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Damage Detection in Composite Beam type Structure by Strain Measurements

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Abstract

In this paper a technique for detecting multiple delamination in a weakly damaged composite beam is presented. The conventional techniques have been successfully used to detect single delamination in composite beams. However, these techniques were not as successful in detecting multiple delaminations particularly with measurement noise in the data. Moreover, the effectiveness of these techniques relies on the reference data with which the information is compared to discriminate the damage. The proposed technique uses the perturbation in the strain measurements along the beam axis to localize multiple delaminations. A Bayesian data fusion technique developed previously is used here with strain measurements to localize the delaminations by suppressing the noise. The smart statistical fusion of several likelihood functions screens out the false noisy peaks from the damage indices and accurately highlights the delamination locations. The simulation results in this paper indicate that the proposed technique accurately detects both delaminations with severity as small as 4% even when the data are contaminated with noise level up to 20% of the measured time response signal. For further smaller delaminations, the proposed technique was able to detect one damage clearly with 5% noise level.

Key Words: Gapped Smoothing Method, Damage detection, Composite; Strain measurements,

1. Introduction

The composite materials, due to their superior properties such as light weight, high stiffness, and strength, etc. are widely and popularly used in many engineering disciplines. The crucial problem with composite materials is the formation of delaminations and/or debonds which are not visible on the surface of the structure. These types of damage in composite structures may substantially reduce their stiffness or strength leading to tragic consequences. So, for useful service life of structure, efficient damage detection methods are required. In structural health monitoring (SHM) vibrational features-based techniques have been developed for damage detection. The commonly used techniques are frequency-based method, mode shape method, curvature-based method and strain energy method. The changes in natural frequencies caused by damage are usually very small, even for severe damage [1-4]. Thus, it is difficult to detect small damage based on change in natural frequencies. The method also loses its credibility in higher frequency modes. Mode shape-based methods alone are not very sensitive to damage, which makes them more useful for preliminary damage detection instead of accurate damage detection [5-7]. Furthermore, optimization algorithm or pattern recognition techniques are needed for accurate damage detection [5-7].

The curvature mode shapes can be used in lower modes for damage detection. At higher modes, the differences in curvature modes generate false indications of damage [6]. U. Baneen and J. E. Guivant [8] developed the technique for composites structures which did not require a baseline model for damage detection. Beams of different width of delamination were excited under impact loading and frequency response functions (FRFs) were determined at different locations of beam. Damage indices were obtained using the Gapped smoothing method (GSM) based on curvature mode shape along with Bayesian approach to reduce the effect of the noise. The technique was able to successfully detect the single delamination with minimum severity up to 8.3% of beam length. This technique was further extended for plate-type structures also [9]. Another study was carried out to detect and localize damage in aluminum plate-type structure [10]. The detection method was based on mode shape curvatures. The damage was indicated by measuring the difference between mode shape curvatures and their smoothed polynomial. The research revealed that with low degree of measurement noise, high-density transverse displacement measurements from scanning laser vibrometer were needed for successful damage detections. The technique was able to detect severe damage only.

Comparatively, curvature mode shapes are better damage indicator than mode shapes; however, their effectiveness cannot be fully exploited due to measurement noise [11]. The mode shapes from the experimental data always have noise, which is enhanced by taking second difference approximation to obtain curvature mode shapes. To avoid the errors associated with the second difference approximations, the strain energy method has been used by many researchers for damage detection. A novel strain energy-based method was developed and applied on Euler-Bernoulli beam [7]. In this novel approach, strain modes were used to obtain elemental modal strain energy. The method was tested by using numerical simulation and then it was validated experimentally. It worked well for single damage; however, it was difficult to detect multiple small structural damage with same accuracy. Moreover, the technique requires the damaged element to contribute to the measured modes energy to work effectively. In another study, an improved modal strain energy method was used to detect and localize damage in beam structure without using baseline data. [12]. Various damage scenarios were considered with 25% and 50% severity for both single damage and multiple damage cases. It was found that the method could reduce the noise, but it was not able to detect single and multiple slots with good accuracy. Furthermore, it was observed that the effectiveness of the technique varies with the location of damage.

