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Computer Vision Technique for Blind Identification of Modal Frequency of Structures from Video Measurements †

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Abstract: Operational modal analysis (OMA) is required for the maintenance of large-scale civil structures. This paper developed a novel methodology of non-contact-based blind identification of modal frequency of a vibrating structure from its video measurement. There are two stages in the proposed methodology. The first stage is extracting the motion data of the vibrating structure from its video using a complex steerable pyramid. In the second stage, the principal component analysis combined with analytical mode decomposition is used for modal frequency separation from the motion data. Numerical validation of the methodology on a 10 DOF model is presented. The application of the proposed methodology on the London Millennium Bridge is also presented.

Keywords: vibration measurement; video camera; multi-scale decomposition; complex steerable pyramids; principal component analysis; analytical mode decomposition

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1. Introduction

In structural health monitoring (SHM), modal analysis of structures is considered an important aspect. The operational modal analysis (OMA) relies only on the response data collected from the sensor attached to the structure, independent of the force excitation [1]. Modal parameters depend on the accuracy of the data collected from the sensors attached to the structure. Sensors commonly used for the OMA are contact accelerometers, adding additional mass to the structure. These mass loading effects can be corrected, but they are not accurate [2]. Physically attached sensors have proved that spatial resolution of the measurement critically limits the effectiveness of standard mode shape-based damage detection and localization methods [3]. Non-contact methods of OMA overcame the drawbacks of the sensor-based measurement. Microwave interferometers are used to analyzes the interference reflected off the vibrating target surface for displacement response [4]. Laser Doppler vibrometer (LDV) measures the velocity of a point projected by a focused laser beam, using the doppler shift between the incident and scattered light returning to the measuring instrument [5–7]. LDV provides accurate results and can be used to find the modal parameters of structures that are inaccessible. However, microwave interferometers and LDV are expensive. Other methods through computer vision techniques, such as Digital Image Correlation and 3-Dimensional point tracking techniques, can estimate modal parameters from a video measurement. However, these techniques require a speckle pattern/markings placed on the structure [8,9].

An alternative non-contact measurement system is to practice the computer vision technique using a digital high-speed video camera which is low-cost, convenient and desired for high-resolution measurement. Generally, civil structures like bridges and other large structures have a low natural frequency, so cameras capable of recording video 30 frames per second (FPS) can be used. The video should neither have disturbances nor artifacts. The spatial domain consists of pixel information such as intensity levels, whereas the temporal part contains the framerate of image sequences in a video. Pixels of each frame contain the motion data of the objects in the video, which can be magnified using, a phase-based video motion magnification technique can magnify the local motions of objects and translate the noise present in the video [10]. It enables to refer to the subtle motions, which are hard to perceive through naked eyes. Each frame in the video is decomposed to multi-scale and multi orientations using complex steerable pyramids [13]. The multi-scale decomposition of the video frames enables measuring phase information of each frame, which can be manipulated to magnify the motion in the video. Phase-based video motion magnification works as a base for many methods like modal identification of simple structures [12], OMA of a light pole-viaduct system [13,14]. Recently, Yang et al. [15] proposed a BSS technique using PCA and a complexity pursuit algorithm.

In this paper, a computer vision-based vibration measurement of the structures using the PCA and analytical mode decomposition (AMD) methods for blindly identifying the modal frequencies. Firstly, the current methodology is validated on a 10 degree of freedom (DOF) system numerical model and the proposed methodology is applied to the practical field measurement videos of the London Millennium Bridge and natural frequencies are extracted. The obtained results are in good agreement with the reference sensor values.

2. Methodologies

The two main methodologies are implemented in this study to obtain the modal frequencies from a camera-based video measurement. Figure 1 demonstrates the flowchart of the proposed method for OMA using non-contact video measurements with comprehensive procedures essential in each step.

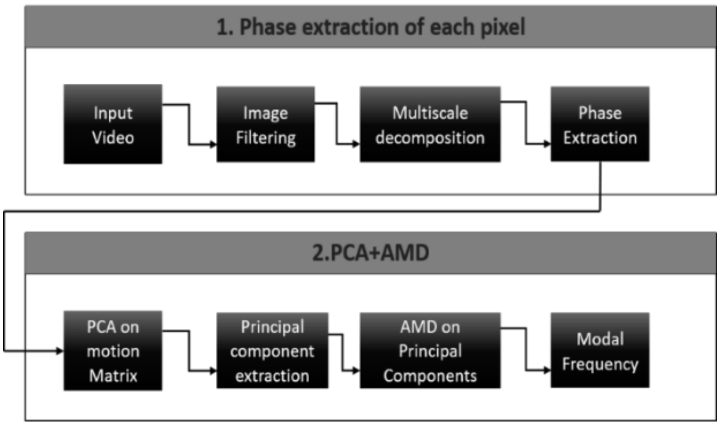


Figure 1. Flowchart of the proposed method for OMA using non-contact video measurements.

