

Article

Study on Stay Cable Anomaly Identification Method Based on Multi-Point Displacement of the Main Girder for River-Crossing Bridge

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Abstract

To enhance the accuracy and real-time performance of anomaly detection for stay cables in cable-stayed bridges, especially those in water-rich environments, this paper proposes a stay cable anomaly identification method based on multi-point displacement measurements of the main girder. First, combined with finite element modeling, two anomaly identification indicators—"fitted displacement" and "effective displacement" of the main girder—are constructed, and their correlations with the location and severity of cable damage are clarified. Second, a gray level–displacement mapping model based on the Eulerian perspective is established, enabling non-contact, high-precision displacement measurement suitable for remote and distributed monitoring conditions. Subsequently, using a scaled cable-stayed bridge model in the laboratory, the feasibility and effectiveness of the method are verified through multi-condition experiments. Finally, the whale optimization algorithm (WOA)-optimized random forest model, enhancing the accuracy and stability of cable anomaly classification and identification. The results demonstrate that the proposed method offers significant advantages in accuracy, real-time performance, and intelligent recognition. It shows great potential for application in the health monitoring and safety management of water-related cable-stayed bridges, providing a new approach and technical support for intelligent safety diagnosis and reinforcement.

Keywords: cable-stayed bridge; stay cable anomaly identification; main girder displacement; gray level–displacement mapping; WOA-optimized random forest model; vision measurement



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1. Introduction

In recent years, with the rapid advancement of bridge engineering technology, long-span cable-stayed bridges have been extensively constructed both domestically and internationally, particularly in water-rich areas such as river crossings and coastal zones. Their structural performance and safety are critical due to the demanding environmental conditions and operational requirements. As essential load-bearing components in cable-stayed bridges, stay cables transmit deck loads to the bridge towers. However, during long-term service, especially in challenging environments such as railway bridges subject to frequent cyclic train loads, water-related bridges are susceptible to environmental corrosion, impact loads, wind-induced vibrations, and fatigue effects. These factors can lead to corrosion,

wire breakage, relaxation, or even cable fracture. If such anomalies are not detected and addressed promptly, they may compromise the overall structural stability and even lead to bridge collapse, posing serious safety risks and potentially causing significant economic losses [1–3].

Globally, there have been multiple bridge accidents caused by stay cable anomalies. For example, the Kohlbrand Bridge in Germany and the Maracaibo Bridge in Venezuela required replacement of damaged cables due to corrosion; the Morandi Bridge in Genoa, Italy, collapsed due to cable fractures caused by corrosion. These accidents resulted in substantial casualties, economic losses, and social impacts [1]. Domestically, large-scale maintenance and cable replacement have been conducted on bridges such as the Yin Hai Bridge in Guangzhou and the Yellow River Bridge in Jinan, underscoring the importance and urgency of stay cable condition monitoring and anomaly detection technology, especially for water-related structures. The long-term service performance of cable materials is also influenced by their surface integrity and resistance to fatigue damage. Advanced surface treatment techniques, such as ultrasonic surface rolling processing, have been shown to significantly enhance the mechanical properties and fatigue resistance of metallic materials by refining surface microstructures and introducing compressive residual stresses. Although such treatments are primarily applied in the manufacturing and repair of high-performance alloys [4], their underlying principles suggest potential value for improving the durability of cable anchorage components or protective sheathing in future bridge designs.

Traditional cable inspection methods can be classified into direct and indirect methods. Direct methods include visual inspection, infrared thermography, ultrasonic testing, magnetic particle inspection, and acoustic emission techniques [5–8]. While these approaches can detect local damage, they often involve long inspection cycles, expensive equipment, susceptibility to environmental interference, and difficulties in automation and real-time monitoring. For water-related buildings, which are often remotely located and widely distributed, these limitations are particularly pronounced. Cable-climbing robotic inspection technology has improved efficiency but still faces challenges such as low signal-to-noise ratios and difficulties in identification under complex environmental conditions [9,10].

