Research Article

DIC-Based Operational Modal Analysis of Bridges

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A new method has been proposed to identify the natural frequencies and mode shapes of a bridge model, in which the digital image correlation (DIC) technique is used to track the dynamic displacement. A key issue in vibration-based damage detection for a bridge is to determine its modal parameters. It is difficult to use traditional acceleration sensors to obtain the accurate mode shapes of bridges as the sensors are only deployed on a few measurement points of the bridges. In this article, the DIC technique is used to capture the movement of the entire experimental bridge model. A steel truss is used as a bridge model and stimulated by a hammer; its dynamic displacement is recorded by using a digital video camera. The correlation analysis is used to track the displacement of the points of interest, and their displacement time histories are inputted into a modal analysis system; the natural frequencies and mode shapes of the bridge model were obtained by both operational modal analysis (OMA) and traditional experimental modal analysis (EMA) methods. (1) The DIC results are compared with those obtained by a traditional acceleration sensor-based method; the natural frequencies obtained by the two measurement methods are very close. (2) The DIC results are sensitive to the amplitude of the measured displacement and the shooting distance; small displacement amplitudes and long shooting distance may result in the low quality of the measured time-history curves, and low-frequency noise signals might be observed in their power spectral density (PSD) curves, while they can be easily solved by the filtering method in this article. (3) In addition, the first frequencies obtained by EMA and OMA are very close, which validates the applicability of the DIC measurement under ambient excitation. The research has illustrated the feasibility of the DIC method for obtaining the modal parameters of the bridges.

1. Introduction

The vibration-based damage detection (VBDD) is a key method in structural health monitoring [1]. Early identification and quantification of structural damage play a significant role in ensuring the lifetime safety and avoiding catastrophic events of bridges. The basic idea of VBDD methods is to use the functional relationship between structural physical properties and dynamic response to identify structural damage [2, 3]. Hence, the change in vibration parameters can be assumed as indicators of damage. The indicators for structural damage, including the modal strain energy, flexibility matrix, and mode curvature [4–6], are constructed from the natural frequencies and mode shapes of a structure [3]. Therefore, the primary task in the vibration-based structural damage detection is to identify

the natural frequencies and mode shapes of the structure [7]. The traditional measurement methods for modal parameters, such as using acceleration sensors and strain gauges, can only obtain the values of mode shapes at a few measurement points due to the deployment limitations [8]. This disadvantage hinders the application of VBDD methods in practical engineering, as the accurate calculation of the modal strain energy or other damage indicators requires complete information of measured mode shapes. Thus, it is important to develop full-field and noncontact measurement techniques, such as DIC, to obtain vibration data to detect structural damage.

DIC is a full-field, nondestructive, and noncontact vision measurement technique based on digital image processing and numerical computation; it has been commonly used to track the surface displacements of deforming structures [9].

The DIC method tracks the changes of a small region (called subset) during deformation by comparing the similarity between the reference subset and the target subset (i.e., calculating the correlation of their gray-scale value distributions) [9]. After 3 decades of development, the DIC method has been applied in many disciplines and has made remarkable achievements. It has been widely used in civil engineering for displacement and strain measurement [10, 11]. The DIC method is also used in crack identification of concrete bridges and reinforced concrete beams [12, 13] and also used to measure soil movement in geotechnical engineering (more often called PIV, particle image velocimetry) [14, 15]. In structural vibration, the DIC method has been used to measure structural dynamic responses and extract modal parameters [16–19] and health monitoring of bridges [20, 21]. To measure three-dimensional (3D) movement of objects, the 3D DIC has been developed according to the stereo vision principle, and two series of images are needed for capturing the 3D movement of points of interest [22, 23]. As the natural frequencies of bridges are relatively low and the vibration amplitude is large, e.g., for long-span bridges, the lowest natural frequency is between 0.1 and 1 Hz and the peak vibration amplitude could be up to 30–100 cm [24]. It is expected that the time history of the dynamic displacement can be captured with a digital camera and processed with the DIC method. The time-history curves obtained by the DIC method can be used to extract the modal parameters of the structures monitored [25].

