A Hybrid Method for Damage Detection Using Acceleration Response of Bridges

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Abstract. Damage detection algorithms employing the traditional acceleration measurements and the associated modal features may underperform due to the limited number of sensors used in the monitoring and the smoothing effect of spline functions used to increase the spatial resolution. This study presents a hybrid structural health monitoring method for vibration-based damage detection of bridge-type structures to overcome such problems. The proposed method is based on sensor fusion from conventional and computer vision-based acceleration measurements. Three commonly used damage measures are presented and employed: mode shape curvature method, modal strain energy method, and modal flexibility method. The accuracy of these algorithms with the conventional structural health monitoring approach is demonstrated in a numerical case study, where damage scenarios are simulated on a simply-supported bridge. The efficiency and accuracy of the proposed hybrid health monitoring methodology are demonstrated in a case study where the conventional acceleration measurements fail to detect and locate the damage. The outcomes of this study indicate a strong potential of the proposed method for damage detection.

Keywords: Damage detection · Vibration-based · Structural health monitoring · Computer vision · Curvature · Strain energy · Modal flexibility

1 Introduction

Vibration-based damage detection in civil structures is a subject that has been investigated intensively in the past decades. Numerous approaches that utilize modal properties of structures or other properties originating from the modal features have been developed [1, 2]. Bridge structures formed the focus of several studies employing vibration signatures [3–6]. The most common modal features used for damage detection and location include modal curvature, modal strain energy, and modal flexibility. However, these methods are known to suffer significantly from the measurement uncertainties and sensitivity of damage indicators to the location and severity of the damage. One of the well-documented reasons for these shortcomings is the limited number of sensors generally used in the monitoring and the smoothing effect of spline functions to increase the spatial resolution [7].

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Computer vision provides an attractive alternative to solve this problem; however, the size of the bridge relative to the sensor resolution presents challenges regarding the resolution of the measured vibrations. In order to alleviate this problem, this study proposes a hybrid vibration-based structural health monitoring and damage detection methodology. The proposed methodology combines the use of conventional accelerometers with computer vision, *i.e.*, fuses the data from different sensors. The method leverages the increased spatial resolution of computer vision at the sensitive regions providing virtually continuous information, whereas the accelerations in other regions are measured using traditional sensors. Therefore, the method benefits from the strength of both approaches. As an example, in Fig. 1, the computer-vision system provides continuous information for the highlighted portion, which is the camera's area of sight and the left-side of an isolated bridge deck, whereas the sparsely distributed conventional acceleration sensors measure the vertical accelerations at discrete locations.

A standard video camera is used to measure a specific portion of the bridge. The modal displacements in this part provide continuous modal information, and they are combined with the modal displacements obtained from the conventional sparse measurement system. As such, the amount of modal information about the bridge is increased and a better fit for a spline function can be achieved. Also, the previously mentioned smoothing effect of the spline fit can be eliminated in the region measured using computer-vision.