Indirect methods detect anomalies by monitoring variations in the bridge's global dynamic parameters (e.g., natural frequencies, mode shapes) or static parameters (e.g., displacement, strain, cable force), combined with finite element analysis, modal analysis, and machine learning techniques [11–17]. These methods avoid the complexity of direct contact with the cables and offer advantages such as non-invasiveness, automation, and strong real-time capabilities, making them highly suitable for remote and distributed water-related structures [18–27]. Among them, the anomaly detection method based on multi-point displacement of the main girder is particularly simple and effective, as cable anomalies cause changes in the displacement of the main girder anchorage points. Monitoring these displacements can indirectly reflect the cable's condition. Recent advances in domain adaptation and attention-based mechanisms, such as the SPW-SVDD health indicator framework combined with temporal-self-attention, have demonstrated robust performance in capturing degradation trends across different working conditions [28]. Such data-driven strategies offer valuable methodological references for bridge anomaly detection under environmental and loading variations.

In recent years, computer vision technology has been widely applied in structural health monitoring for bridges due to its non-contact measurement, remote operation, high efficiency, and real-time capabilities. By extracting structural surface motion information through image processing techniques, high-precision measurements of displacement and vibration can be achieved, greatly improving monitoring convenience and accuracy [29–37].

These features align well with the needs of water-related buildings, which often require automated and intelligent monitoring solutions. Additionally, advancements in machine learning methods have provided strong support for anomaly detection based on displacement data, facilitating the intelligent diagnosis and safety management of water-related infrastructure.

Against this background, the present study proposes a stay cable anomaly detection method based on multipoint displacement measurements of the main girder, tailored to the unique challenges of water-related structures such as remote siting and distributed installations. The method integrates finite element modeling, machine vision measurement, and a deep learning assisted classification framework. Rather than simply applying displacement measurements for cable condition inference, this study introduces two physically meaningful anomaly indicators—fitted displacement and effective displacement—derived from finite element simulations, which capture deviations from expected structural behavior under operational conditions. To enable practical deployment in field environments where conventional sensors are difficult to install and maintain, a grey level–displacement mapping model based on the Eulerian approach is developed, allowing efficient, real-time, and dense multipoint displacement measurement of the main girder without target markers. The effectiveness of the proposed anomaly indicators is validated through a scaled laboratory bridge model. Furthermore, a random forest model optimized by the whale optimization algorithm is established to automatically classify different cable anomaly conditions. This framework collectively advances beyond existing displacement-based indirect diagnosis methods by transforming raw displacement data into interpretable indicators, enabling high-resolution field measurement without physical sensors, and providing an intelligent diagnostic tool for safety assessment and reinforcement decision-making in water-related bridge infrastructures.

2. Methods

2.1. Construction of Stay Cable Anomaly Identification Indicators Based on Finite Element Analysis

2.1.1. Finite Element Model Development

This study is based on a river-crossing cable-stayed bridge project, with the overall rendering shown in Figure 1. The finite element method (FEM) was used to establish the structural model of the cable-stayed bridge, taking into account geometric nonlinearity, beam–column effects, and sag effects. The finite element model is shown in Figure 2. The main girder and towers were simulated using beam elements, while stay cables were modeled using truss elements, with a reduction in elastic modulus to simulate cable anomalies. After applying vehicle loads, multi-point displacement responses of the main girder were obtained, and two anomaly indicators—fitted displacement and effective displacement—were proposed. Fitted displacement was obtained by fitting multiple measurement point data using orthogonal polynomials and calculating the change in root mean square error (RMSE) to reflect cable anomalies; effective displacement was obtained by performing time-domain integration and normalization of the main girder displacement time history and identifying anomaly locations based on local peaks.