In addition to the detection of damage using modal strain energy method, damage was also quantified by using an improved differential evolution (DE) algorithm [13]. This work was carried out on laminated composite plates. The damaged elements were initially identified using modal strain energy method. Then the damage was quantified using an improved DE algorithm by minimizing a mode shape error. Regardless of the effect of noise, the results showed that with less computational effort damage was located and quantified. In another work, a Cornwell Indicator based on strain energy fraction was developed [14]. The method was applied on composite beams with single and multiple damage considering different boundary conditions. It was tested numerically by introducing damage in the form of loss of rigidity. The method detected the single and multiple damage, but the accuracy was highly dependent on the selected threshold value for improved Cornwell indicator. The same study on composite beams was also investigated by using a residual force method (FRM) along with Genetic algorithm (GA) [15]. The beams were tested numerically, and it was found that the proposed method was able to detect damage with severity as low as 25% for single and multiple damage cases. However, the method still needs to be validated through experiment.

As discussed above, most of the techniques can successfully detect single damage but failed to detect multiple damage with same accuracy particularly in composite beams. To exploit the benefits of strain energy, this paper presents a strain-based GSM with Bayesian data fusion technique to reduce the undesirable effects of noise. Composite beams with multiple delaminations at different locations and of varying width were considered. In ANSYS, harmonic analysis was carried out on the composite beam. The responses in terms of strain based FRFs were extracted at points along the beam length. The results were first generated by using direct GSM. Then to test the efficacy of the proposed technique, different levels of noise were added to the extracted responses.

2. Damage index with GSM and Bayesian Fusion Approach

The GSM assumes that the second difference of mode shape which is curvature (κ) of an undamaged beam can be characterized by a smooth surface which can be mathematically represented by a single variable gapped polynomial [12].

$$\kappa_i = \sum_{m=0}^{n} C_m x^m \qquad (1)$$

where κ_i of *i*th mode represents curvature of supposedly undamaged beam; n refers to the degree of the gapped polynomial (here it is cubic polynomial) while C_m denotes the coefficients acquired by curve-fitting. The smooth surface of the curvature exhibits distinct features at the damaged locations on the beam structure. The GSM exploits these features of the curvature mode shapes to locate damages [12]. The curvatures in Eq. 1 are usually obtained by double differentiation of displacement mode shapes which not only enhances any distortion due to damage but also intensify the measurement noise. This problem can be avoided by directly measuring the curvatures instead of obtaining them from double differentiation. According to Euler-Bernoulli beam theory, there is a direct relationship between curvature and strain at beam's surface when the beam is bending [1]. Hence strain measurements can be used as curvature data. The GSM computes the damage index by measuring the squared difference between the strain data from damaged beam and the curve-fitted strain data. The damage location across the beam can be then ascertained by looking at the highest value of damage index peak.

These peaks of damage indices provide an estimate for the damaged locations on the beam structure. However, measurements taken in the presence of noise, linear and nonlinear distortions due to random sources, can affect the damage indices which may lead to false indications. A Bayesian fusion (BF) process was proposed in a study to avoid these false indications [8]. In this BF method, the existence of damages is modeled through a probability density function defined as a product of independent likelihood terms,

$$p(x) \propto p^0(x).\prod_{i=1}^{n} L_i(x) \qquad (2)$$

Each likelihood term L_i is computed from individual damage index function. Since the probability density function includes a lot of likelihood terms, some are bound to be inconsistent due to the presence of outliers. For that reason, a pruning process is used that assisted in removing these inconsistent likelihoods. The pruning process ranks the *K* of the *N* likelihood terms with respect to their computed values at the locations of interest. The top *K* likelihood terms from the ranking list are then selected. The resulting likelihood expression is as follows [12].

$$p(x_m) = p^0(x_m).\prod_{k=1}^{K} L_{i(k)}(x_m)$$
$$L_{i(k)}(x_m) \geq L_j(x_m), \forall \frac{j}{j} \neq i(r), 1 \leq r \leq K \qquad (3)$$

The removal of inconsistent likelihoods imparts robustness to the model against noise as it makes the occurrence of false peaks as well as the skipping of damaged locations less likely.

