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Modal identification of structure under varying environmental conditions

Deyi Zhang[1], Yuequan Bao, Feng Zhou, Hui Li

Summary

Modal identification is essential in structural health monitoring (SHM) because that the modal parameters are often used for model updating and damage detection. However, in practical situations, the variation of environmental conditions (e.g. temperature, temperature gradients, humidity, etc.) will impede the reliability of modal identification. In this paper, firstly, the relation of frequency change and variation of environment temperature of space structure is investigated. Then, a structural state assessment method by combing autoregressive moving average (ARMA) and PCA is proposed. The acceleration data from China National Aquatics Center is employed as an example. The results show that variation of frequencies with increasing of temperature and wind velocity is not notable. That is because the temperature difference and velocity variation are little.

Introduction

In SHM, a lot of vibration based damage detection methods have been proposed and many of them identify the damage using the changes of modal parameters such as natural frequencies, modal damping ratios and mode shapes [1]. Unfortunately, in practical situations, the modal parameter changes due to varying environmental conditions (e.g. temperature, humidity, wind velocity, etc.) are often much more important, and hence they mask the changes caused by the damage of the structures. Therefore, it is important to eliminate environmental effects in modal identification.

Recently, many people are interested in investigating the methods for eliminating environmental effects. Yan et al. proposed an environmental effects elimination method based on PCA and the results showed that the PCA is useful for eliminating environmental effects in damage detection [2, 3]. Ni et al. used the PCA combining with frequency response functions (FRFs) and neural networks to detect the seismic damage of structure [4]. In this method the PCA is used to the measured FRFs for dimensionality reduction and noise elimination [4].

The paper is organized as follows. Next section describes the China National Aquatics Center and the monitoring system. The relations of frequency with temperature and wind velocity are investigated. In section 4, a state assessment method by combing ARMA and PCA is proposed for monitoring the state of structure. Finally, some conclusions are given in section 5.

[1]School of Civil Engineering, Harbin Institute of Technology, Harbin, 150090, China. Email: zhangdeyi@hit.edu.cn

The China National Aquatics Center

The China National Aquatics Center, also known as the 'Water Cube', is an aquatics center that is built for the swimming competitions of 2008 Summer Olympics. Comprising a steel space frame, it is the largest ETFE clad structure in the world. The National Aquatics Center as shown in Fig. 1 has been installed a SHM system in 2007. The SHM system has 240 fiber Bragg grating strain sensors, 22 accelerometers, 22 wind pressure sensor and one anemometer. The finite element model is shown in Fig. 2 and Fig. 3, which is constructed by ANSYS 9.0.

Figure 1: China National Aquatics Center

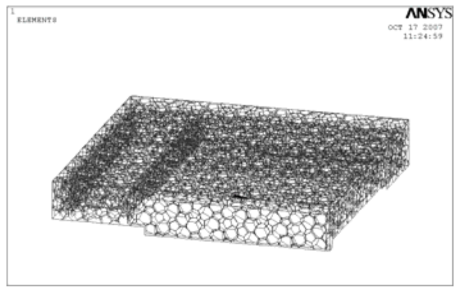

Figure 2: Finite element model of 'Water Cube'

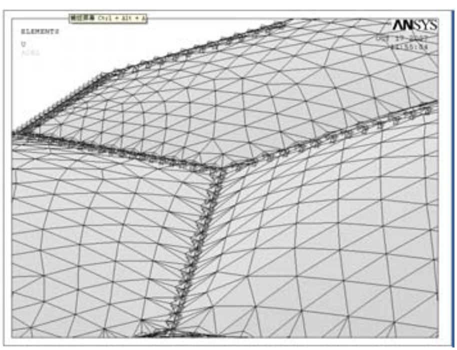

Figure 3: Joint between membrane structure

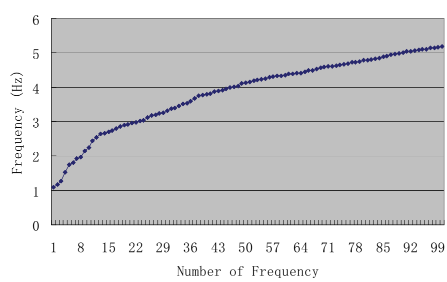

Figure 4: First 100 frequencies

Variation of measured natural frequencies

The first 100 frequencies calculated from the finite element model are shown in Fig. 4, which shows that the 'Water Cube' is a structure with closely-spaced natural frequencies. The modal identification of the structure with closely-spaced modal is a difficult problem in the world. In this example, firstly, we use the polynomial fit