The bridge is a river-crossing cable-stayed bridge with a double-tower, double-cable-plane, semi-floating, five-span continuous composite girder design, with spans of 32.9 + 115.4 + 340 + 115.4 + 32.9 m. The main girder is an I-shaped beam, and the bridge towers consist of upper, middle, and lower tower columns and crossbeams. The tower columns adopt a single-cell, single-box hollow box section. Main technical parameters: design load of Grade I highway, design speed of 100 km/h, bridge deck width of 33 m, tower material is C50 concrete with an elastic modulus of 3.45×10^4 MPa, main girder material is steel with an elastic modulus of 2.1×10^5 MPa, and stay cables are OVM250

series epoxy-coated steel strands with a standard strength of 1860 MPa and an elastic modulus of 1.95×10^5 MPa.



Figure 1. Overall effect diagram of a certain river-crossing bridge.

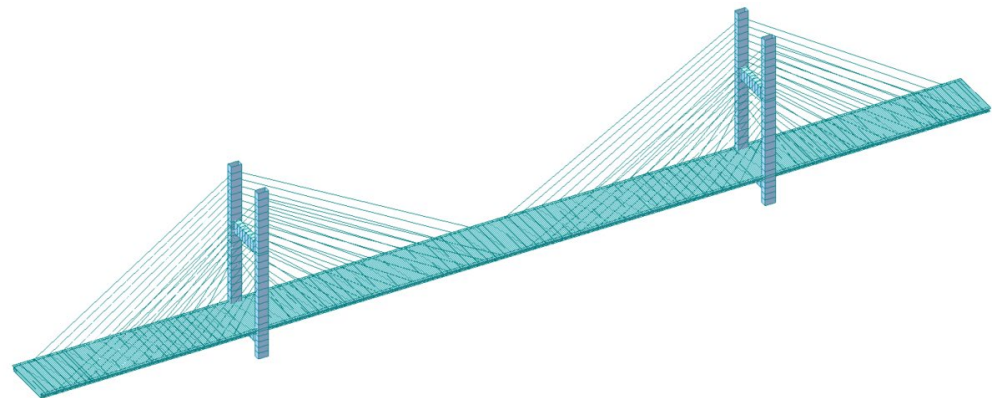


Figure 2. Finite element model of cable-stayed bridge.

The FEM model discretizes the structure into 1011 nodes, 902 beam elements, and 104 truss elements. The side piers are simplified as elastic supports, and the connections between the main girder, towers, and stay cables are modeled using rigid and elastic connections.

2.1.2. Construction of Anomaly Indicators

Anomalies in stay cables are typically manifested as changes in the cable's cross-sectional area and elastic modulus. The tensile force of a stay cable is mainly borne by the steel strands; if some of the strands break or age, the mechanical performance of the cable will degrade. In this study, anomalies are simulated by reducing the cross-sectional area and the elastic modulus.

When a cable anomaly occurs, defects in the material lead to a reduction in cross-sectional area, which in turn increases the cable stress. The relationship between the cross-sectional area A and the effective cross-sectional area A' can be expressed by the anomaly degree D :

$$D = \frac{A'}{A} \quad (1)$$

Here, $D = 1$ indicates that the cable is intact, and $D = 0$ indicates complete failure.

For elastic modulus reduction, based on the axial force state of the stay cable, the relationship between effective stress σ' and the effective cross-sectional area A' of the material is:

$$\sigma' = \frac{F}{A'} \quad (2)$$

where F is the axial force acting on the cable; The reduction of elastic modulus also affects the mechanical performance of the cable, and the relationship between the anomaly degree D and elastic modulus reduction is:

$$E' = E \cdot D \quad (3)$$

where E is the elastic modulus in the intact condition, and E' is the elastic modulus under the anomaly condition.

2.1.3. Fitted Displacement Indicator of the Main Girder

As an integral structure, the main girder of a bridge exhibits a certain correlation among its measurement points. The correlation refers to the spatial and temporal association of displacement responses between different points. When the bridge is in a healthy state, this correlation is manifested as consistency in displacement responses among measurement points, which can be represented by curve fitting to capture the displacement variation trend, thus reflecting the effect of cable anomalies on the main girder displacement.

