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Structural Identification by Means of a Digital Image Correlation Technology †

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Abstract: Structural health monitoring has gained increasing research interest, particularly due to the societal concerns tied to the aging of current civil structures and infrastructures. By managing datasets collected through a network of sensors deployed over monitored structures, (big) data analytics can be executed. Traditional inertial sensors, such as accelerometers or strain gauges, necessitate intricate cable arrangements and lead to high maintenance costs. Lately, there has been a growing interest in non-contact, vision-based approaches to tackle the aforementioned issues. Among these methods, Digital Image Correlation (DIC) can furnish a representation of tracked displacements at various points of a structure, particularly if physically attached targets are employed. In this study, a video capturing the vibrations of a structure is analyzed, with a focus on specific points, such as structural nodes where damage could be initiated or whose responses could be impacted by the mentioned damage. Displacement time histories are acquired, and a blind source identification technique is adopted to delve into the data and assess the structural health. The proposed methodology demonstrates its capacity to accurately extract the vibration frequencies and mode shapes of the structure, even when they change in time due to damage.

Keywords: structural health monitoring; damage detection; vision-based methods; digital image correlation

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1. Introduction

Monitoring the structural condition of civil structures is of critical importance. Modal analysis methods play an important role in identifying the dynamic characteristics of structures, e.g., by exploiting the vibrational response of the structures themselves. Blind source separation methods are a category of output-only measurement techniques [1] which require installing sensors at different locations over the structure to obtain the information to process. Throughout the structural lifespan, these sensors might deteriorate, leading to a decline in the measurement accuracy. Among the latest non-contact measurement approaches, the utilization of video cameras for measurement collection has increased. Initially, the vibration of the structure is captured using a high-speed camera. By converting the video into a number of frames and through the application of various image processing algorithms, distinctive features are then extracted. Subsequently, modal analysis is executed to obtain the aforementioned dynamic characteristics. The merits of this approach can be listed as: high-resolution measurements at all points, cost-effectiveness, and straightforward installation.

Digital image correlation (DIC) method, renowned for its efficacy in image processing, has progressively gained applications to quantify surface deformations. This is attributed to its capability to accurately quantify displacements and assess strains [2–

10]. In early studies, stress analysis was carried out in a two-dimensional frame but neglecting out-of-plane displacements may lead to errors in the calculation of the in-plane components. For this reason, studies have been conducted in a full three-dimensional context [10–13].

Due to the potential damage of the target, methods have been proposed to extract image features invariant to intensity variations and rotation [14,15]. These features are tracked across different frames to obtain the displacements. These methods are called feature-based. Youn et al. [16] initially obtained frames of a vibrating 6-story model, and subsequently of selected regions from the images. In the field of experimental solid mechanics, it is of interest to obtain mechanical properties, and assess the deformation experienced by a specimen when subjected to an external load [17–20]. In this context, DIC can capture full-field data to enable the application of constitutive equations, facilitating the simultaneous tuning of multiple material properties [21–23].

Civil structures exposed to significant lateral forces such as strong winds and earthquakes are susceptible to damage due to stiffness reduction. By comparing the structural response with a baseline model, damage identification can be obtained [24–27]. In this paper, a video of a vibrating beam has been adopted to investigate the sensitivity of displacements at various sampling points to a structural damage. We have employed the DIC technique, to allow a precise assessment of the displacement of the said locations. Additionally, we have adopted the blind source separation method to extract relevant frequency information. The results demonstrate the feasibility of DIC data obtained at sparse locations, as input for an identification process. Furthermore, changes in the frequency of vibrations of the structure, can be correlated to the damage pattern.

2. Digital Image Correlation Overview

To generate a deformation map using the DIC method, the initial step consists in the identification of the positions of sampling points, distributed across the reference undeformed image. Then, an area surrounding each sampling point is employed; this is achieved by means of a square correlation window consisting of p × p pixels. By moving the second window to find the maximum correlation between reference and deformed subsets, the surface displacement at that point can be determined. Generally, identifying the correspondence of a single pixel between two images is challenging. The grayscale value of a single pixel can match with numerous other pixels in the second image, resulting in the lack of unique correspondence. To assure the accurate application of DIC, a measurement surface with random texture or artificial targets is adopted.