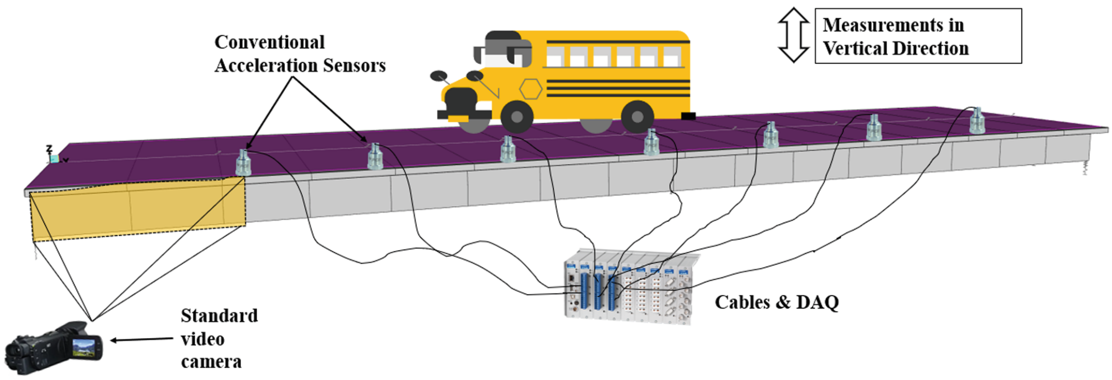


Fig. 1. Proposed methodology illustrated on an isolated one-span bridge deck

The methodology is tested using a numerical example. For this purpose, a numerical study of a simply-supported bridge was conducted under different damage scenarios. The benchmark case simulated a conventional vibration measurements system with low spatial resolution, whereas the hybrid monitoring system had an increased resolution near the supports, where the conventional approaches are known to struggle most in detecting and locating damage [8]. The analyses were carried out by changing the locations and extent of the damage. The efficacy of three damage sensitive parameters was investigated and results from the proposed hybrid methodology are compared to those obtained from a conventional monitoring set-up where the sensors are sparsely located.

2 Damage Sensitive Features

The common practice in damage detection studies is to measure the structure's vibration signals at discrete locations and employ the mode shapes and the damage sensitive features presented herein. Dynamic identification using the measured signals provides the modal information, such as the mode shapes, at the measurement locations. Then, the spatial resolution of the mode shapes is increased by fitting continuous functions, like splines or polynomials, to measured values and interpolating the in-between to cover the entire space. While this procedure is necessary to detect the damage location with higher accuracy, especially when the damage is in a narrow region, the fitted function to the discrete mode shape data often smoothens the data concealing the subtle changes in the mode shape due to damage.

In this study, three vibration-based damage indicators widely used in structural health monitoring literature are used. The reader is referred to other studies [1, 7–9] for a detailed review of these methods.

2.1 Mode Shape Curvature

For structures that can be represented with the Bernoulli-Euler formulation under flexural actions, the curvature at a specific location x can be calculated using the moment at that location $M(x)$ and the flexural stiffness $EI(x)$ of the cross-section. In Eq. (1), the curvature $v''(x)$ is

$$v''(x) \approx M(x)/EI \tag{1}$$

where E is the elasticity modulus of the material, and I is the moment of inertia of the cross-section. Equation (1) shows that the curvature is inversely proportional to the flexural stiffness of the beam. Therefore, under the same loading conditions, the damage at a given cross-section, *i.e.*, reduction in the flexural stiffness, will increase the curvature at the damage location. In this regard, one can track the changes in curvature to detect and locate damage [10]. Moreover, the extent of the damage at a given cross-section can also be estimated using the changes in the curvature [8].

The modal curvature of a beam at the discrete measurement points equally spaced at a distance h can be approximated using the central difference theorem. Accordingly, the second derivative of the modal displacement at the degree of freedom (DOF) k of a mode shape ϕ can be computed using Eq. (2).

$$v''(\emptyset_k) \approx \frac{\emptyset_{k-1} - 2\emptyset_k + \emptyset_{k+1}}{h^2} \tag{2}$$

where $v''(\emptyset_k)$ is the curvature value of the specific mode shape at the k^{th} DOF.

The difference between the modal curvature of the potentially damaged state and the undamaged state is evaluated to detect and locate the damage. The absolute summation of the modal curvature differences for all significant modes is calculated and used as a damage indicator.

2.2 Modal Strain Energy

The modal strain energy is defined as the strain energy stored in a structure as it deforms purely in the pattern of its particular mode shape [8]. As a structure experiences damage, its flexural stiffness is almost always going to decrease, leading to a decrease in the amount of energy absorbed compared to the undamaged structure. Thus, damage at a particular location of the beam results in a deviation from the original strain energy distribution, and this change can be used to detect and locate damage.