Curve fitting is a mathematical method used to find a function that approximates given data points without necessarily passing exactly through each point. The goal is to make the function as close as possible to the data points overall while maintaining smoothness. Unlike interpolation, which requires the curve to pass through all given data points, fitting focuses on representing the overall trend. Polynomial fitting is a commonly used method. When the polynomial order is high, the condition number of the coefficient matrix increases, leading to numerical instability and large errors. To address this, orthogonal polynomials can be used to ensure a small condition number and improve fitting stability.

Let the displacements collected from multiple measurement points of the main girder at the same time be $x_0, x_1, \dots, x_k$, where k is the number of measurement points, and the fitted curve is a polynomial function of these displacements. Using the least squares method, the error function K is defined as:

$$K = \sum_{i=1}^k (x_i - \hat{x}_i)^2 \quad (4)$$

where x_i is the fitted displacement. Minimizing this error function yields the optimal fitting curve:

$$\frac{\partial K}{\partial a_n} = 0 \quad (5)$$

By fitting the data using orthogonal polynomials, the final result can be expressed as:

$$\hat{x}(t) = \sum_{n=0}^m a_n x(t)^n \quad (6)$$

where a_n is the polynomial coefficient, and m is the polynomial order. This fitted curve can well reflect the displacement variation trend of the main girder measurement points.

To evaluate the fitting error, the Root Mean Square Error (RMSE) is calculated as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^n ((y_i^t)' - y_i^t)^2}{n}} \quad (7)$$

The Root Mean Square Error Difference (RMSED) between the fitted displacements before and after a cable anomaly is then computed as:

$$RMSED(i) = RMSE_{dam}(i) - RMSE_{nondam}(i) \quad (8)$$

where nondam denotes the structure without anomalies, dam denotes the structure with anomalies, and i is the measurement point index.

By comparing RMSED values before and after the anomaly, the anomaly location can be identified. If the RMSE change at a measurement point is significantly greater than at other points, the anomaly location corresponding to that point can be determined.

2.2. Multi-Point Main Girder Displacement Identification Method Based on Grayscale–Displacement Mapping Model

2.2.1. Perspective Transformation for Target Motion

In target motion analysis, the Eulerian perspective and the Lagrangian perspective are two commonly used methods. The Eulerian perspective focuses on the overall state of the flow field, analyzing displacement by observing the structural motion state, while the Lagrangian perspective focuses on the trajectory of each material point. For bridge displacement measurement, the Eulerian perspective offers higher efficiency and is particularly suitable for structural health monitoring, as it effectively avoids the high computational cost and complexity of the Lagrangian method. Therefore, the Eulerian perspective is adopted to construct the motion model (Figure 3).

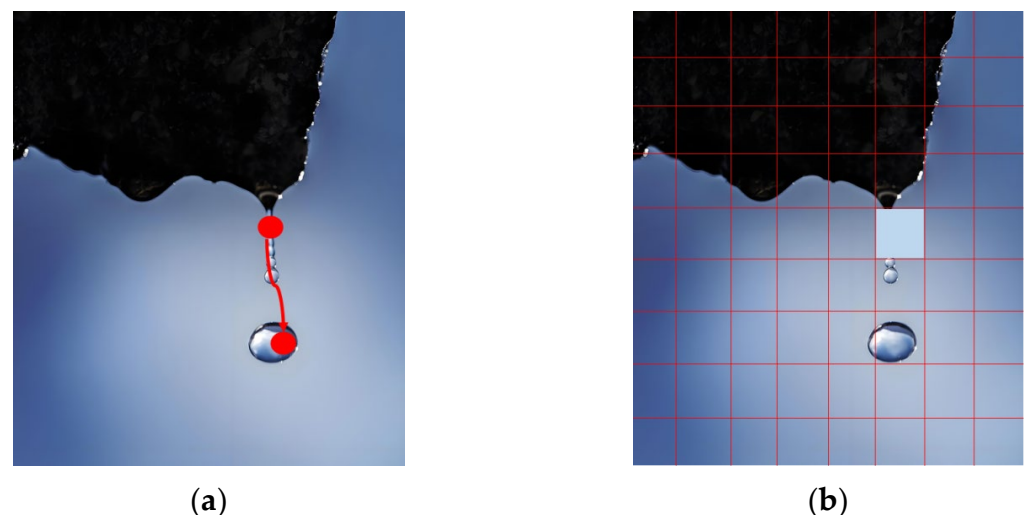


Figure 3. Motion recognition diagram of the two methods: (a) Lagrangian perspective; (b) Eulerian perspective.