By handling the frames at the initial and current time, a comparative analysis can be conducted between the deformed image(s) and the reference one. The regions of interest, which contains the sampling points, must be defined in the reference image. To achieve efficient, accurate, and robust subset matching, an objective function that combines a similarity or dissimilarity metric between the reference subset and its deformed counterpart has to be formulated. There are different correlation criteria in the literature, which can be categorized into four groups [28]: cross-correlation, sum of absolute difference, sum of squared difference, and parametric sum of squared difference ones. In practice, the intensity changes between images may be induced by various reasons. Thus, a robust correlation criterion should be used to assess the intensity variations in the deformed images, otherwise significant displacement errors may occur due to the mismatch of the intensity change model. Based on this discussion, a zero-mean normalized cross-correlation (ZNCC) criterion is used in this paper, according to:

$$ZNCC(u,v) = \frac{\sum_{x,y}\left(f_n(x,y)-\bar{f}_n\right)\left(f_d(x-u,y-v)-\bar{f}_d\right)}{\sqrt{\sum_{x,y}\left(f_n(x,y)-\bar{f}_n\right)^2\sum_{x,y}\left(f_d(x-u,y-v)-\bar{f}_d\right)^2}} \quad (1)$$

where: $f_n(x,y)$ and $f_d(x-u,y-v)$ are the intensity values; f is the pixel in the locations (x,y) and $(x-u,y-v)$ of the p × p square window in the first undeformed frame and the current deformed frame; $\bar{f}_n$ and $\bar{f}_d$ are the average of the intensity value of the p × p square window in the first undeformed frame and in current deformed frame. The location with maximum ZNCC provides the displacement.

3. Identification Procedure

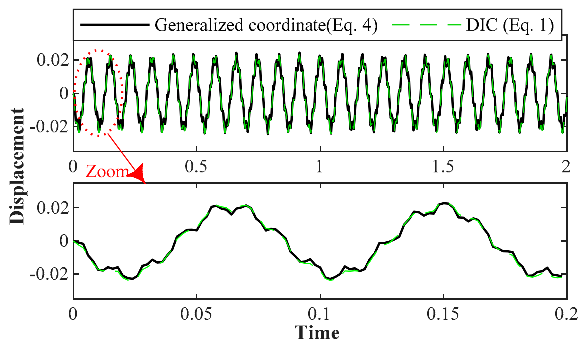
To show how the vibration frequencies and mode shapes of the structure can be determined, a video of a vibrating beam is here adopted. At a later stage, the elastic properties of the structure have been decreased to simulate damage and the DIC applied to obtain the displacement field. By comparing the identified frequencies corresponding to the different structural stiffness, we show that the displacement obtained with the DIC can be used for damage detection.

The number of excited modes used in the model is assumed smaller than the number of sampling points. We thus need a dimension reduction technique to reduce the dimension of the displacement matrix. By applying a singular value decomposition (SVD) to the displacement matrix $\boldsymbol{D}$, *and* and by considering the corresponding non-zero singular values, the dimension of the problem is reduced The complexity Pursuit (CP) can be next adopted to obtain the modal frequencies and excited modes.

4. Numerical Investigation: Cantilever Beam

A model of a vibrating cantilever beam with a fixed end is here considered, as excited by an initial velocity. The following beam properties are considered: mass per unit length 0.051 Kg/m, length 0.18 m, Young's modulus 1.91 × 10^{11} Pa and moment of inertia 0.124 × 10^{-12} m^4. A video of a vibrating beam is generated using three modes. The number of points at which the vibrations have been measured and used to create a video, is set to 37. By using the generated video, displacement has been measured at 12 sampling points using the DIC. By adopting the identification procedure based on SVD-CP, the vibration frequencies and mode shapes are obtained.

Moving to the results of the analysis, in Figure 1a a comparison is presented between the actual displacement used to generate the video, and the displacement obtained by applying the DIC to the video. The displacements result to be in perfect agreement in their time evolutions. Figure 1b shows the results in terms of the displacement measurements at three locations of top, middle, and bottom of the beam.



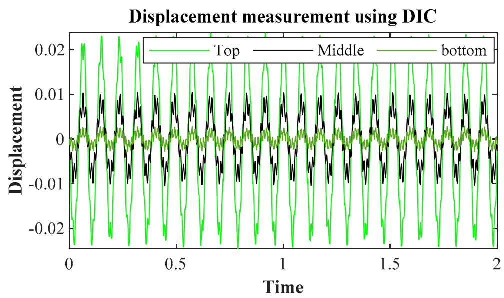
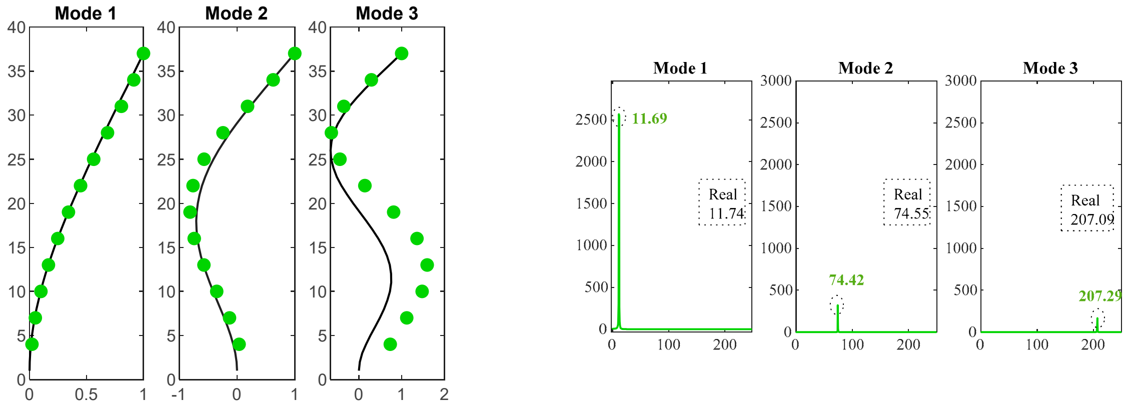


Figure 1. Displacement time histories for the vibrating beam: (**a**) comparison between the DIC results and the actual time evolution; (**b**) measurements at three locations.

