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Lower-order modal parameters identification for offshore jacket platform using reconstructed responses to a sea test

Fushun Liu [a,*], Huajun Li [a], Wei Li [b], Dongping Yang [c]

[a] Department of Ocean Engineering, Ocean University of China, Qingdao 266100, China
[b] Hydro China Huadong Engineering Corporation, Hangzhou 310014, China
[c] Technology Inspection Center, China Petroleum & Chemical Corporation, Dongying 257062, China

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ABSTRACT

Usually only a few of lower-order modes of interest extracted from stochastic response under the excitation of environmental forces, such as waves, winds or ice, could be obtained from sea tests of offshore jacket platforms; and what is more serious, this lower-order modal information is often buried in noises, which will be a challenge for identifying the modal parameters of interest. In this article, we propose an improved modal parameter identification method by reconstructing a new response consisting of only lower-order frequencies, and apply this method to a real offshore jacket platform located in the north of Liaodong Bay, China. One theoretical contribution is that the fainter modes could be isolated as one expected by defining reasonable pass band width and centering frequency. The elimination of noisy modes is realized by reconstructing the Eigensystem Realization Algorithm (ERA) block data matrix using the reconstructed responses. The other contribution is that the difficulty in judging whether an identified mode is due to noise or a genuine one has been resolved properly. A numerical offshore jacket platform is chosen to illustrate the procedure and demonstrate the performance of the proposed scheme. Numerical results indicate that: (1) lower-order frequencies can be isolated successfully using FFT filtering, and unexpected peaks in auto spectral density can be removed effectively using our smoothing procedure; (2) modal parameters of interest such as frequencies and damping ratios both can be identified properly by reconstructing Hankel matrix with a small dimension of ERA. Using sea test data measured from accelerometers mounted at the joints of the test platform, we find that our approach outperforms traditional ERA because no noisy modes are introduced. Though traditional ERA could identify two of the first three modal frequencies and damping ratios using the same segment of measured sea data, the dimension of Hankel matrix reaches 1000 times 1000, with a large amount of noisy modes. The achievement may contribute to two research areas: (1) signal processing when fainter frequencies are expected to be isolated, and (2) modal parameters identification when amount of noisy modes exist using traditional methods, such as ERA. Specifically, accuracy and efficiency of modal parameters identification (interested) of offshore jacket platforms can be improved.

1. Introduction

To measure the response data of jacket-type offshore structures, limited number of sensors is usually installed on the deck above water level because of the relatively easy access and maintenance of these sensors. However, the measured responses from these sensors are often buried in noises because of the exposure to external loads such as waves, wind, earthquakes, operational loads, and all kinds of measurement errors. It is therefore necessary to develop an appropriate technique for extracting accurate and meaningful modal information from response data collected from the limited number of sensors, because these parameters such as modal frequencies and mode shapes are essential to model updating and damage detection of offshore structures [1,2], especially when the measured modes are seriously spatial incomplete [3–5].

Estimating modal frequencies and damping ratios for conventional offshore structures has long been an interesting research topic [6–9], and many algorithms have been developed to estimate modal parameters based on the measured data such as the Frequency Response Function (FRF) or the equivalent Impulse Response Function (IRF). The problem is that the measured FRF and IRF may not be clean enough for estimating the modal parameters with proper accuracy because of measurement noises. Traditional way of identifying genuine physical modes is by setting the computational model order higher than the true system order, but then the so-called noise modes would be absorbed [10]. Among many researchers who advocated the usage of an over-determined system for improving the accuracy of parameter identification in noisy situations, Braun and Ram [11] described the strategy to determine the necessary extent of over determination and the procedure for distinguishing true system modes; in particular, an efficient perturbation method based on the singular value decomposition was presented.

Different from the classical ways – increasing the dimension of block matrix of ERA intentionally for absorbing noise in the modal parameter estimation process, our approach is to estimate modal parameters using reconstructed response consisting only of lower-order frequencies of interest. The easiest way to obtain each

* Corresponding author. Tel.: +86 53266781672; fax: +86 53266781550.
E-mail address: percyliu@ouc.edu.cn (F. Liu).

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component of reconstructed response is the application of a low-pass filter. But low-pass filters can be used only for noise cancellation with known a priori bandwidth. Another important element in the modern theory of statistical signal extraction was provided by the papers of Kalman [12] and Kalman and Bucy [13], which dealt with the filtering and forecasting, in discrete and continuous time. But the problem is how to adjust Kalman filter if there is no information about the accuracy of measurement instrument and there is no possibility to determine precise model of the system and the measurement [14]. Sanliturk and Cakar [15] presented a method based on Singular Value Decomposition (SVD) for the elimination of noise from measured FRFs so as to improve the quality of the measured data. Hu et al. [16] proposed a different approach from the traditional methods for estimating modal parameters from this noisy IRF. But it will be very difficult to identify fainter modal parameters compared with some noisy ones.

In this article, the Eigensystem Realization Algorithm (ERA) [17] will be used for modal parameter identification of a system; especially, the construction of block data matrix aiming at improving computational efficiency and eliminating noisy modes, from reconstructed response consisting of lower-order frequencies of interest, will be discussed. Synthesized measurements of a numerical offshore platform will be used to demonstrate the performance, and illustrate the procedure as well. Furthermore, sea test data measured from accelerometers mounted at joints of a four-leg jacket-type offshore platform located in the north of Liaodong Bay will be used to demonstrate the approach.