3. Noise Model

Several sources and experimental factors including imperfections in excitation mechanism, sensors, strain measurement and environment induced external disturbances in the beam frequency response; contribute to the noise in the FRF signal. The noise is modeled after Gaussian random variable under the assumption that noise distributions of component sources add up to the Gaussian distribution. Noise is added to the strain time histories at each measurement point. Representing $y_i(t)$ as the noise-free strain-based time-domain response, the corresponding noisy signal $\hat{y}_i(t)$is obtained [16,17] as follows:

$$\hat{y}_i(t) = y_i(t) + \left(\frac{e}{100}\sigma(y_i(t))R(t)\right) \qquad (4)$$

Where *e* represents the noise percentage with $e = 5, 10$ and 15 indicating 5, 10 and 15% noise levels, respectively. $\sigma(y_i(t))$ refers to the standard deviation of the signal $y_i(t)$. The term $R(t)$ is the random value sampled (at time *t*) from zero mean and unit variance normal random variable. Hence the amount of noise can be conveniently controlled by varying single parameter *e*. Once noise is added, Fast Fourier Transform (FFT) can be used to transform the noisy time-domain signal to frequency-domain for further analysis detailed in the following section.

4. Numerical Simulation

According to Euler-Bernoulli beam theory, Eq. 5 can be used to find the natural frequencies ω_n of the cantilever beam analytically [18].

$$\omega_n = \frac{(\beta_n L)^2}{2\pi}\left(\sqrt{\frac{EI}{\rho A L^4}}\right) \qquad (5)$$

where, β_n are mode shape coefficients dependent on *n*; *EI* is the flexural rigidity; *A* and ρ are the cross-sectional area and density of the beam, respectively.

Table.1: Comparison of natural frequencies of cantilever beam

Frequencies (Hz)	Healthy Beam		Damaged Beam (Simulated)		
	Analytical	**Simulation**	**Case 1**	**Case 2**	**Case 3**
Mode 1	49.49	49.60	49.56	49.60	49.61
Mode 2	310.13	307.41	305.45	307.12	307.39
Mode 3	868.36	846.025	838.23	844.41	845.89
Mode 4	1701.62	1618.82	1590.34	1614.67	1618.5
Mode 5	2812.93	2600.01	2572.27	2599.02	2599.95

A comparison of natural frequencies acquired analytically and from simulation is given in Table 1 for both healthy and damaged beams. To evaluate the applicability of the technique, the beam was modelled and analyzed in ANSYS. A cantilever glass fiber reinforced plastic (GFRP) beam with dimensions and other physical properties described in Table 2, was modeled in ANSYS. Various damage scenarios based on damage locations and damage severity, as described in Table 3 for unit-normalized beam length, were considered. In this paper, structural damage in the form of two delaminations are symbolized as D1 and D2 as shown in Fig.1. Here the damage severity is defined as delamination length per beam length, in percentage.

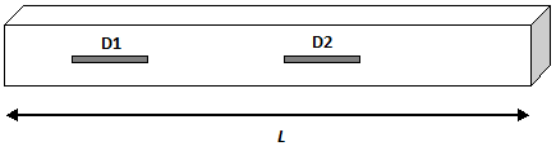


Fig.1: Beam schematic illustrating both delaminations

Table 2: Properties of composite beam

Properties of GFRP Beam	
Length	$600mm$
Width	$35mm$
Height	$30mm$
Young's modulus	$25\ GPa$
Poisson's ratio	0.3
Density	$1850\ kg/m^3$
Damping ratio	0.01031

In ANSYS, initially seven blocks were modelled to create the two delaminations in beam. These blocks were then merged, except where the delamination was present. After that, the damaged beam was meshed with an appropriate element size of 5 mm that included 5040 elements in total. Harmonic analysis with frequency range 0 to 2.6 kHz, was then performed that included first five bending modes. Finally, the response in terms of elastic strain was extracted at equidistant points along the beam length.