For the i^{th} mode shape of a Bernoulli-Euler beam with length L and flexural stiffness EI, the amount of strain energy corresponding to the deformation in that mode shape pattern is represented in Eq. (3). When the beam is divided into N subregions, then the energy stored in each subregion j of the beam is given by Eq. (4).

$$U_i = \frac{1}{2}\int_0^L EI\left(\frac{\partial^2(\emptyset_i)}{\partial x^2}\right)^2 dx \tag{3}$$

$$U_{ij} = \frac{1}{2}\int_k^{k+1} (EI)_j\left(\frac{\partial^2(\emptyset_i)}{\partial x^2}\right)^2 dx \tag{4}$$

where k_{j} and $k_{\mathrm{j+1}}$ are the start and end coordinates of the subregion j.

Assuming that the flexural stiffness remains constant within the subregions; the fractional energy F_{ij} can be defined as the ratio of energy stored in the subregion j to the total energy stored in the beam when the i^{th} mode shape is considered.

$$F_{ij} = {}^{U_{ij}}\!/_{U_i} \tag{5}$$

The fractional energies are calculated for m number of measured modes using Eq. (5) and then used in Eq. (6) to determine the damage index βj. The βj is the ratio of the sum of the fractional energies in the damaged state to the undamaged state of the structure, and its higher values indicate the damage locations.

$$\beta_j = \frac{\sum_i^m F_{ij,dmg}}{\sum_i^m F_{ij,und}} \tag{6}$$

2.3 Modal Flexibility

Flexibility can be thought of as a deformation of a structure corresponding to associated unit load applied at a specific DOF, and the flexibility matrix [G] is defined as the inverse of the stiffness matrix [K]. The elements of the flexibility matrix G_{ij} are defined as the displacement at DOF i caused by a unit load applied at DOF j. The deformation pattern that a structure will attain when a unit load is applied at a specific DOF is given by the associated column of the flexibility matrix.

$$\{\mathbf{f}\} = [\mathbf{K}]\{\mathbf{u}\} \rightarrow \{\mathbf{u}\} = [\mathbf{K}]^{-1}\{\mathbf{f}\} = [\mathbf{G}]\{\mathbf{f}\} \tag{7}$$

The modal flexibility matrix $[\mathrm{G}]_{\mathrm{nxn}}$ is calculated using the modal vectors obtained from n measurement locations as in Eq. (8) [11].

$$[\mathbf{G}] \approx \frac{1}{\boldsymbol{\omega}^2}\{\boldsymbol{\varphi}_i\}\{\boldsymbol{\varphi}_i\}^{\boldsymbol{T}} \tag{8}$$

The contribution of each mode to the flexibility matrix is weighted by the inverse of the circular frequency of the mode. Hence, this scaling reduces the effect of the modes with higher frequency on the flexibility matrix. This assumption might become helpful in OMA applications as the higher frequency modes are more challenging to identify. On the other hand, this might provide counterproductive by masking the contribution of the higher modes to the damage-sensitive features.

The potential damage that causes the reduction in the stiffness of a structure will cause an increase in flexibility. As such, the change in the flexibility of the structure between its undamaged and damaged states, **[ΔG]**, can be computed from the difference of the respective matrices:

$$max_j = max[\Delta \mathbf{G}] = \max\left([\mathbf{G}]_{und} - [\mathbf{G}]_{dmg}\right) \tag{9}$$

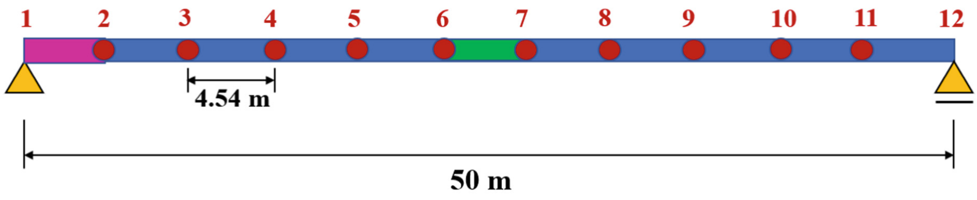
where the flexibility matrices are calculated from the measured mode shapes using Eq. (8). The absolute maximum values of each column indicate the maximum change in the flexibility for that specific DOF. Consequently, the column of the **[ΔG]** matrix corresponding to the largest $\max_j$ shows the degree of freedom where damage is located.