The OMA is a modal identification method based on response signals only, which means the modal analysis of bridges can be carried out with OMA under operational conditions. Compared with the traditional Experimental Modal Analysis (EMA), which requires both excitation and response signals, the OMA provides a feasible and efficient way for modal analyses of large structures such as bridges [26, 27] and ships [28]. Since the identification results based on the OMA method reflect the dynamic characteristics of the system under actual working states, it is also commonly applied to modal tests of automobiles [29]. As the OMA method does not interfere with the normal use of bridges, it becomes more popular for the modal identification in bridge engineering. A variety of OMA methods have been developed during the past twenty years, and they are usually divided into the following two categories: frequency-domain methods and time-domain methods; among them, frequency-domain methods are more commonly used. In the frequency-domain methods, the natural frequencies are identified by peak-picking (PP) of the power spectral density (PSD) curves [30], and the corresponding mode shapes are determined by response transmissibility (RT) or the PSD transmissibility (PSDT) [31]. Compared with the PP method, the improved frequency domain decomposition (FDD) method has better identification effect for dense modes. The time-domain methods include Ibrahim time domain (ITD), eigensystem realization algorithm (ERA), stochastic subspace identification (SSI), and ARMA-Type methods. More details are seen in [32].

In this article, a method is proposed to extract the modal parameters of bridges with the OMA theory from DIC data,

which does not hinder the normal operation of the measured structures. The dynamic displacements of a bridge model are collected with a digital camera and analyzed by the DIC method, and then the displacement time histories at the measurement points are imported into a modal analysis system to get the frequencies and mode shapes via the OMA method. Finally, results obtained by the DIC method are compared with those obtained by the acceleration sensors.

2. Method

The frequency response function (FRF) is defined, and the identifying theory of modal parameters is first provided; then, the RT [33] and PSDT are defined, and the modal identification method based on OMA is presented. Finally, the DIC principle is utilized to process the dynamic displacement at the points of interest.

2.1. Operational Modal Analyses

2.1.1. Modal Identification Based on FRF. The vibration equation of a multi-degree-of-freedom (MDOF) system is

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = \mathbf{f}(t), \quad (1)$$

where $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ are the mass matrix, damping matrix, and stiffness matrix; the displacement vector is described as $\mathbf{x} = [x_1 \ x_2 \ \cdots \ x_N]^T$; N is the number of degrees of freedom; $\dot{\mathbf{x}}$ and $\ddot{\mathbf{x}}$ are the velocity vector and acceleration vector separately; and $\mathbf{f}(t) = [f_1(t) \ f_2(t) \ \cdots \ f_N(t)]^T$ is the external force vector applied to the system.

The Laplace transformation of the above equation is

$$(s^2\mathbf{M} + s\mathbf{C} + \mathbf{K}) \cdot \mathbf{x}(s) = \mathbf{f}(s), \quad (2)$$

where s is a complex variable and $\mathbf{x}(s)$ and $\mathbf{f}(s)$ are the Laplace transformations of $\mathbf{x}(t)$ and $\mathbf{f}(t)$, respectively. The transfer function matrix, $\mathbf{G}(s)$, is defined as

$$\mathbf{x}(s) = (s^2\mathbf{M} + s\mathbf{C} + \mathbf{K})^{-1} \mathbf{f}(s) = \mathbf{G}(s) \cdot \mathbf{f}(s). \quad (3)$$

Assume that the system has the r -th natural frequency, ω_r , and the corresponding mode shape $\varphi_r = [\varphi_{r1} \ \varphi_{r2} \ \cdots \ \varphi_{rN}]^T$, where $r = 1, 2, \dots, N$. All mode shape vectors form a mode shape matrix, Φ , which satisfies the orthogonality property and is also normalized with respect to the mass matrix:

$$\begin{aligned} \Phi^T \mathbf{K} \Phi &= \Lambda, \\ \Phi^T \mathbf{M} \Phi &= \mathbf{I}, \end{aligned} \quad (4)$$

where $\mathbf{I}$ is a unit matrix and Λ is a diagonal matrix consisting of the eigenvalues, $\omega_1^2, \omega_2^2, \dots, \omega_N^2$. To decouple the MDOF equations, the Rayleigh damping $\mathbf{C} = \alpha\mathbf{M} + \beta\mathbf{K}$ is commonly presumed, which leads to

$$\begin{aligned} \Phi^T \mathbf{G}^{-1} \Phi &= \Phi^T (s^2\mathbf{M} + s\mathbf{C} + \mathbf{K}) \Phi \\ &= s^2\mathbf{I} + s(\alpha\mathbf{I} + \beta\Lambda) + \Lambda. \end{aligned} \quad (5)$$