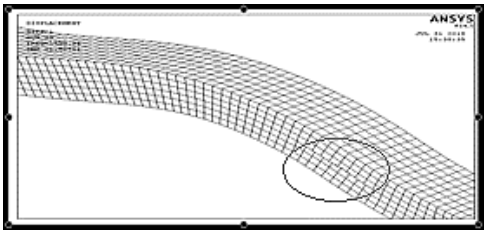


Fig. 2: Beam with Delamination

The first five strain modes in bending were extracted from the response and damage indices were generated by using GSM. These damage indices with noise-free response clearly indicated the two delaminations as shown in Fig.3(a). The noise generates many false peaks in damage indices and thus cover the useful information. Hence Bayesian data fusion technique is employed to reduce the noise by enhancing the peaks indicating the true damage locations. To examine the efficacy of the technique, the response is contaminated with random noise in time domain to make it closer to an experimental response. For each damage scenario, damage indices are generated by considering varying levels of noise as presented in sections 5, 6 and 7.

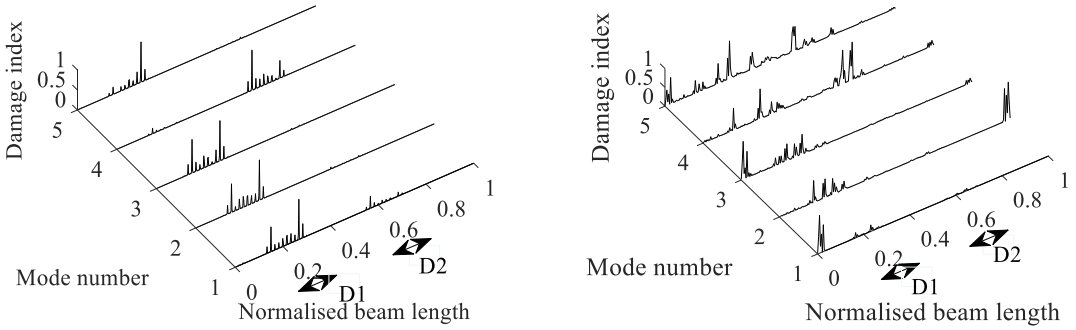
5. Case1: Damage width 8% of length

Damage indices for Case1, as shown in Fig.3, were obtained from the first five extracted strain modes using GSM. In all figures, D1 and D2 show the width of first and second delamination, respectively. The peaks for D1 are clearly visible in all modes as shown in Fig 3(a). In first and fourth modes, damage indices show noticeable peaks for D2 while these peaks have comparatively smaller magnitude in second, third and fifth mode. To examine the effectiveness of the technique, the measured response is contaminated with noise up to noise levels of 5, 10, and, 15%. For 5% noise, Fig. 3(b) shows that only D1 is somewhat visible in all modes while except in the fourth mode, D2 is lost in noise. For other noise levels of 10% and 15%, several false positive peaks are present as shown in Figs.3(c) and 3(d). Although being noticeable, these peaks are not consistent for each strain mode.