3 Numerical Applications

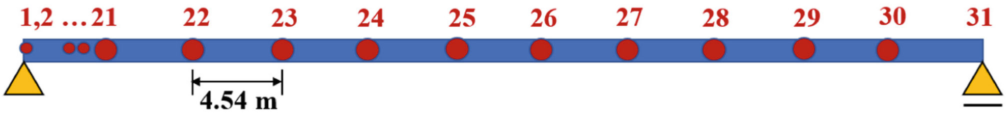
Presented damage sensitive features are applied on a simply-supported beam represented with a Bernoulli-Euler formulation. The beam's modulus of elasticity and the moment of inertia are 32.7 GPa and 5.47 m^4, respectively. Here, the beam could represent a simple structure such as a single-span bridge. It is assumed that the numerically obtained mode shapes via eigen-value analysis of the numerical model are identical to the mode shapes acquired from an experimental modal identification from accelerograms recorded by a set of accelerometers. In this regard, a 50-m-long span is divided into 11 equal length segments, *i.e.*, 4.54 m long pieces, simulating a traditional instrumentation setup where 12 sensors are deployed at the locations shown Fig. 2a.

On the other hand, the hybrid method proposed in this study enables continuous information at the sides of the bridge. To approximate this phenomenon numerically, the segment of the bridge between Points 1–2, i.e., the first segment, is divided into 20 pieces, such that modal displacements are measured at an interval of 0.23 m along this segment (Fig. 2b) simulating a case where the vibrations and the associated mode shapes of the first 4.54 m of the beam is extracted using computer-vision algorithms [12, 13]. Therefore, in the hybrid monitoring system setup, 31 sensor locations are taken into account and more detailed information is obtained close to the abutment, where the vibration-based damage detection methods traditionally struggle. On the other hand, conventional, sparsely located sensor setup is used towards the middle of the beam as the aforementioned damage sensitive parameters have a much higher success rate in detecting the damage located in this region. Please note that, only the first half of the beam is considered here due to the symmetry of the beam.

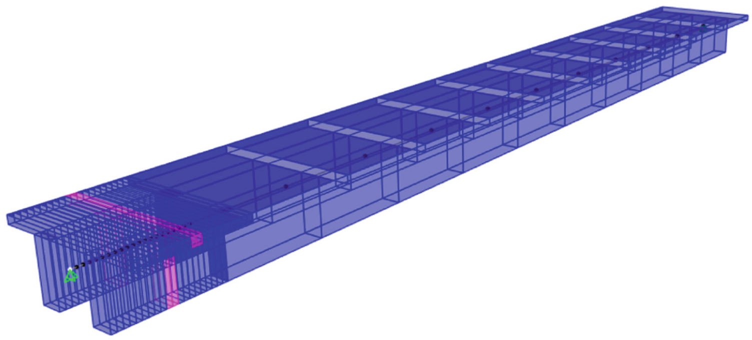
The aim of the numerical examples presented in this section is twofold. First, the capabilities of traditional damage sensitive parameters are demonstrated for two different damage scenarios, where slight damage is spread across a significant length of the beam i) in the middle between sensor locations 6 and 7 and ii) near the support between sensor



(a) Measurement points of a traditional monitoring system



(b) Measurement points of the hybrid monitoring system



(c) A typical bridge cross-section, the refined first segment and damage

Fig. 2. (a) Simply-supported beam representation, and (b) exemplary bridge cross-section and (c) damage location at the refined segment

locations 1–2, as shown in Fig. 2a with magenta and green colors, respectively. Only the traditional monitoring system is used to detect and locate the damage. Then, in the second case, the damage is concentrated at a length of 0.45 m near the abutment as shown in Fig. 2c. For this case, the efficacy of both the traditional sensor setup (Fig. 2a) and the proposed hybrid method (Fig. 2b) in detecting and locating damage is evaluated. This comparison highlights the shortcoming of the traditional system and the efficiency of the proposed methodology. In both cases, the structure's first four vertical mode shapes are used to compute the damage sensitive parameters.