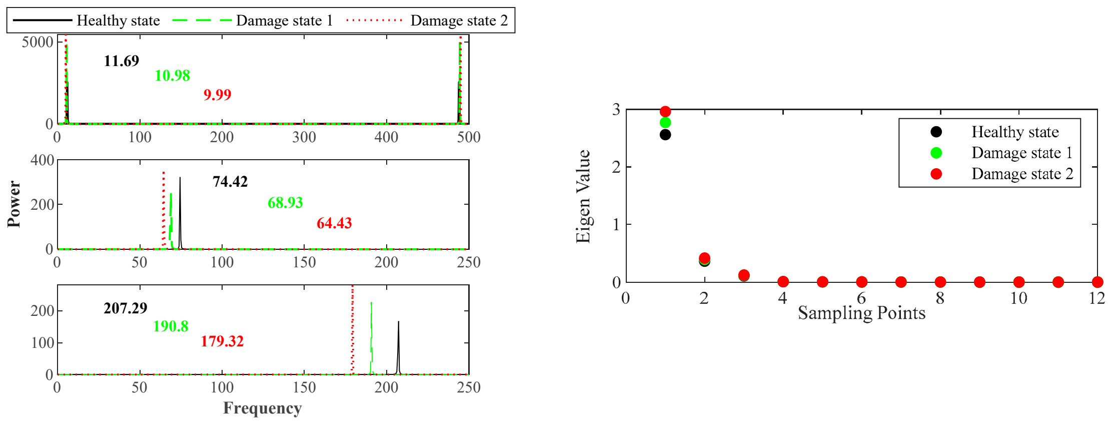
As the purpose of this research is to identify mode shapes and vibration frequencies, Figure 2a shows the mode shapes in the actual state and as obtained via the SVD-CP, using the DIC at the said 12 locations along the longitudian axis of the beam. It can be observed that the first and second modes have acceptable agreement, but this is not the case for the third mode. The reason for this could be the small amplitude of the vibrations in this case study. As can be seen in Figure 2b, the power spectrum associated with the vibration frequency of the third mode is in fact very small.



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

Figure 2. Comparison between the actual and estimated beam features, using DIC-SVD-CP-based method for the healthy state: (**a**) mode shapes; (**b**) frequencies of vibration.

To model the damage in the structure, the structural stiffness has been reduced in two different scenarios by 15% and 25%, respectively. In Figure 3a, the identified frequencies are gathered for the undamaged and damaged scenarios, as obtained with the procedure based on SVD-CP on DIC measurements. The singular values are reported in Figure 3b for these three scenarios. It can be seen that only the first three values are non-zero; through this outcome, it is possible to understand how to reduce the displacement matrix dimensionality to the number of the excited modes.



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

Figure 3. Comparison of the results relevant to the three considered states: (**a**) identified frequencies; (**b**) eigenvalues.

To establish a criterion to quantify the structural damage, results are collected in Table 1. Here, the vibration frequencies corresponding to the first, second, and third modes are separately reported, as divided by those corresponding to the healthy state and subtracted from unity. Values in the last column show that, for the first damaged state, the criterion applied to the three modes respectively leads to an error amounting to 21%, 6.4%, and 1.2%. Hence, the results corresponding to the second and third modes prove to be more accurate. In the second scenario, the measured damage levels using the vibration frequencies leads to an error amounting to 5.2%, 0%, and 0.7%, respectively.

Table 1. Results provided by the damage criterion.

Ratio of Frequency	Mode 1	Mode 2	Mode 3	1-√α
1—(DamageState1/Healthy)	0.061	0.073	0.079	0.078
1—(DamageState2/Healthy)	0.141	0.134	0.135	0.134

5. Conclusions

This research has been devoted to data collection from a video of the vibrations of a structure, achieved through the Digital Image Correlation technique. The acquired displacements have been employed to discern the beam modal parameters and the mode shapes using a blind source separation approach. The findings showcase the effectiveness of this method in accurately measuring displacements. Furthermore, damage has been ad-hoc introduced in the model of the structure by altering the material elasticity; with two different scenarios, an exploration of frequency and amplitude variations in the resulting vibrations has become possible.

The estimation of displacement and frequency through video-based measurements underscores the potential of the DIC framework in the realm of structural health monitoring. In future studies, models capable of inducing damage at specific locations will be incorporated. Additionally, as the DIC method needs a judicious selection of the analysis window, a further in-depth investigation in this regard looks necessary.

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