Table 3: Different damage scenarios

Damage scenario	**Damage Severity (%)**	**Location along unit normalized beam length**	
		D1	**D2**
Case1	8	0.166-0.250	0.583-0.666
Case2	4	0.166-0.208	0.583-0.625
Case3	1.6	0.166-0.183	0.583-0.600

To suppress the noise while highlighting the useful information, Bayesian approach as described in section 2 is applied. The *K* of *N* likelihoods were varied to acquire the estimated damage indices in Figs.4-7. As can be seen in Figs.4 and 5, both delaminations D1 and D2 are accurately detected for 5 and 10% noise levels. Even for 15% noise, both delaminations can be detected for the first three cases of *N* and *K* as shown in Fig.6. To examine the method, noise was further increased to 20% and estimated damage indices were generated. Fig.7 indicates a visible D1 in all cases. Although peak of D2 is shifted a bit but it is consistent throughout. For other noise levels too, although D2 is localized but there is a very slight shift too. A possible explanation of this shift could be due to the severity of delamination. During bending the parts above and below the delamination move separately particularly for D2 which is towards the free end of cantilever beam, so that might cause a shift of peaks on one side.



(a) without noise

(b) 5% noise

(c) 10% noise

(d) 15% noise

Fig. 3: Case1 damage indices from strain modes using GSM

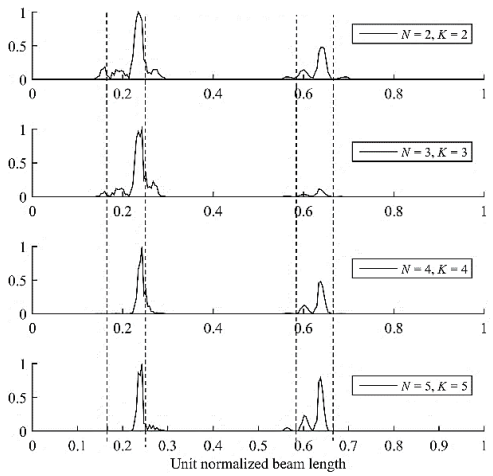


Fig. 4: Case1 estimated damage index - 5% noise

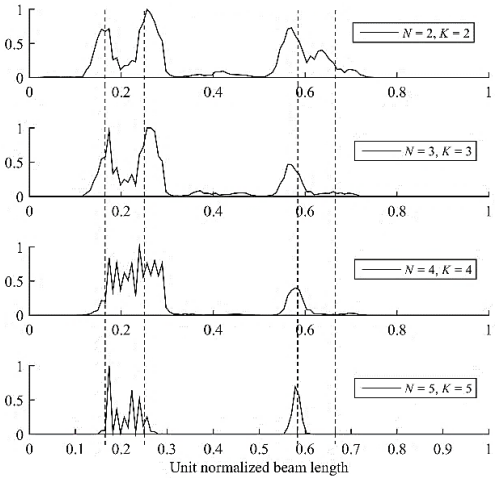


Fig. 5: Case1 estimated damage index - 10% noise

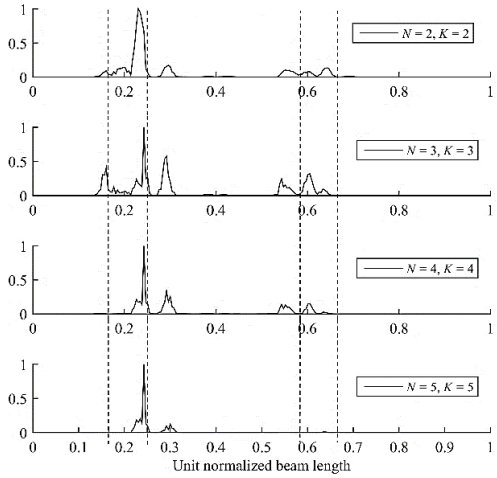


Fig. 6: Case1 estimated damage index - 15% noise

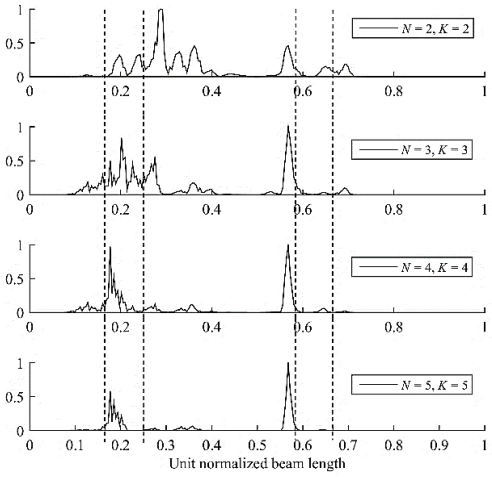


Fig. 7: Case1 estimated damage index - 20% noise

6. Case2: Damage width 4% of length

For case2, the damage indices were initially generated by applying GSM only. As the delamination is less severe, so the damage indices showed many false peaks. By applying Bayesian, the estimated damage indices were obtained for all four noise cases as shown in Figs.8-11. Both peaks for D1 and D2 can be clearly seen for 5, 10 and 15% noise levels consistently. Even for 20% noise, D2 is clearly visible in all cases of N and K. Although the peak for D1 is comparatively smaller but that is also consistent through out as can be seen in Fig.11. Result of case2 for 20% noise is better than case1. As this is less severe so the parts of beam above and below the delamination do not move as much as the severe delamination.

7. Case3: Damage width 1.6% of length

For this case of multiple delaminations with very low severity, the damage indices from direct GSM with 5% and 10% noise levels show many false peaks. The estimated damage indices after the application of Bayesian approach provide clear detection of D1 for 5% noise. While the peak for D2 is shifted in all cases with some false peaks. For 10% noise, D1 is detected only for $N = 2, K = 2$ while for all other cases the damage is lost in noise as can be seen in Fig.13.