2.1. Phase Extraction Using Complex Steerable Pyramids

The time history response of a structure can be measured from a video, as the frames contain the temporally displaced intensity of a pixel represented by $I(x+d(x,t))$, where x is the pixel coordinate and $d(x,t)$ represent spatially local and temporally varying motion. A multi-scale and multiband decomposition technique are used to extract the phase $d(x,t)$ encoded in the $I(x+d(x,t))$, is known as the complex steerable pyramid. According to Simoncelli and Freeman [11], the steerable pyramid algorithm initially divides a given image into a high-frequency part and a low-frequency part. They are then applying the band-pass-oriented filters b_P sequentially to the low-frequency image followed by down sampling. It forms a pyramid, including high-frequency and low-frequency residuals and levels with certain scales and orientations.

The phase $d(x,t)$ of each pixel is extracted by constructing the complex steerable pyramids. Phase contains a temporal mean$2\pi\omega x$; after removing the temporal mean, we get

$d'(x,t) = 2\pi\omega d(x,t)$ which can be expressed by modal superposition as a linear combination of modal responses.

$$d'(x,t) = \phi(x)q(t) = \sum_{i=1}^{n} \tau_i(x)q_i(t) \quad (1)$$

where $\phi(x)$ is a mode shape matrix with $\tau_i(x)$ as the i^{th} mode shape and *q(t)* is the modal response vector with $q_i(t)$ as i^{th} modal coordinate. Equation (1) is overcomplete with high spatial dimension (due to large number of pixels) and low modal dimension over the complete model, so the modal identification problem cannot be solved directly [15]. The dimension of the phase matrix is reduced by PCA and then AMD is used for separating the signals.

2.2. Principal Component Analysis

The obtained motion matrix is large in terms of the matrix's data is represented by its principal components. So, dimension reduction is accomplished by PCA. The singular value decomposition of the motion matrix (d') is,

$$d' = U\Sigma V^T = \sum_{i=1}^{n} \sigma_i u_i v_i \quad (2)$$

where Σ is a diagonal matrix containing *t* (*t* is the number of elements) diagonal elements σ_i as the *ith* singular value ($\sigma_1 \geq \ldots \geq \sigma_i \geq \cdots \geq \sigma_T$) and *U, V* are the matrices of the left and right singular vectors obtained by eigen value decomposition (EVD) of the covariance matrices of d'.(refer Equations (3) and (4))

$$d'd'^T = U\Sigma^2 U^T \quad (3)$$

The rank of d' is *r* if the number of non-zero singular values is *r*. σ_i is directly related to the *ith* principal direction vector of d'. If its mass matrix is proportional to its uniform mass distribution identity matrix for a lightly damped structure, then; principal directions will converge to mode shape direction [15]. The structure's active modes, under broadband excitation, are projected on to the r principal components. Empirically, it is observed that principal active components are less compared with the matrix's spatial dimension. So PCA significantly reduce the dimension of the motion matrix by projecting it linearly onto a small number of principal components.

$$\zeta = U_r^T d' \quad (4)$$

where ζ is a matrix containing principal components of d'. PCA also reserves the matrix ζ, d' is obtained by using,

$$d' = U_r \zeta \quad (5)$$

These principal components contain the information of the dominant frequency modes. The average of these principal components is taken as input for analytical mode decomposition.

2.3. Analytical Mode Decomposition

AMD uses a signal decomposition theorem based on a Hilbert transform. This method separates general time series into time functions whose Fourier spectra are nonvanishing over two mutually exclusive frequency ranges. A bisecting frequency separates it with multiple steps. An original time series with multiple closely spaced frequency components are decomposed into many signals, each dominated by a single frequency component [16]. Let *x(t)* denote a real-time series of *n* significant frequency components $(\omega_1, \omega_2, \ldots, \omega_n)$all positive in $L^2(-\infty, +\infty)$ of the real-time variable *t*. It is decomposed into *n* signals $x_i^{(d)}(t)$ (*i* = *1,2…., n*) whose Fourier spectra are equal to $\hat{X}(\omega)$ over n mutually exclusive frequency ranges ($|\omega| < \omega_{b1}$), ($\omega_{b1} <|\omega| < \omega_{b2}$), …, (($\omega_{b(n-2)} <|\omega| < \omega_{b(n-1)}$)), and (($\omega_{b(n-1)} < |\omega|$).

