, it can be seen that when the first-order AR model coefficients of nodes 1-5 are used, the recognition rate for damage conditions (C2-C3) shows a trend of first increasing and then decreasing with the increase of the principal component order. In the increasing stage (n is 1, 2, 3), due to the gradual weakening of the effect of environmental factors, the information of the structure itself is revealed, and the sensitivity of the damage index based on the PCA method continues to increase. When the principal component order increases to 3, the cumulative variance contribution rate reaches 98.8593%. At this time, the damage identification rate of the structure is the highest. This also shows that there are still some defects when using the traditional analysis method to determine the order of the principal components.

4.2. Analysis of Test Results

The PCA method is used to extract the features of the training samples. The eigenvalues and variance contribution rates of the principal components of each order are shown in Table 3. The test considers the influence of mass on the structure of the OP. In order to make the damage identification result more accurate, the principal component order n is selected as 1, 2, 3, and 4, and the projection matrix T of the response is [U1], [U1, U2], [U1, U2, U3], [U1, U2, U3, U4].

Table 4. Eigenvalues of covariance and their variance contribution rates under the influence of quality

Eigenvalue serial number	Eigenvalues	Variance contribution rate (%)	Cumulative contribution rate (%)
1	4.63	92.69	92.69
2	0.22	4.30	96.99
3	0.09	1.71	98.70
4	0.05	1.00	99.70
5	0.02	0.30	100.00

In order to compare and analyze the influence of the principal component order on the damage index SPE, Figure 5 shows the correct rate of structural damage identification when n is 1, 2, 3, and 4.

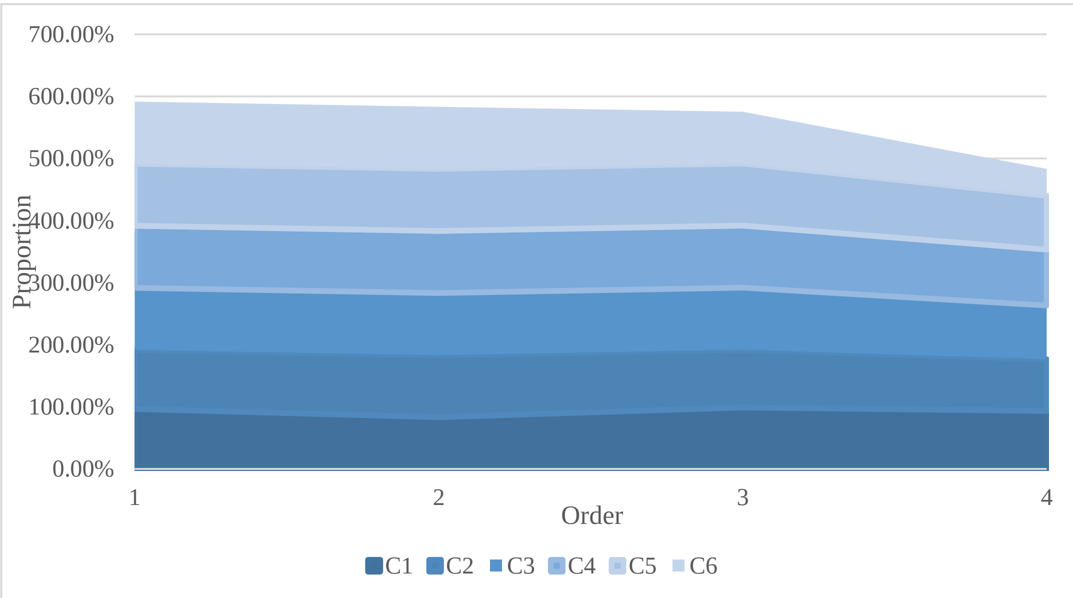

Figure 5. Analysis of structural damage identification rate based on PCA method under the influence of mass

From the analysis of the above chart, it can be seen that the damage indexes of all other working conditions (C2~C6) except working condition C1 exceed the control limit, and the identification is correct. The edge of the critical control limit will also cause some disturbance to the recognition result. The results of the test model show that the PCA technique can effectively remove the influence of environmental factors on the damage identification of OP structures.

The results of numerical simulation and experimental model show that: when the PCA technique is used, if the number of variables is assumed to be m, the peak value of the damage identification rate of the structure usually appears in the first few order mains in the range of [m/2, m-1]. on the ingredients. Therefore, when performing PCA, the first m-1 or m-2 order principal components can be directly selected for calculation, which reduces the detection time and obtains a higher detection and recognition rate.

5. Conclusion

Structural health monitoring plays an important role in ensuring the safety of large and complex structures such as marine engineering structures during service, effectively preventing the occurrence of serious accidents, and performing timely maintenance after damage diagnosis. The important content of structural health monitoring research is how to judge the damage of the structure in the early stage. Therefore, a systematic study is carried out on the current status and deficiencies of parameter identification and damage identification at this stage, CP-BSS is introduced into the field of modal identification, and combined with Hilbert transform and support vector machine in statistical machine learning to identify structural parameters, An exploratory study of the health monitoring system was carried out.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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