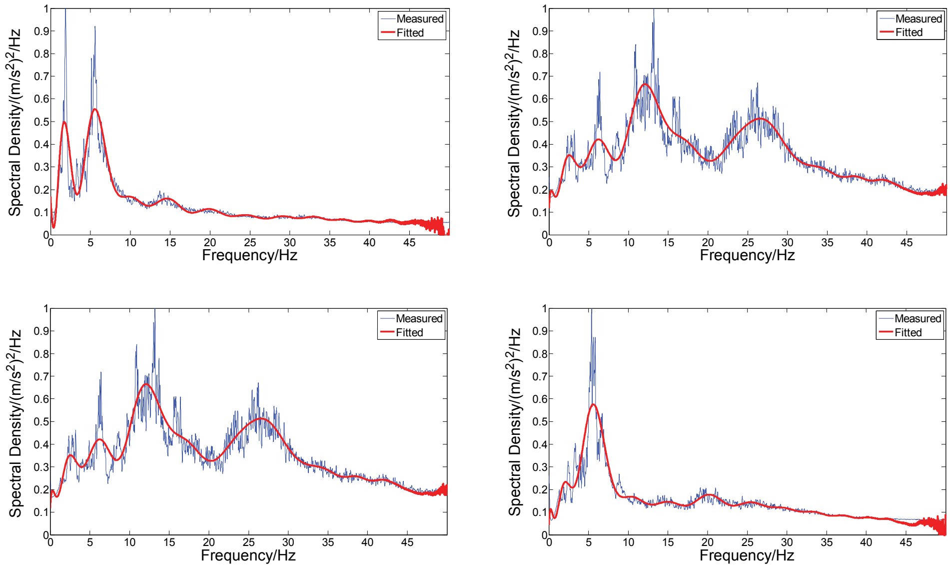

Figure 5: Power spectra fitted results of acceleration data from four accelerometers

methods to fit the power spectrum. Then the peak picked method is used to extract the frequency. However, it should be indicate that this frequencies identification method is an approximate method and only can give an estimation results. The results are shown in Fig. 5, which show the results of four acceleration data from four different accelerometers. It can be seen that all the fitted results power spectra have two peaks near the frequency of 3Hz and 5Hz. So, these two frequencies are extracted and used for investigating the relation of frequency with temperature and wind velocity. The results are shown in Fig. 6, which show that the variation of frequencies with increasing of temperature and wind velocity is little. That is because the temperature difference and velocity variation are little.

ARMA combing PCA methods for structural condition assessment

In this section, a time series algorithm by combing autoregressive moving average (ARMA) and PCA is presented for structure condition assessment. The vibration signals obtained from sensors are modeled as autoregressive moving average time series. Before fitting the ARMA models to the sensor data, the standardization of acceleration time histories has been performed, and the trend and stationary in the data also has been checked. Then the coefficients of the ARMA model are estimated by the Burg algorithm and the optimal model order is determined using the Akaike Information Criteria (AIC). The residuals obtained finally are tested to determine if they are normal and independent and identically distributed. The ARMA

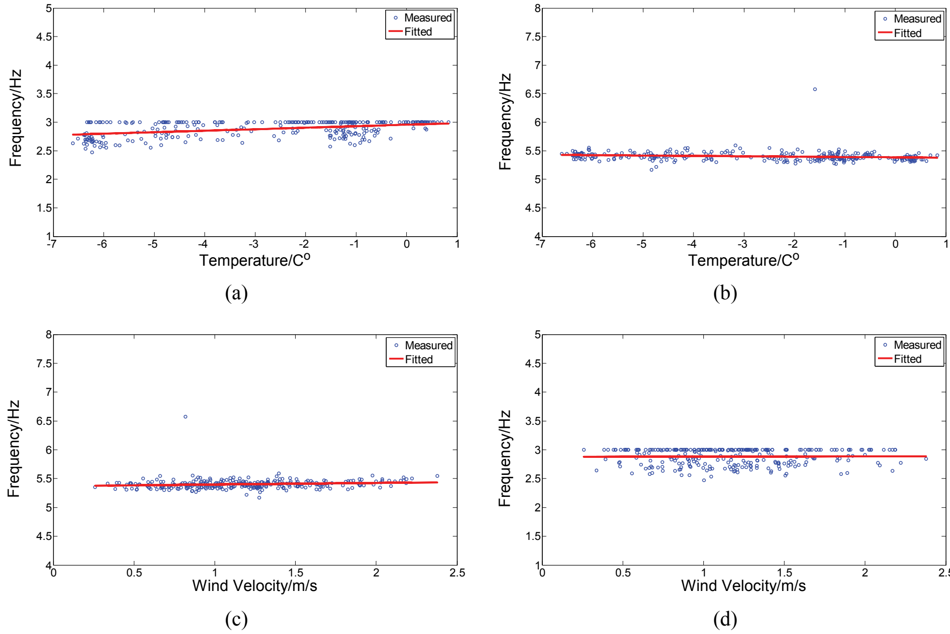

Figure 6: Relations of frequency with temperature and wind velocity: (a) and (b) effects of temperature; (c) and (d) effects of wind velocity

model is given by

$$x(n) = -\sum_{i=1}^{n_a} \alpha(i)x(n-i) + \sum_{j=1}^{n_b} \beta(j)u_x(n-j) + e_x(n) \tag{1}$$

where $x(n)$ is the normalized acceleration signal, $\alpha(i)$ and $\beta(j)$ are the ith and jth AR and MA coefficient respectively; n_a and n_b are the model orders of the AR and MA processes, respectively, and $e_x(n)$ is the residual term.