$$x(t) = \sum_{i=1}^{n} x_i^{(d)}(t) \tag{6}$$

Here, $\hat{X}(\omega)$ is the Fourier transform of x(t), ω represents a frequency variable, and $\omega_b \in (\omega_i, \omega_{i+1})$ (*i* = *1, 2, …,n-1*) are *n-1* bisecting frequencies. Each signal has a narrow bandwidth in the frequency domain and is be determined by,

$$x_i^{(d)}(t) = g(t) - g(t), \dots, x_n^{(d)}(t) = x(t) - g_{n-1}(t) \tag{7}$$

$$g_i(t) = \sin(\omega_{bi}t)\, H[x(t)\cos(\omega_{bi}t)] - \cos(\omega_{bi}t)\, H[x(t)\sin(\omega_{bi}t)] \tag{8}$$

where i = 1, 2, …., n-1, $g_o(t) = 0$ and H represents Hilbert transform.

3. Validation of Proposed Method on Numerical Model

The proposed method, which uses PCA and AMD to identify the modal frequencies, is applied to a 10-DOF model for validating the technique. The twelve DOF model is excited with an initial velocity at the twelfth DOF, and the output is collected at all the 10-channels in terms of displacement *y(t)*. The 10-DOF system is represented as masses connected with springs, as shown in Figure 2.

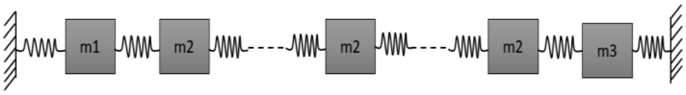


Figure 3. Schematic representation of a 10-DOF dynamic numerical model.

Among twelve masses, the first (m1) and last (m3) masses are 2 kg, and all masses are 1 kg, as represented in Figure 2. The stiffness of all the springs used is 20 KN. The damping matrix is taken proportional to the mass matrix. The first four theoretical mode shapes are used to construct the new response $\bar{y}(t)$. The new displacement response $\bar{y}(t)$ is the input for the PCA. The PCA gives the number of components through the eigenvalues of the covariance matrix of displacement data, and it identified that there are only four active components. The results are shown in Figure 4 and Table 1.

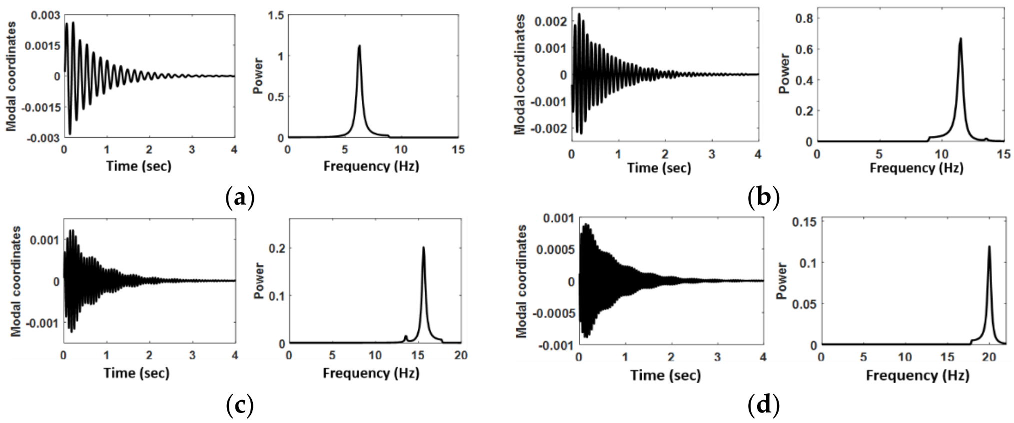


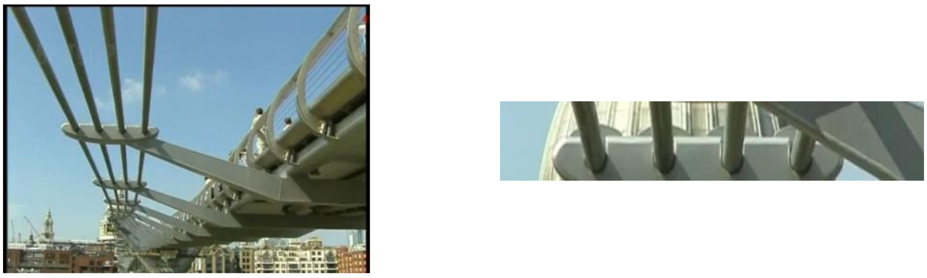
Figure 4. Four different modes of the numerical model identified by the proposed method (**a**) Mode 1 frequency-5.3 Hz (**b**) Mode 2 frequency-10.1 Hz (**c**) Mode 3 frequency-13.9 Hz (**d**) Mode 4 frequency-17.7 Hz.