Then, get

$$\Phi^{-1} \mathbf{G}(\Phi^T)^{-1} = \begin{bmatrix} \ddots & & \\ & \frac{1}{s^2 + s(\alpha + \beta\omega_r^2) + \omega_r^2} & \\ & & \ddots \end{bmatrix}. \quad (6)$$

The transfer function matrix can be described as

$$\mathbf{G}(s) = \Phi \begin{bmatrix} \ddots & & \\ & \frac{1}{s^2 + s(\alpha + \beta\omega_r^2) + \omega_r^2} & \\ & & \ddots \end{bmatrix} \Phi^T. \quad (7)$$

Assume that $s = j\omega$ with $j^2 = -1$. Then, the FRF matrix $\mathbf{H}(j\omega)$ of the system is obtained:

$$\begin{aligned} \mathbf{H}(j\omega) &= \Phi \begin{bmatrix} \ddots & & \\ & \frac{1}{-\omega^2 + j\omega(\alpha + \beta\omega_r^2) + \omega_r^2} & \\ & & \ddots \end{bmatrix} \Phi^T \\ &= \Phi \begin{bmatrix} \ddots & & \\ & \frac{1}{-\omega^2 + 2j\omega \cdot \omega_r \xi_r + \omega_r^2} & \\ & & \ddots \end{bmatrix} \Phi^T \\ &= \begin{bmatrix} H_{11} & \cdots & H_{1N} \\ & H_{22} & \\ \vdots & \ddots & \vdots \\ & \cdots & H_{op} & \ddots \\ H_{N1} & \cdots & H_{NN} \end{bmatrix}, \end{aligned} \quad (8)$$

where

$$\begin{aligned} \xi_r &= \frac{\alpha}{2\omega_r} + \frac{\beta\omega_r}{2}, \\ H_{op}(j\omega) &= \sum_{r=1}^N \frac{\varphi_{ro}\varphi_{rp}}{\omega_r^2 + 2j\xi_r\omega\omega_r - \omega^2}. \end{aligned} \quad (9)$$

As ξ_r is very small, when ω approaches ω_r , the FRF approaches its maximum point; around this maximum point, the r -th mode plays a leading role. Thus, by ignoring the other modes, the FRF around the maximum point is approximately equal to

$$H_{op}(\omega_r) = \frac{\varphi_{ro}\varphi_{rp}}{2j\xi_r\omega_r^2}. \quad (10)$$

Thus, the natural frequencies can be determined by the frequencies corresponding to the peak points of the FRF amplitude. If the excitation force is fixed at the p -th degree of freedom and the FRF is measured at each degree of freedom (i.e., $o = 1, 2, \dots, N$), the r -th mode shape vector can be obtained from the measured FRF by the following formula:

$$\begin{bmatrix} \varphi_{r1} \\ \varphi_{r2} \\ \vdots \\ \varphi_{rN} \end{bmatrix} = \frac{2j\xi_r\omega_r^2}{\varphi_{rp}} \begin{bmatrix} H_{1p}(\omega_r) \\ H_{2p}(\omega_r) \\ \vdots \\ H_{NP}(\omega_r) \end{bmatrix}. \quad (11)$$

As $((2j\xi_r\omega_r^2)/(\varphi_{rp}))$ can be regarded as a constant number, the mode shape of the structure can be identified from a single row or column of $\mathbf{H}(j\omega)$ as follows:

$$\Phi_r = \lim_{\omega \rightarrow \omega_r} [H_{1p}(\omega), H_{2p}(\omega), \dots, H_{NP}(\omega)]^T. \quad (12)$$

2.1.2. Definition of RT and PSDT. The RT is commonly used to identify the modal parameters of a structure in the OMA theory. The RT, $T_{io}(\omega)$, between the degrees of freedom, i and o , can be defined as [33]

$$T_{io}(\omega) = \frac{X_i(\omega)}{X_o(\omega)}, \quad (13)$$

where $X_i(\omega)$ and $X_o(\omega)$ are the Fourier transforms of $x_i(t)$ and $x_o(t)$ which represent the response time histories at the degrees of freedom i and o , respectively.

