Structural crack localization and identification based on FBG

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Abstract. The current structural crack detection still suffers from the problems of single detection target, inability to achieve true acoustic emission crack signal separation, and poor portability of the sensing system. To address this phenomenon, in this paper, based on the use of fast blind source signal separation, combined with the designed structural crack sensing detection model, we will first coarsely localize the crack location area, and within this area, we will use the designed structural multi-crack parameter identification algorithm to achieve the multi-crack location identification purpose. The experimental results show that the proposed method achieves an average localization accuracy of 1.95 cm and a localization time delay of about 25 ms. It provides a feasible method for structural crack detection.

1. Introduction
In the existing research, the method of crack detection is divided into two main steps: crack location determination, and crack parameter identification.

1. Development of structural crack location identification technology. The principle of crack detection by eddy current method i.e. when in a magnetic field of certain strength, eddy currents will appear when cracks appear[1]. In addition, the eddy currents generated near the crack and the crack have the opposite effect of the applied magnetic field, and the sensor can measure the physical quantity through the induction of its own coil, and the analysis of the acquired magnetic field information can realize the identification of the crack information[2]. Such methods have obvious defects is itself a strong electromagnetic interference, power consumption is serious; according to existing research shows that the current research is mostly based on single-point crack detection, when there are multiple damage, the response signal in the inter-board transmission shows the mixing of multiple source signals, single-point crack parameter identification method is difficult to apply, which also greatly limits the promotion of some damage detection methods[3,4].

2. Structural crack parameter the development of identification technology. The identification of structural crack information is mainly the identification of various parameters representing its main information, so that it can be convenient for the staff to refer to the maintenance[5]. With the need of national development strategy, the crack information detection of engineering structure is particularly important. In the early research, the crack location identification methods are roughly divided into: acoustic emission method and ultrasonic Lamb wave method[6,7]. The former thinks that the crack is a kind of acoustic emission signal, and the characteristic parameters of the crack can be identified by
qualitative analysis of the information collected by using appropriate sensing and detection technology. The existing research is not ideal in the recognition effect, and further research is needed to improve the positioning accuracy [8,9].

From the above analysis, it can be seen that FBG based far field crack identification technology has a certain research value. The method can improve the detection accuracy according to the relationship between the far field strain signal collected by the sensor and the transmission time, combined with the proposed detection model and signal processing algorithm.

2. Related Work
To address the existing problem of single crack recognition target of acoustic emission signal and the need to separate the collected crack source signal when multiple cracks exist, the prerequisite of separation needs to know the number of source signals in advance and other shortcomings.

In addition, the complexity of the environment in which the actual engineering application is located leads to the problem that the acoustic emission signals of non-crack target detection are easily mixed with some impact signals and friction between obstacles in the process of signal acquisition. Therefore, a strongly weighted center-of-mass method is used to deal with the pseudo-crack original problem, and the signals other than cracks are removed.

Meanwhile, a wavelength offset extraction method by virtue of a threshold reference is constructed to address the problem of insufficient accuracy in identifying the center wavelength position offset of the existing FBG sensing signal. In addition, the existing crack identification methods have the disadvantages of large errors and high data processing delays, and a strain signal or acoustic emission signal model that relies on the sensor-detected impact or crack damage generation while building an FBG detection platform is proposed and designed to improve the above shortcomings.

3. Proposed Method
3.1. Multi-crack acoustic emission signal separation method
Independent Component Analysis (ICA) refers to the separation of individual signals from a mixture of multiple signals that are independent of each other. ICA is described as follows: the observed signal matrix X is formed by linear combination of N source signal matrices S, and the Nth order square matrix A is called the mixing matrix, then we have

\[ X = AS \]

The purpose of the blind source signal separation is to find the unmixing matrix B such that

\[ Y = BX \]

Where Y is the output matrix, where B is the inverse of A. The approximation matrix of the mixing matrix is obtained by approximating A one by one through multiple operations. The infinite approximation between the separated signal and the source signal is the final goal of the separation, and if the elements in Y are independently distributed, it is the estimated value of the requested S.

In order to separate the mixed signals quickly and accurately, the Fast ICA algorithm (Fast ICA) based on the negative change of entropy function is used in this paper. The degree of separation between the independent components can be determined by calculating the value of negative entropy. Negative entropy is defined as

\[ Ng(Y) = H(Y_{\text{Gass}}) - H(Y) \]

where \( Y_{\text{Gass}} \) is the same variance as Y, which is the differential entropy of the random variable.

\[ H(Y) = -\int P_Y(\xi) \log P_Y(\xi) d\xi \]

From information theory, if the variance is the same, the higher the differential entropy of a random variable whose distribution is Gaussian regular. If Y has a Gaussian distribution, Ng(Y) = 0; conversely, the smaller it is, the larger Ng(Y) is. Therefore, the magnitude of negative entropy can be used as an evaluation indicator of the degree of separation between signals. To establish the signal separation block
diagram, the fiber grating sensor acquires the signal to behave as a multi-point crack signal of the mixed signal, after the separation process output as an independent source signal.