2.2.2. Correlation Between Grayscale Changes and Image Displacement

When exploring the relationship between grayscale changes and image displacement, it is assumed that the grayscale distribution of the image shifts along a certain direction, and a displacement function related to time is defined. We assume the image grayscale function is continuous and the displacement change is small. However, since image grayscale values are discrete, the displacement function may exhibit significant changes

in practical applications, necessitating further adjustments to the model to accommodate this discreteness and discontinuity. For edge regions, a model describing the relationship between grayscale changes and displacement is established, capable of capturing dynamic changes in the time series, as shown in Equations (9) and (10).

$$\phi(x, t) \approx g(x) + \varphi_x(t) \frac{\partial g(x)}{\partial x} \quad (9)$$

$$\phi(x, t) \approx \phi(x, 0) + \varphi_x(t) \frac{\partial g(x)}{\partial x} \quad (10)$$

Through Equations (11) and (12), displacement changes in the x and y directions can be obtained, and further combined to derive Equation (13), which indicates that the displacement of a fixed observation point in the image can be calculated based on grayscale changes and variations in the initial grayscale values. This derivation is based on two preconditions: the grayscale of the foreground and background is continuous and does not contain displacement information. Additionally, the displacement change needs to be linear to maintain the accuracy of the formula. In practical operations, especially with manually marked points, these conditions are difficult to fully satisfy, so further model optimization may be needed to improve identification accuracy.

$$\varphi_x(t) \approx \frac{\phi(x, t) - \phi(x, 0)}{\frac{\partial g(x)}{\partial x}} \quad (11)$$

$$\varphi_y(t) \approx \frac{\phi(y, t) - \phi(y, 0)}{\frac{\partial g(y)}{\partial y}} \quad (12)$$

$$\varphi(t) = (\phi(x, y, t) - \phi(x, y, 0)) \left(\frac{1}{\frac{\partial \phi(x, y, 0)}{\partial x}} + \frac{1}{\frac{\partial \phi(x, y, 0)}{\partial y}} \right) \quad (13)$$

2.2.3. Development of a Grayscale-to-Displacement Mapping Model

Under the Eulerian perspective, edge information in the image is key to displacement identification. By analyzing the foreground and background regions in the image, a mapping model based on grayscale values is established. It is assumed that the grayscale distribution of the foreground and background is uniform within their respective regions, and the shape of the foreground edge approximates a straight line, thus establishing the geometric relationship between the foreground and background (Figure 4).

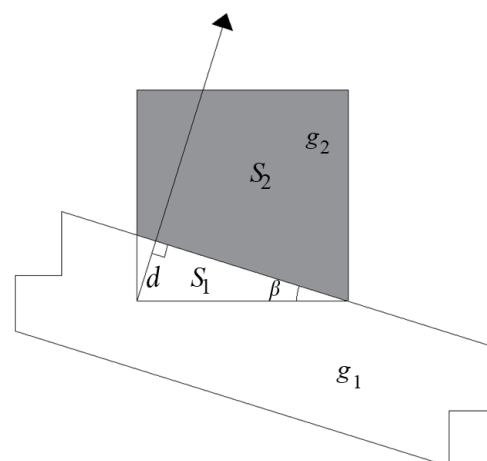


Figure 4. Foreground—background gray distribution.