Nair [5] used the ARMA coefficients to develop features that can characterize damage state of a structure. Because these coefficients have a close relation with system poles, i.e. frequency and damping of a structure. Nair found that the first AR coefficient normalized by the square root of the sum of the squares of the first three AR coefficients provides the most robust damage sensitive feature. The proposed DSF is defined as follows:

$$DSF = \frac{|\alpha(1)|}{\sqrt{\alpha(1)^2 + \alpha(2)^2 + \alpha(3)^2}} \tag{2}$$

After got each DSF at every time analysis interval for every sensor, the Principal Component Analysis (PCA) is used to obtain one new Principal Component (PC) of DSF.

PCA is a multivariate analysis technique which can reduce the dimensionality and give us the main variable tendency [6]. Given an observed $m \times n$ dimensional matrix $\mathbf{X} = [x_1, \cdots, x_n]$, the goal of PCA is to reduce the dimensionality of $\mathbf{X}$. This is realized by finding r principal axes p_i with $i = 1, \cdots, r$ onto which the retained variance under projection is maximal. These axes, denoted as principal directions or PCA modes, are given by the eigenvectors associated with the r largest eigenvalues of the covariance matrix Σ:

$$\Sigma = E\left[(x-\mu)(x-\mu)^T\right] \tag{3}$$

where $E[\cdot]$ is the expectation and $\mu = E[x]$ is the mean of the data. If the principal directions are collected in a matrix $\mathbf{P} = [p_1, \cdots, p_r]$, then $z = \mathbf{P}^T(x-\mu)$ is a reduced r-dimensional representation of the observed vector x. Among all linear techniques, PCA provides the optimal reconstruction $\hat{x} = \mu + \mathbf{P}z$ of x in terms of the quadratic reconstruction error $\xi = \|x - \hat{x}\|^2$. After obtained all the principal components (PC) of the *DSF*, then one new PC of *DSF* has been formed below:

$$DSF_{new} = a_1 p_{DSF\,1} + \cdots + a_r p_{DSF\,r} \tag{4}$$

where a_i is the contribution percentage of the ith PC in the whole PCs, and a_i is given below:

$$a_i = \frac{\lambda_i}{\sum\limits_{i=1}^{r} \lambda_i} \tag{5}$$

where λ_i is the eigenvalue of the ith PC.

In this paper, DSF_{new} has been used to characterize the state of the structure and to see whether it changed with the environmental factors. The results are shown in Fig. 7, which show that the changes of *DSF* and DSF_{new} indexes with increasing of temperature and wind velocity are not notable. That is because the temperature difference and velocity variation are little. Besides, this structure is so rigid that these little environment effects can not contribute to notable changes of structural modal parameters.

Conclusions

In this paper, the effects of temperature and wind velocity on structural frequencies of space structure are investigated and a new method based on ARMA and PCA is proposed for structural condition assessment. The acceleration data from China National Aquatics Center is employed as an example. The results show that variation of frequencies and the DSF_{new} indexes with increasing of temperature and wind velocity is not notable. That is because the temperature difference

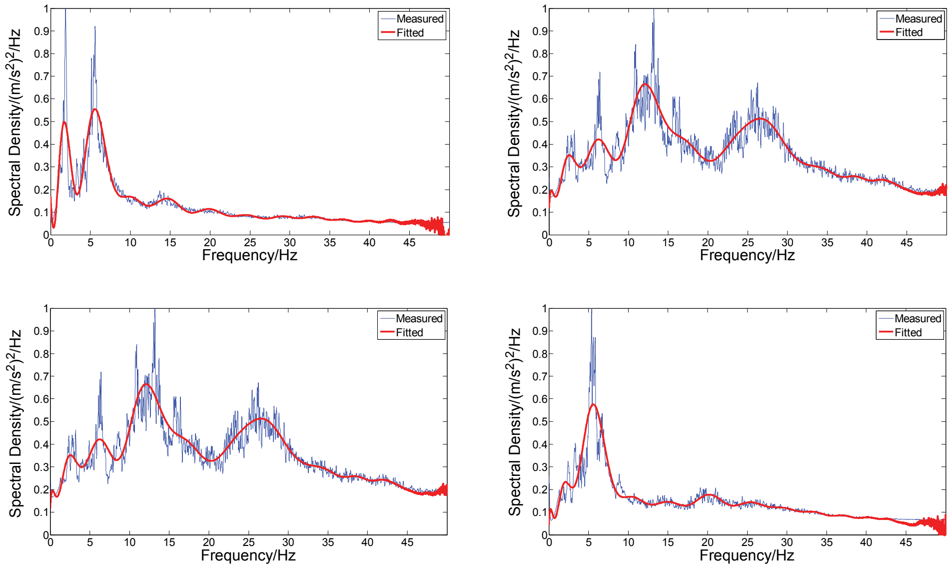

Figure 7: Relation of *DSF* and DSF_{new} indexes with temperature and wind velocity: (a) and (b) are the effects of temperature and wind velocity of one accelerometer, respectively; (c) and (d) are the effects of temperature and wind velocity, respectively

and velocity variation are little. Besides, this structure is so rigid that these little environment effects can not contribute to notable changes of structural modal parameters.

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