The PSDT, $\hat{T}_{io}$, is more commonly used for modal identification [31]:

$$\hat{T}_{io}(\omega) = \frac{S_{i,o}(\omega)}{S_{o,o}(\omega)} = \frac{X_i(\omega)X_o^*(\omega)}{X_o(\omega)X_o^*(\omega)} = T_{io}(\omega), \quad (14)$$

where $X_o^*(\omega)$ is the conjugate of $X_o(\omega)$ and $S_{o,o}(\omega)$ is the PSD of $x_o(t)$; meanwhile, $S_{i,o}(\omega)$ is the cross-power spectrum (CPS) for $x_i(t)$ and $x_o(t)$.

2.1.3. Modal Identification Based on PSDT. From equations (13) and (14), the relationship between the PSDT and FRF can be expressed as

$$\hat{T}_{io}(\omega) = \frac{X_i(\omega)}{X_o(\omega)} = \frac{H_{ip}(\omega) \cdot F_p(\omega)}{H_{op}(\omega) \cdot F_p(\omega)} = \frac{H_{ip}(\omega)}{H_{op}(\omega)}, \quad (15)$$

which demonstrates that the PSDT is numerically equal to the ratio of the FRF values measured at the degrees of freedom, i and o , under the same excitation at the p -th degree of freedom; in the equation, $F_p(\omega)$ is the Fourier transform of $f_p(t)$.

When the excitation frequency, ω , approaches the natural frequency, ω_r , of the system, $\hat{T}_{io}(\omega)$ represents the ratio of the r -th mode shape at the degrees of freedom i and o :

$$\lim_{\omega \rightarrow \omega_r} \hat{T}_{io}(\omega) = \frac{H_{ip}(\omega_r)}{H_{op}(\omega_r)} = \frac{\varphi_{ri}}{\varphi_{ro}}. \quad (16)$$

For the same o -th degree of freedom as a reference with the i -th degree of freedom being changed (i.e., $i = 1, 2, \dots, N$), the r -th mode shape can be obtained as

$$\begin{bmatrix} \varphi_{r1} \\ \varphi_{r2} \\ \vdots \\ \varphi_{rN} \end{bmatrix} = \varphi_{ro} \begin{bmatrix} \hat{T}_{1o}(\omega_r) \\ \hat{T}_{2o}(\omega_r) \\ \vdots \\ \hat{T}_{No}(\omega_r) \end{bmatrix}. \quad (17)$$

Therefore, the r -th mode shape can be constructed from the PSDT:

$$\Psi_r = \lim_{\omega \rightarrow \omega_r} \{\hat{T}_{1o}(\omega), \hat{T}_{2o}(\omega), \dots, \hat{T}_{No}(\omega)\}. \quad (18)$$

In summary, the natural frequency can be determined by picking the peaks in the PSD plots of the response of a degree of freedom [34]. The PSDT is calculated to determine the mode shape (Figure 1).

2.2. DIC for Tracking the Movement of a Point. For any two images with the area of A , their gray-scale distributions are expressed as $I(x, y)$ and $J(x, y)$, and the correlation of the two images is defined as [35]

$$C = \frac{\iint_A I(x, y)J(x, y)dxdy}{\sqrt{\iint_A I^2(x, y)dxdy} \cdot \sqrt{\iint_A J^2(x, y)dxdy}}. \quad (19)$$

Here, x and y are the pixel coordinates of the images. According to the Cauchy-Schwarz inequality, it is obvious that the correlation coefficient is not larger than 1. The correlation represents the similarity between the two images; the larger the correlation coefficient is, the more similar the two images are.