Table 1. Comparison of the estimated frequency value with theoretical values.

Mode	Frequency (Hz)		Error %
	Theoretical	**Estimated**	
1	6.25	6.30	0.8
2	11.45	11.50	0.09
3	15.62	15.60	0.13
4	20.03	20.00	0.15

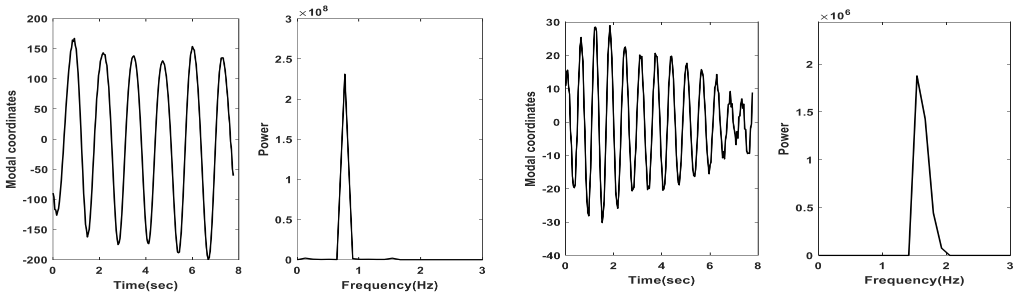
4. Implementation of Proposed Method on Full-Scale Video Measurement of London Millennium Bridge

The proposed method is implemented on the full-scale field measurement to obtain the vibration response of the London Millennium footbridge, also known as the wobbly bridge [17]. It is a steel suspension bridge, as shown in Figure 5, and it shows the cropped frame of a video [18] to the region of interest used for the blind identification of modal frequency. The cropped video has a resolution of 480 p, 480 pixels in width, and 60 pixels in height. The number of frames used is 600, with a frame rate of 30 FPS. The bridge swaying occurs as the pedestrians' walking frequency, and the bridge's natural frequency range matches well. Only three frequencies are detected as the pedestrians walking pattern might have only three dominant frequencies. The three modes are identified from the EVD plot from the implementation of the PCA-AMD algorithm. The modal coordinates and their frequencies values are presented in Figure 6. The modal coordinates are not accurate and are non-decaying due to the pedestrian's movement. Table 2 shows the comparison between the estimated results with the sensor data, and they are in good agreement with more than 99% accuracy. The results have revealed that the proposed method can be extended to other spontaneous robust non-contact OMA structures.

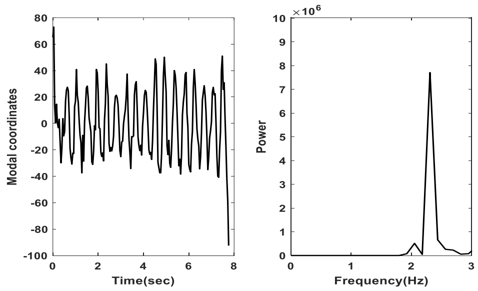


(**a**) (**b**)

Figure 5. Frame used for analysis (**a**) Original Frame (**b**) Cropped frame used for analysis.



(**a**) (**b**)



(**c**)

Figure 13. Modal coordinates and respective frequency values for Millennium Bridge. (**a**) Mode 1 frequency of 0.769 Hz (**b**) Mode 2 frequency of 1.53 Hz (**c**) Mode 3 frequency of 2.31 Hz.

Table 2. Comparison of the estimated frequency value with sensor values.

Mode	Frequency (Hz)		Error %
	From Ref. [17]	Estimated	
1	0.77	0.769	0.13
2	1.54	1.53	0.65
3	2.32	2.31	0.43

5. Conclusions

This study develops a hybrid output-only OMA algorithm that uses PCA and AMD to blindly extract the modal frequencies and modal coordinates from line-of-sight video measurement of the structures. The 10-DOF dynamic numerical model validation resulted in more than 99% accuracy in detecting the modal frequencies. The proposed methodology is implemented on practical full-field videos recorded on the London Millennium Bridge, resulting in the modal frequencies with an accuracy of 99%. The modal coordinates are non-decaying in nature for the bridges because of the external loading factors.