![Block diagram of signal separation principle](image)

**Fig. 1 Block diagram of signal separation principle**

Now, taking the example of cracks appearing at two points, the different crack signals collected by FBG are separated using Fast ICA algorithm. At the time of crack event generation, the noise interference signal is \( n(t) \) and the crack acoustic emission signal \( s_i(t) \) in a short time range, then the signal collected by the sensor is expressed as a superposition of two signals

\[
x(t) = a_{ij}[s_j(t) + n(t)]
\]

where \( a_{ij} \) is the element in the mixing matrix, \( i \) is the number of sensors \((i=1,2,3,4)\), and \( j \) is the number of crack events \((j=1,2, \cdots, n)\). Then the above equation yields

\[
X_{new} = A_{new}S_{new}
\]

The specific flow of the separation algorithm is as follows

![Fast ICA signal separation process](image)

**Fig. 2 Fast ICA signal separation process**

Where, \( \theta \) is the parameter learning rate. From the above process, the final result of the combination of source signals, i.e., each independent source signal \( y_i(t) \), is obtained, and the negative entropy criterion shows that \( y_i(t) \) is the \( x_i(t) \)-approximation value, which contains the signal characteristics generated by the impact, i.e., it can be used in the subsequent impact localization calculation.

The stress wave information generated by a single point crack can be obtained by separating \( y_i(t) \) from the multi-source point crack signal, which means that the multi-crack localization problem is also converted into a single-point crack localization processing problem. Based on the separation of the
mixed signals, the identification of crack location information can be realized one by one by combining the hyperbolic localization model.

3.2. Method of locating multiple cracks in a structure

Four FBG sensors are laid out on each of the four sides of the quadrilateral flat plate, perpendicular to each side. When cracks P1 and P2 are generated, accompanied by crack stress waves, the FBG can acquire the strain information containing the crack parameters in time. Each sensor acquires the mixed information of the stress waves generated by multiple cracks, and the mixed signals of the multi-crack acoustic emission signals are separated by the signal separation technique. Then the letters acquired by the four sensors are processed to obtain the parameter information of each crack.

![Figure 3](image)

Figure. 3 Schematic diagram of acoustic emission from multiple cracks in a structure (this figure shows two cracks as an example)

![Figure 4](image)

Figure. 4 Positioning schematic

The hyperbola has the property that the difference of the distance from a point on the hyperbola to the two foci is a constant value of $2a$; if the distance from the foci to the origin is $c$, then we have $c^2 = a^2 + b^2$.

When the impact point is at point P, the stress wave generated by the impact source at point P will propagate around point P. Assuming the propagation speed of the stress wave in the aluminum alloy plate is $V$, the time to reach FBG1 is $t_1$, $t_2$ to reach FBG2, $t_3$ to reach FBG3, and $t_4$ to reach FBG4. where $t_i$ ($i = 1, 2, 3, 4$) is the time to reach the FBG sensor at the initial moment of the stress wave generation, which is generated by the impact after computer acquisition is obtained. With the hyperbolic localization model, the crack coordinates can be calculated.

4. Experiment

In order to verify the validity of the design theory, the experimental platform of multi-source crack localization was built as shown in Fig. The experimental system: 600 mm×600 mm×2 mm aluminum alloy plate (model: 3A21), Young's modulus of 7100 MPa, Poisson's ratio of 0.33. Four FBG sensors (fiber grating center wavelengths of 1540 nm, 1543 nm, 1546 nm, 1548 nm at room temperature) were selected according to the experimental design. The model of fiber demodulator is Honglin FI-104, the maximum frequency demodulation is 2000 Hz, and the demodulator demodulation wavelength range is 1525 nm–1565 nm.
The experimental results of crack localization are given in Table. The farthest and nearest 20 sets of position data from FBG are selected in the experiment, and the average of 10 experimental data is taken as the predicted positioning coordinates. The error between the predicted positioning coordinates and their corresponding actual coordinates is also calculated.