To track the movement of a point (P) in the reference image during the deformation (Figure 2(a)), consider the correlation between the reference subset surrounding the point of interest, $P(x, y)$, and the deformed subset surrounding the point $Q(x', y')$ in the deformed image (Figure 2(b)), where $x' = x + \Delta x$ and $y' = y + \Delta y$. The reference subset and the deformed subset have the same area (S) but different locations by the displacement of $(\Delta x, \Delta y)$; hence, their correlation is the function of $(\Delta x, \Delta y)$:

$$C(\Delta x, \Delta y) = \frac{\iint_S I(x, y)J(x + \Delta x, y + \Delta y)dxdy}{\sqrt{\iint_S I^2(x, y)dxdy} \cdot \sqrt{\iint_S J^2(x + \Delta x, y + \Delta y)dxdy}}. \quad (20)$$

By gradually varying the displacement $(\Delta x, \Delta y)$, a matrix of the correlation coefficient is obtained. The real displacement of the point of interest (P) maximizes the

function, $C(\Delta x, \Delta y)$; that is, at this movement $(\Delta x, \Delta y)$, the deformed subset is most similar to the reference subset.

The movement of the bridge model is recorded by a digital video camera. The recorded images are processed by the DIC method to obtain the displacement time histories of the points of interest, which are inputted into a dynamic analysis system along with the excitation force time history, and the FRFs, PSDs, and CPSs are obtained and then the modal parameters are extracted.

2.3. Filtering. In general, the original signal mainly contains three types of components: the real vibration signal $R_i(t)$, drift term $D_i(t)$, and random noise $N_i(t)$ [36]:

$$x(t) = R_i(t) + D_i(t) + N_i(t). \quad (21)$$

For the drift term representing a zero drift in the signal, it shows a peak near 0 Hz on the PSD curve, which might mix up with the low-frequency signals. Generally, this term is mainly reflected in low-frequency component, and it can be eliminated. The acceleration signal can be extracted from the displacement time history after the second-order differential calculation (equation (23)), which has little effect on the peak position on the PSD curve.

$$y_k = x_{k+2} + x_k - 2x_{k+1}, \quad (22)$$

where x_k is the original signal and y_k is the new one after the differential filtering [37]. The signal processing with the differential filter can enhance the high-frequency part of the signal and make the real vibration signal more obvious.

As random noise causes obvious burrs on the PSD curves of the original signal for small signal-to-noise ratio, a smoother data sequence can be computed by moving average filtering [38] based on the statistical characteristics of random noise; the m similar sample queues are recorded continuously, and these arithmetic means are computed as a new data queue. This is a very simple and effective method to suppress the random noise and obtain a smoother curve.

$$y_k = \frac{1}{m} \sum_{i=0}^{m-1} x_{i+k}. \quad (23)$$

In this article, the signal averaging techniques are used to process the signal with $m = 5$.

3. Tests

3.1. Experimental Setups and Instruments. The truss model (Figure 3(a)) has 28 spans and a total length of 9.8 m. Each span has dimensions of 0.35 m $\times$ 0.35 m $\times$ 0.35 m. The truss is composed of 353 rods connected by 112 bolted balls. The length of the yellow rod and the red rod is 0.35 m and 0.50 m, separately; the bolted balls have a diameter of 50 mm (Figure 3(b)). The truss is made of Q235 steel and simply supported at both ends.

The experimental instruments (Figure 4) for modal analysis include two acquisition systems: JM3840 (Jing-Ming Technology Inc., Yangzhou, China) for collecting signals by acceleration sensors and a digital video camera (D5300, Nikon Corporation, Japan) for recording truss images processed by the DIC.

FIGURE 1: OMA flowchart.

FIGURE 2: Tracking point movement by the DIC method. (a) Reference image. (b) Deformed image. (c) Displacement of the subset.

FIGURE 3: Experimental setup for modal analyses and the bridge model. (a) Bridge model. (b) Model components. (c) Node locations.

- (1) For the sensor-based response measurement, the impulse force is produced and measured by a hammer instrumented with a force sensor and the acceleration time histories are collected by the acceleration sensors with nominal sensitivity of 100 mV/g. Both the time

histories of the external force and responses are inputted into the kit software associated with the acquisition instrument (JM3840), the FRFs, PSDs, and CPSs are obtained, and then the modal parameters are extracted by using the kit software.

FIGURE 4: Experimental instruments. (a) Data acquisition system. (b) Excitation hammer/sensors. (c) Computer. (d) Digital video camera.