Institutional Review Board Statement:

Informed Consent Statement:

Data Availability Statement:

References

1. Doebling, S.W.; Farrar, C.R.; Prime, M.B. A summary review of vibration-based damage identification methods. *Shock. Vib. Dig.* **1998**, *30*, 91–105.
2. Ashory, M.R. *Correction of Mass-Loading Effects of Transducers and Suspension Effects in Modal Testing*; SPIE Proceedings Series; 1998; pp. 815–828.
3. Fan, W.; Qiao, P. Vibration-based damage identification methods: a review and comparative study. *Struct. Health Monit.* **2011**, *10*, 83–111.
4. Farrar, C.R.; Darling, T.W.; Migliori, A.; Baker, W.E. Microwave interferometers for non-contact vibration measurements on large structures. *Mech. Syst. Signal Process.* **1999**, *13*, 241–253.
5. Stanbridge, A.B.; Ewins, D.J. Modal testing using a scanning laser Doppler vibrometer. *Mech. Syst. Signal Process.* **1999**, *13*, 255–270.
6. Saravanan, T.J.; Gopalakrishnan, N.; Hari, B.K. Damage identification in structural elements through curvature mode shapes and non-linear energy operator. *Compos. Mater. Eng.* **2019**, *1*, 33–48.
7. Saravanan, T.J.; Gopalakrishnan, N.; Rao, N.P. Damage detection in structural element through propagating waves using radially weighted and factored RMS. *Measurement* **2015**, *73*, 520–538.
8. Saravanan, T.J.; Nishio, M.; Suzuki, T. Computer Vision based In-plane Strain Field Monitoring for Identification of Local Damages in Structural Members. *Struct. Health Monit.* **2019**, *2019*, doi:10.12783/shm2019/32465.
9. Saravanan, T.J.; Nishio, M. Estimation of In-Plane Strain Field Using Computer Vision to Capture Local Damages in Bridge Structures. In *Advances in Condition Monitoring and Structural Health Monitoring*; Springer, Singapore, 2021; pp. 461–469.
10. Wadhwa, N.; Rubinstein, M.; Durand, F.; Freeman, W.T. Phase-based video motion processing. *ACM Trans. Graph. (TOG)* **2013**, *32*, 1–10.

11. Simoncelli, E.P.; Freeman, W.T. The steerable pyramid: A flexible architecture for multi-scale derivative computation. In International Conference on Image Processing, Washington, DC, USA, 23–26 October 1995; Volume 3, pp. 444–447.
12. Chen, J.G.; Wadhwa, N.; Cha, Y.J.; Durand, F.; Freeman, W.T.; Buyukozturk, O. Modal identification of simple structures with high-speed video using motion magnification. *J. Sound Vib.* **2015**, *345*, 58–71.
13. Saravanan, T.J.; Siringoringo, D.M.; Fujino, Y.; Wangchuk, S. Operational modal analysis of light pole-viaduct system from video measurements using phase-based motion magnification. In *Bridge Maintenance, Safety, Management, Life-Cycle Sustainability and Innovations*; CRC Press: Boca Raton, FL, USA, 2021; pp. 1629–1637.
14. Thiyagarajan, J.S.; Siringoringo, D.M.; Wangchuk, S.; Fujino, Y. Implementation of video motion magnification technique for non-contact operational modal analysis of light poles. *Smart Struct. Syst.* **2021**, *27*, 227.
15. Yang, Y.; Dorn, C.; Mancini, T.; Talken, Z.; Kenyon, G.; Farrar, C.; Mascareñas, D. Blind identification of full-field vibration modes from video measurements with phase-based video motion magnification. *Mech. Syst. Signal Process.* **2017**, *85*, 567–590.
16. Chen, G.; Wang, Z. A signal decomposition theorem with Hilbert transform and its application to narrowband time series with closely spaced frequency components. *Mech. Syst. Signal Process.* **2012**, *28*, 258–279.
17. Pavic, A.; Willford, M.; Reynolds, P.; Wright, J. Key results of modal testing of the Millennium Bridge, London. In Proceedings of the Footbridge, Paris, France, 20–22 November 2002.
18. The Millennium Bridge in London. 2019. Available online: https://www.youtube.com/watch?v=y2FaOJxWqLE&t=2s (accessed on 4 May 2021).