3.1 Case I

In Case I, only the traditional monitoring system is used. To simulate minor damage, a reduction of 10% in the bending stiffness of the beam is considered to spread out for a length of 4.54 m, i.e. between two sensors. Two damage locations, one at the middle of the beam between sensors 6–7, and one on the side near the support between sensors 1–2 are considered separately to demonstrate the damage detection methods' capability to detect damage at different parts of the beam. For both damage scenarios, the change in the structural frequencies is subtle, the maximum being equal to 0.1%.

Note that only the measured points, *i.e.*, sensor locations, are used in the calculations. The results are presented in Fig. 3 and can be refined in between the measurement points using a spline or polynomial fit to the acquired mode shapes. Figure 3 demonstrates clearly that the classical damage sensitive measures used in this paper are capable of detecting and locating the damage for both damage scenarios.

3.2 Case II

The second case uses both monitoring strategies and demonstrates and highlights the superiority of the proposed hybrid monitoring strategy. As a more realistic feature commonly encountered in real-life applications, the damage is positioned between two sensor locations in the traditional monitoring system. This time a 10% reduction in the bending stiffness of a 0.45 m long portion between 2.05–2.50 m, measured from the left support, is simulated. It should be noted that, the damage scenario simulated in this case is much more realistic compared to Case I where the damage was assumed to be spread out for a length of 4.54 m. The change in the structural frequencies due to the simulated damage is negligible.

To increase the resolution of both traditional and the hybrid set-up, cubic splines are used. As such, the modal displacements and the associated damage sensitive parameters is computed at 221 equidistant points (i.e., 220 long intervals) for both sensor setups. This procedure is a standard one used in practice in order to increase the spatial resolution of the data when the sensors are sparsely located.

Figure 4 presents the damage sensitive parameters computed using both the traditional sensor setup and the proposed hybrid methodology. All three damage sensitive measures provide a much improved performance when they are used in conjunction with the proposed hybrid methodology compared to the traditional sparse sensor setup. Although it can be argued that the damage is detected using the traditional setup, the smoothing effect of the spline function prevents all three parameters from correctly locating the damage. On the other hand, the damage sensitive parameters at the damaged location reach much higher values compared to their counterparts at the undamaged locations when the proposed hybrid methodology is used. This difference, which is especially visible for modal curvature and modal strain energy parameters, shows promise in avoiding potential negative effects of measurement noise, which is not considered in this article. Furthermore, the hybrid methodology can satisfactorily identify the damage location.

It is intuitive that if the mode shapes present significant changes, then the possibility of presented damage detection methodologies capturing such changes is increased. Therefore, we finally inspect the difference between the damaged and undamaged modal displacements obtained using the hybrid monitoring approach in Fig. 4. Dashed vertical lines in the figure indicate the damage interval, and it is clear that the change in the modal displacements is the maximum in this interval for all mode shapes.