- (2) For the DIC-based response measurement, the dynamic movement of the truss is recorded by the digital video camera and the images are processed by the DIC method presented in Section 2.2; the displacement time histories of the points of interest are obtained and inputted into the kit software, and the modal parameters are gained by analyzing the PSDs and CPSs of response signals of different points.

3.2. Test Aims and Plans. The test aims and plans are as follows:

- (a) Validate the DIC results by comparisons with those obtained by the sensor-based method. The bridge model is excited by the instrumented hammer and the excitation force is collected; the acceleration is collected by acceleration sensors at nodes 1, 5, 9, 13, 17, 21, 25, and 29. The movements of bridge model are recorded and saved as the digital images for DIC analysis; the movements of the points of interest are tracked and imported into the dynamic signal analysis system.
- (b) Investigate the influence on the DIC results of the shooting distance of the digital video camera. The bridge model is excited by hammer for 5 times and the movement of bridge model is recorded with the shooting distance of 0.3 m, 0.9 m, 2 m, and 4 m. The movement of node 15 is analyzed.
- (c) Investigate the influence on the DIC results of the amplitude of the measured displacement. The bridge model is excited, and the movement of the bridge model is recorded with the shooting distance of 2 m. The displacement of node 15 (near the truss middle) and node 28 (close to the right end) is recorded and analyzed.
- (d) Compare the identified frequencies between the FRF method (with force input) and the PSD method (without force input). The natural frequency is

extracted with both methods, and comparisons are made to validate the applicability of the DIC-based OMA in vibration measurement under ambient excitation.

The bridge model is excited along the vertical direction. As the vibration along other directions is not evident, only the acceleration and displacement along the vertical direction are measured. Hence, 2-dimensional DIC is used in this study.

4. Results

4.1. Comparisons of Measurements by DIC and Acceleration Sensors. The time histories of the displacement (obtained by the DIC) and acceleration (obtained by a sensor) at node 15 and their PSD curves are shown in Figure 5.

Both time histories display typical damped free vibration. The first natural frequencies are 4.42 Hz and 4.49 Hz indicated, respectively, by the PSD curves of the DIC and sensor measurements, and the relative error is 1%. The PSD curve of the sensor measurement shows the second frequency of 16.97 Hz, while no other peaks could be found on the PSD curve of the DIC measurement.

4.2. Influence on DIC Results of the Shooting Distance of the Digital Video Camera. The displacement time histories (measured by the DIC) of node 15 at different shooting distances are shown in Figures 6(a) and 6(b); and their PSD curves are shown in Figures 6(c) and 6(d).

A peak value at 4.42 Hz can be seen on both PSD curves, while another peak at 0.12 Hz and some burrs can also be observed on the PSD curve for the shooting distance of 4 m. These were caused by the zero drift and random noise of the DIC processes. A longer shooting distance leads to a lower resolution of the images, which magnifies the zero drift and random noise during the DIC processes.

The zero drift and random noise could be removed by the filtering (including the moving average filtering and

FIGURE 5: Comparisons of measurements by the DIC and sensor. (a) Time history by DIC. (b) Time history by the sensor. (c) PSD by DIC. (d) PSD by the sensor.

FIGURE 6: Continued.

FIGURE 6: DIC measurements of node 15 obtained from 2 m and 4 m away. (a) Time history at 4 m. (b) Time history at 2 m. (c) PSD at 4 m. (d) PSD at 2 m.

differential filtering) presented in Section 2.3. The results after filtering are shown in Figure 7. The filtered time history looks a bit smoother and no drifting is observed.

4.3. Influence on DIC Results of the Amplitude of the Measured Displacement. Figure 8 shows the displacement time histories and PSD curves of node 15 (near the middle) and node 28 (near the end).

The time history at the ending point (node 28) has obvious zero drift as smaller amplitude leads to a lower resolution of the images, which magnifies the zero drift and random noise. While both PSD curves illustrated that the first frequency is 4.42 Hz, a peak value at 0.17 Hz and more burrs can also be found on the PSD curve of the ending point.