2. Preliminary: free response of a system

The finite element representation of an offshore jacket-type platform leads to a system of N second order differential equations, or an N-degree-of-freedom (N-DOF) system. The free vibration of an N-DOF system is expressed as:

$$\mathbf{M}\ddot{\mathbf{v}} + \mathbf{C}\dot{\mathbf{v}} + \mathbf{K}\mathbf{v} = 0 \tag{1}$$

where **M**, **C** and **K** are mass, damping and stiffness matrices, and $\mathbf{v}$, $\dot{\mathbf{v}}$ and $\ddot{\mathbf{v}}$ are response displacement, velocity and acceleration vectors, respectively. Based on the mode-superposition principle, we have

$$\mathbf{v}(t) = \sum_{p=1}^{N} \Phi_p Y_p(t) \tag{2}$$

where $\mathbf{\Phi}_p$ is the pth mode of the system, and $Y_p(t)$ the modal displacement associated with the pth mode. From Eq. (2), the jth element of $\mathbf{v}(t)$ can be expressed as:

$$\mathbf{v}_j(t) = \sum_{p=1}^{N} \mathbf{\Phi}_{jp} Y_p(t) \tag{3}$$

where $\mathbf{\Phi}_{jp}$ is the jth element of $\mathbf{\Phi}_p$.

3. Response reconstruction consisting of lower-order frequencies of interest

Assume a measured response (acceleration or displacement) is expressed by

$$y(t) = \bar{y}(t) + y_{ns}(t) = \sum_{s=1}^{sn} \bar{y}_{f_s}(t) + y_{ns}(t) \tag{4}$$

where $\bar{y}(t)$ represents the genuine response and $y_{ns}(t)$ represents the noise. $\bar{y}_{f_s}(t)$ denotes component at frequency f_s of $\bar{y}(t)$, and sn is the number of genuine response's components.

Take Fourier transform, one has

$$Y(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} y(t) e^{-i\omega t} dt \tag{5}$$

where

$$y(t) = \int_{-\infty}^{\infty} Y(\omega) e^{i\omega t} d\omega \tag{6}$$

Define $Y_{f_1}(\omega), Y_{f_2}(\omega), \ldots,$ as individual components in the frequency domain of $Y(\omega)$, then Eq. (5) can be rewritten as

$$Y(\omega) = \sum_{s=1}^{sn} Y_{f_s}(\omega) \tag{7}$$

As all we know, classical Fourier analysis cannot be applied to a sample function when $y(t)$ is not periodic. This difficulty can be overcome by analysing its autocorrelation function $R_y(\tau)$. Here $R_y(\tau)$ is defined as the average value of the product $y(t)y(t+\tau)$, where τ denotes the time separation.

The spectral density $S_y(\omega)$ of $y(t)$ is the Fourier transform of $R_y(\tau)$ and a function of angular frequency ω,

$$S_y(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} R_y(\tau) e^{-i\omega\tau} d\tau \tag{8}$$

Denoting $\Upsilon(\omega)$ as the FRF of the digital filter and multiplying by $Y(\omega)$, then the filtered but not smoothed response can be found in the frequency domain as

$$Y_f(\omega) = \Upsilon(\omega) Y(\omega) \tag{9}$$

and the filtered but not smoothed response $\dddot{y}_{f_s}(t)$ can be expressed

$$\dddot{y}_{f_s}(t) = \int_{-\infty}^{\infty} Y(\omega) |\Upsilon(\omega)| e^{i(\omega t + \theta(\omega))} d\omega \tag{10}$$

where $\Upsilon(\omega)$ is the absolute value and $\theta(\omega)$ is the phase shift. $\theta(\omega)$ could be obtained by

$$\theta(\omega) = \arctan\left(\frac{Im(Y(\omega))}{Re(Y(\omega))}\right) \tag{11}$$

where $Re(Y(\omega))$ and $Im(Y(\omega))$ represents real and imaginary part of $Y(\omega)$, respectively. Theoretically, the Hankel matrix **H** corresponding to the noisy but band filtered response $\dddot{y}_{f_s}(t)$ in Eq. (10) can be partitioned into two parts

$$\mathbf{H} = \bar{\mathbf{H}} + \mathbf{E} \tag{12}$$

where $\bar{\mathbf{H}}$ and **E** represent Hankel-structured matrices associated with the uncontaminated response and noise parts, respectively. The Hankel matrix **H** can be written as

$$\mathbf{H}_{m\times n} = \begin{bmatrix} \dddot{y}_{f,1} & \dddot{y}_{f,2} & \cdots & \dddot{y}_{f,n} \\ \dddot{y}_{f,2} & \dddot{y}_{f,3} & \cdots & \dddot{y}_{f,n+1} \\ \vdots & \vdots & \ddots & \vdots \\ \dddot{y}_{f,m} & \dddot{y}_{f,m+1} & \cdots & \dddot{y}_{f,m+n-1} \end{bmatrix} \tag{13}$$

where m and n is the number of rows and columns of the Hankel matrix **H.** Singular Value decomposition (SVD) technique is utilized in this paper primarily for the estimation of the rank of the matrix **H** in the process of noise elimination from measured FRFs, i.e.,

$$\mathbf{H}_{m\times n} = \mathbf{U}_{m\times m} \Sigma_{m\times n} \mathbf{V}_{n\times n}^{T} \tag{14}$$

where **U** and **V** are orthogonal matrices, Σ is the real diagonal matrix whose diagonal elements σ_i are called as singular values of **H**, and superscript 'T' denotes transpose of a matrix. Singular values are assumed to be arranged in descending order without any loss of generality, i.e.,

$$\sigma_1 > \sigma_2 > \cdots > \sigma_r \geq 0 \tag{15}$$

Eq. (15) means the number of non-zero singular values, r, determine the rank of matrix **H**.

For theoretical data, the singular values should go to zero when the rank of the matrix is exceeded. For measured data, however, due to random errors and band filtering implemented in the data, the