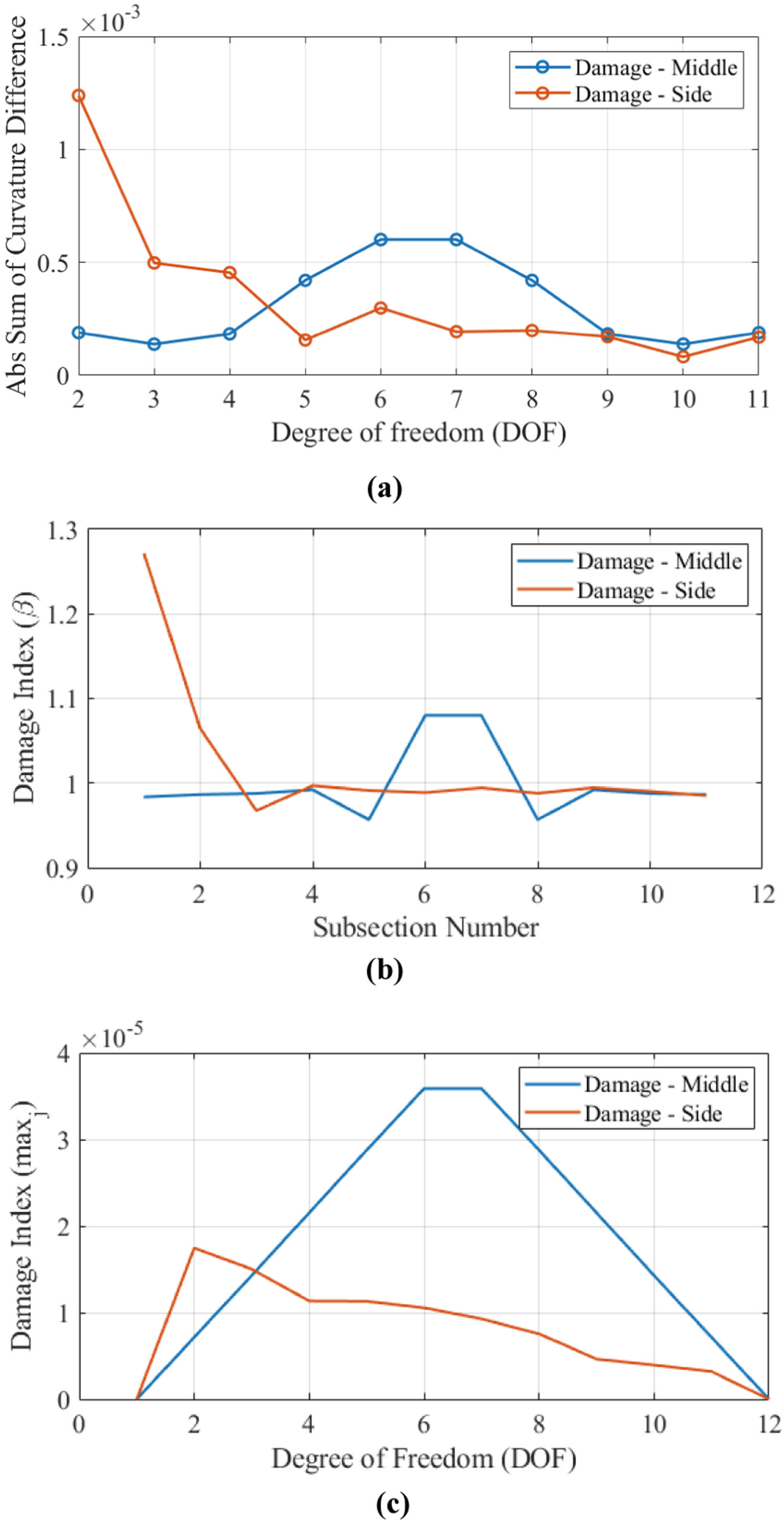


Fig. 3. Results for Case I: (a) Modal Curvature method, (b) Modal Strain Energy method and (c) Modal Flexibility method