The time-history curve at node 28 is further processed with the moving average filtering and differential filtering, and the time history and PSD curves after filtering are illustrated in Figure 9. The free-vibration features are more obvious, and no zero drift is observed on the PSD curve. The peak values near 0.17 Hz disappear, but another peak value exists at 15.84 Hz on the PSD curve; it is likely the second natural frequency by the DIC method, as differential filtering enhances the high-frequency vibration signal. Compared with the second natural frequency obtained by the sensor method (16.97 Hz), the relative error between them is 7%.

4.4. Comparisons of EMA and OMA by DIC Data. The excitation force at node 51 and the displacement time history (measured by the DIC) at node 15 are shown in Figures 10(a) and 10(b); the PSD curve and the FRF amplitude curve are shown in Figures 10(c) and 10(d).

An evident peak frequency can be observed on both curves, but there are more burrs on the FRF curve than on the PSD curve, obtained from the original time history. The

first frequencies obtained by these two methods are very close (4.42 Hz and 4.25 Hz), and the relative error is within 4%. The first mode based on OMA is shown in Figure 11, which is basically consistent with the first mode shape of a simply supported beam.

5. Discussions and Conclusions

5.1. Discussions

5.1.1. The Cause of Peak Frequency near 0 Hz. A low frequency is noticed in experiments for the cases with a longer shooting distance and smaller displacement amplitude, which may mix up with the experimental results. Though it has been filtered completely, the rationality of this operation is worth further discussion. To explore this problem, the displacement-time history of a static point (shown in Figure 3) is collected and analyzed. Figure 12(a) shows that even for a static point, there may also be some fluctuation in the DIC measurements, resulting in the peak frequency near 0 Hz (Figure 12(b)). This phenomenon may be caused by environmental disturbance of the camera, image distortion, or the error of the DIC algorithm. Nevertheless, it can be removed by the filtering method presented in Section 2.3.

5.1.2. The Influence of Differential Filtering on the Result of Frequency Identification. Comparison of Figures 8(d) and 9(b), which are redrawn in Figure 13, shows the second peak frequency at 15.8 Hz on the PSD curve. The frequency value is close to the second frequency measured by the sensor-based method. It resembles the second frequency measured by the DIC method. As discussed above, the DIC method is not sensitive to small amplitude vibration; it is difficult to accurately capture high-frequency vibration with low energy. As the differential filtering is able to enhance high-

FIGURE 7: Filtered DIC data at node 15. (a) Time history at 4 m. (b) PSD at 4 m.

FIGURE 8: Analysis data by DIC obtained from the middle point and the ending point.

FIGURE 9: (a) Time-history curve and (b) PSD curves at the ending point after filtering.

FIGURE 10: Comparisons of EMA and OMA. (a) The force signal. (b) Time history by DIC. (c) Frequency identified by PSD. (d) Frequency identified by FRF.

FIGURE 11: Modal shape obtained by OMA.

FIGURE 12: Analysis data of a stationary point by DIC. (a) Time history of a stationary point. (b) PSD at a stationary point.

FIGURE 13: The frequency identification result of the differential filter. (a) PSD at the ending point. (b) PSD at the ending point after filtering.

frequency vibration, the second peak frequency becomes more obvious on PSD after differential filtering.

6. Conclusions

In this article, the acceleration sensors and the DIC method are used to collect the vibration signals of a bridge model. The natural frequencies and mode shapes are extracted from FRF and PSD curves. The following conclusions can be drawn from these investigations:

- (1) Under the same experimental conditions, obviously, the DIC method has less influence on the structure and a better full-field measurement performance than the acceleration sensor method, and the DIC method also has the same good performance in the extraction of the first natural frequency as the acceleration sensor method.
- (2) It has been illustrated that an ordinary camera is able to obtain the fundamental frequency of the structure with the DIC method. A longer shooting distance or smaller displacement amplitude might cause evident noise in the PSD and FRF curves, but it can be easily removed by the filtering method in this article (moving average filtering and quadratic differential filtering).

In summary, the proposed method is a noncontact detection method which is easy to use and has good detection results; it is applicable to large-scale vibration measurement in bridge engineering. With the further development of image processing algorithm and camera technology, the DIC-based vibration measurement may play an important role in dynamic analysis and damage identification of bridges. Combined with drone technology, the proposed method can be further applied to the bridges that span rivers and valleys [25].

Data Availability

Some or all data, models, or codes generated or used during the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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