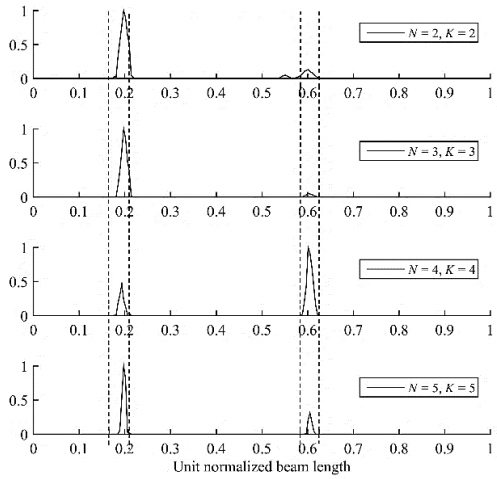


Fig. 8: Case2 estimated damage index - 5% noise

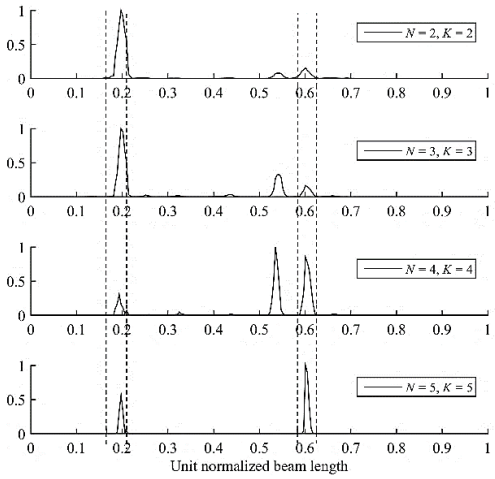


Fig. 9: Case2 estimated damage index -10% noise

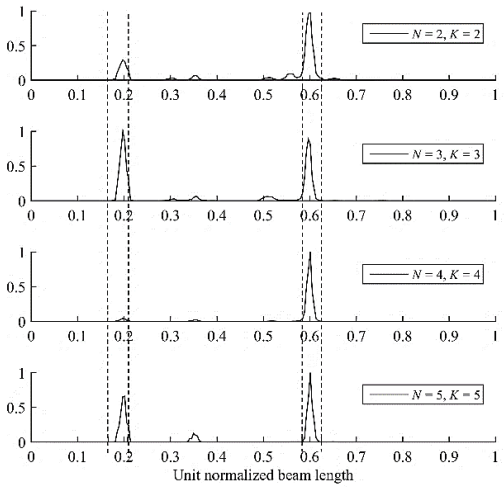


Fig. 10: Case2 estimated damage index -15% noise

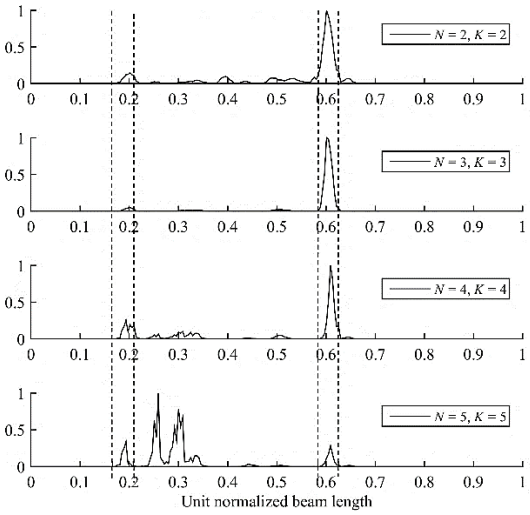


Fig. 11: Case2 estimated damage index -20% noise

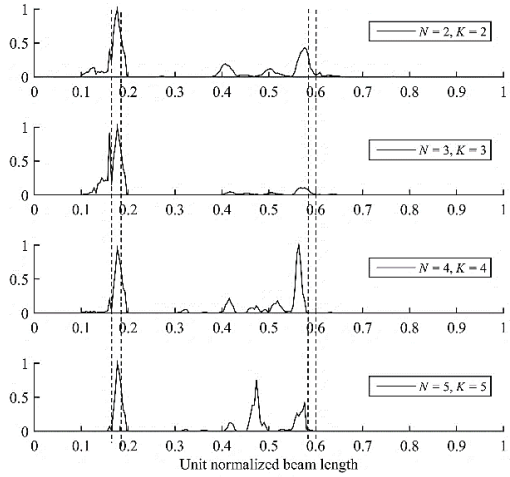


Fig. 12: Case3 estimated damage index - 5% noise

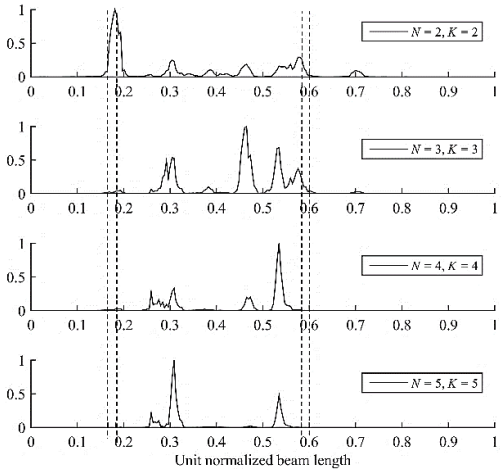


Fig. 13: Case3 estimated damage index - 10% noise

8. Conclusion

Multiple delaminations comprise most common and critical forms of damage in composite structures. In this paper, a strain-based GSM with Bayesian data fusion technique is presented. The noise induced false damage index peaks were efficiently pruned by using the proposed technique. All the results were generated without using any reference data.

Here, the results signify that the accuracy of proposed method was dictated both by the magnitude of noise as well as the severity of delamination. The proposed technique was able to reliably detect multiple delaminations with severity as low as 4% of beam length at noise level as high as 20% of the response signal. When the severity was further reduced to 1.6% of beam length, only one delamination was visible for 5% noise level. It was also noted that for severe delaminations, sometimes the peaks of damage indices shifted due to the significant movement of parts of beam above and below the delamination. This movement reduces slightly for less severe delaminations, hence providing accurate detection with the proposed technique. Another significant finding in this paper is that same results can be achieved by using only first two modes ($K = 2$ for $N = 2$) for all cases. Further enhancements in this research can be made by obtaining measurements at large number of beam locations for an accurate illustration of strain mode shapes. Moreover, by including higher strain modes the detection of less severe delaminations can be improved.

9. References

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