**Table 1 Impact point positioning and error**

| Reference point (group number) | Actual coordinates (point A, point B) (x/cm, y/cm) | Prediction coordinates (point A, point B) (x/cm, y/cm) | Error/ cm (point A, point B) |
|-------------------------------|-----------------------------------------------|-------------------------------------------------|----------------------------|
| 1                             | (0,0), (0,10)                                | (0.24,-0.15), (1.12,11.15)                      | 0.28, 1.61                 |
| 2                             | (10,0), (20,0)                                | (9.83,0.34), (21.24,0.75)                       | 0.38, 1.45                 |
| 3                             | (10,10), (10,20)                              | (9.12,10.67), (10.75,23.35)                     | 1.10, 3.43                 |
| 4                             | (20,10), (20,20)                              | (20.41,10.05), (18.81,18.23)                    | 0.41, 2.13                 |
| 5                             | (-10,10), (-10,20)                           | (-10.26,10.87), (-11.27,23.16)                  | 0.90, 3.41                 |
| 6                             | (-20,10), (-20,20)                           | (-20.15,10.81), (-18.61,20.21)                  | 0.82, 1.41                 |
| 7                             | (-10,-10), (-10,-20)                         | (-10.99,-10.77), (-12.52,-19.11)                | 1.25, 2.67                 |
| 8                             | (-20,-20), (-20,-10)                         | (-21.14,-18.85), (-22.32,-11.12)                | 1.62, 2.58                 |
| 9                             | (10,-10), (10,-20)                           | (12.13,-8.82), (12.21,-18.77)                   | 2.44, 2.53                 |
| 10                            | (20,-10), (20,-20)                           | (21.25,-8.77), (18.81,-21.79)                   | 1.75, 2.15                 |
| 11                            | (10,10), (-10,-10)                           | (12.32,8.71), (-10.23,-12.25)                   | 2.65, 2.26                 |
| 12                            | (20,20), (-20,-20)                           | (21.55,18.95), (-19.85,-18.91)                  | 1.87, 1.10                 |
| 13                            | (-10,10), (-10,-10)                          | (-12.15,11.30), (9.81,-10.33)                   | 2.51, 0.38                 |
| 14                            | (-20,20), (-20,-20)                          | (-22.12,18.83), (19.85,-20.15)                  | 2.42, 0.21                 |
| 15                            | (-10,10), (-5,0)                             | (11.22,9.14), (-5.5,0.35)                       | 1.49, 0.61                 |
| 16                            | (-10,10), (-10,-10)                          | (-11.14,8.81), (-11.34,-8.85)                   | 1.64, 1.77                 |
| 17                            | (-20,20), (-20,-20)                          | (-22.14,19.14), (-18.71,-22.32)                 | 2.31, 2.65                 |
| 18                            | (10,-10), (-10,10)                           | (11.12,-8.82), (-12.30, 12.58)                  | 1.63, 2.89                 |
| 19                            | (20,-20), (-20,20)                           | (18.65,-22.15), (-21.21,18.34)                  | 2.54, 2.05                 |
| 20                            | (-10,10), (-20,20)                           | (-12.25,8.85), (21.11,18.75)                    | 2.53, 1.67                 |

**Average error**

| Error/ cm (point A, point B) | 1.63, 1.95 |

**5. Conclusion**

For the problem of simultaneous detection and identification of multi-point cracks, the stress wave signals generated when cracks appear are collected by FBG sensors, combined with FastICA to separate the multi-point impact event signals, and then the FBG hyperbolic localization model is used to realize...
multi-point cracks for localization. Experiments show that the proposed method can effectively identify multi-point crack coordinate information. It provides a reference for the measurement of multi-point crack localization in engineering applications.

References

[1] Wang Z., Liu M., Qu Y., et al. The Detection of the Pipe Crack Utilizing the Operational Modal Strain Identified from Fiber Bragg Grating[J]. Sensors, 2019, 19(12):2556-2568.

[2] Guo L., Li R., Jiang B., et al. Automatic Crack Distress Classification from Concrete Surface Images using a Novel Deep-width Network Architecture[J]. Neurocomputing, 2020, 397(9):1-18.

[3] Xiao W., Yu L., Joseph R., et al. Fatigue-Crack Detection and Monitoring through the Scattered-Wave Two-Dimensional Cross-Correlation Imaging Method Using Piezoelectric Transducers[J]. Sensors (Basel, Switzerland), 2020, 20(11):23-34.

[4] Tan R., Chen C., Zheng Y., et al. High-precision calibration method for fiber Bragg grating strain sensing based on an optical lever[J]. Optical Fiber Technology, 2020, 38(15):102-117.

[5] Lv C., Wang S., Shi C. A High-Precision and Miniature Fiber Bragg Grating-Based Force Sensor for Tissue Palpation During Minimally Invasive Surgery[J]. Annals of Biomedical Engineering, 2020, 48(2):669-681.

[6] Akbari J., Ahmadifarid M., Amiri A K. Multiple Crack Detection using Wavelet Transforms and Energy Signal Techniques[J]. Frattura ed Integrità Strutturale, 2020, 52(1):269-281.

[7] Fan Z., Li C., Chen Y., et al. Automatic Crack Detection on Road Pavements Using Encoder-Decoder Architecture[J]. Materials, 2020, 25(11):1023-1031.

[8] Yamane T., Chun P J. Crack Detection from a Concrete Surface Image Based on Semantic Segmentation Using Deep Learning[J]. Journal of Advanced Concrete Technology, 2020, 18(9):493-504.

[9] Sayed A F., Mustafa F M., Khalaf A A M., et al. An enhanced WDM optical communication system using a cascaded fiber Bragg grating[J]. Optical and quantum electronics, 2020, 52(10):1811-1821.

Kalhori H., Alamdari M M., Li B., et al. Concurrent Identification of Impact Location and Force Magnitude on a Composite Panel[J]. International Journal of Structural Stability and Dynamics, 2020, 21(11):1561-1572.