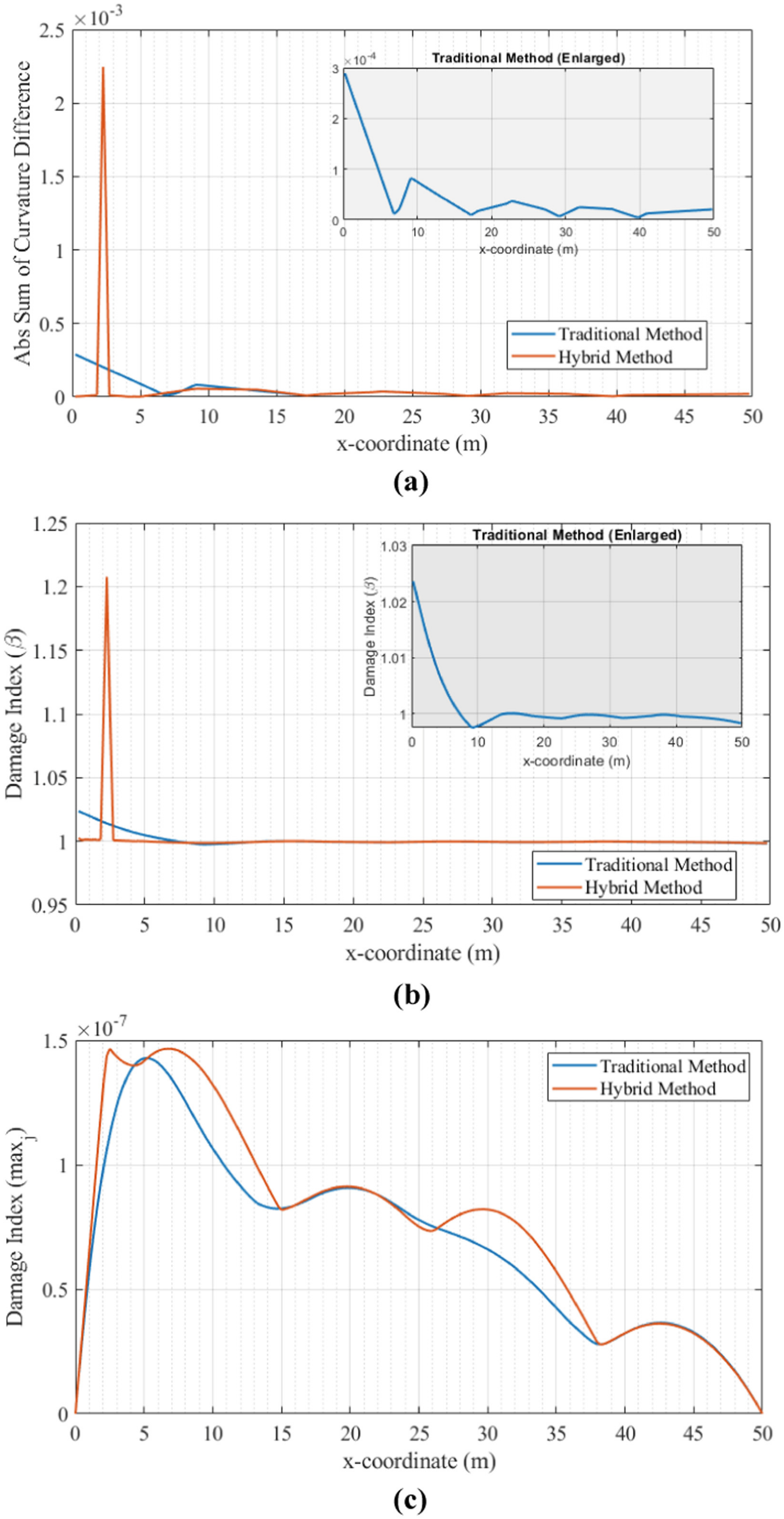


Fig. 4. Results for Case II: (a) Modal curvature method, (b) Modal strain energy method and (c) Modal flexibility method

4 Conclusions

A hybrid monitoring approach based on data fusion from traditional acceleration sensors and computer vision is proposed to detect damage in structures. First, the capabilities and accuracy of three damage sensitive parameters are verified via a numerical study. Then, the efficiency and superiority of the proposed methodology compared to the traditional sparse sensor setups are demonstrated using a more complex example in which the traditional method failed to detect the damage accurately. The hypothetical computer vision provided detailed and continuous information at the sensitive regions of the investigated beam and improved the mode shape estimate compared to that obtained from the traditional health monitoring method using discrete sensor locations. This allowed detecting and locating the damage accurately and showed the strong potential of the proposed structural health monitoring method for damage detection.

The work conducted in this study uses the modal data obtained from an ideal case, and there is not any noise or uncertainty in the modal measurements. Future work will incorporate the measurement noise and uncertainty to simulate an actual application. A parametric study for changing damage locations and severity will also be carried out.

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