By deriving this model, the spatial pixel distance relationship between edge changes and displacement in the image can be further analyzed, as shown in Equation (14). Here, S_1 is the foreground coverage area, β is the angle of the foreground region boundary, and d is the distance between the edge and the vertex of the subregion within the foreground coverage area.

$$d = \begin{cases} \frac{S_1}{w}, \beta = 0 \\ \sqrt{2S_1 \sin \beta \cos \beta}, & S_1 \leq \frac{S \tan \beta}{2} \\ \frac{\cos \beta}{2} \left(\frac{2S_1}{\sqrt{S}} + \tan \beta \sqrt{S} \right), & \frac{S \tan \beta}{2} < S_1 \leq S \left(1 - \frac{\tan \beta}{2} \right) \\ \cos \beta \left(\sqrt{S} (1 + \tan \beta) - \sqrt{2 \tan \beta \cdot (S - S_1)} \right), & S \left(1 - \frac{\tan \beta}{2} \right) < S_1 \leq S \end{cases} \quad \beta \in (0^\circ, 45^\circ] \quad (14)$$

2.3. Multi-Point Displacement Data-Driven Stay Cable Anomaly Identification

2.3.1. Setting of Stay Cable Anomaly Variables

To verify the effectiveness of stay cable anomaly indicators in practical environments, this section adopts the method of loosening the stay cable to simulate anomalies. Unlike the simulation environment, anomaly identification in real environments needs to consider more variables and environmental factors. Therefore, theoretical analysis is first conducted to explore how changes in the elastic modulus of the stay cable affect anomaly settings. The natural frequency of the stay cable is measured using Fourier transform, and the first-order frequency differences between the normal and loosened states of the stay cable are analyzed, as shown in Equation (15) and Table 1. In the experiment, by measuring the frequency changes under different force states of the stay cable, it is confirmed that the elastic modulus of the stay cable significantly decreases after loosening. This change provides a theoretical basis for subsequent anomaly identification.

$$T_s = \frac{4m_s l^2 f_n^2}{n^2} - \frac{n^2 \pi^2 EI}{l^2} \quad (15)$$

In Equation (15), n is the order of the stay cable's natural frequency, f_n is the n -th order natural frequency of the stay cable, l is the calculated length of the stay cable (distance between fixed ends), EI is the bending stiffness of the stay cable, where E is the elastic modulus of the stay cable material, and m_s is the mass per unit length of the stay cable.

Table 1. First order frequency measurement results of target cable.

Stay Cable State	Stay Cable First-Order Frequency (Hz)	Force State 1	Force State 2
Normal		8.529	9.808
Loosened		5.962	6.608

2.3.2. Experimental Setup at the Test Site

In the experimental setup, a 1:70 scale model of the Guanhe Bridge on the Lianyungang-Yancheng section of the Jiangsu Coastal Expressway was selected. The model is a double-tower, double-cable-plane, three-span cable-stayed bridge. Experimental equipment includes a high-resolution camera and a remote-controlled vehicle. By properly configuring the camera and vehicle, the experiment ensures accurate measurement of displacement changes on the main girder. The total length of the model bridge is 9.1 m, with a span combination of 2.15 + 4.8 + 2.15 m. The equipment parameters used in the experiment are shown in Table 2. By precisely controlling the uniform speed of the vehicle, the operating

condition of the actual bridge under traffic load is simulated, ensuring the reliability and authenticity of the experimental results.

Table 2. Test equipment parameters.

Equipment	Parameters	Model
Camera	Resolution: 3840 × 2160; Sampling frequency: 25 Hz	Sony FDR-AX700
Push-rod displacement meter	Range: 0–50 mm	DH5G103
Strain gauge	Sampling frequency: 0–100 Hz	DH5920

2.3.3. Experimental Condition Design

During the experiment, the trolley was moved across the bridge deck at a constant speed to simulate real-world vehicle passage. Three iron plates, each weighing approximately 20 kg, were placed on the trolley. Stay cable anomalies were created by adjusting the tension of the stay cables at their anchor points on the bridge deck.

A camera was used for orthophotography of the black-and-white markers shown in Figure 5 as the trolley fully traversed the bridge. The displacement of the 12 main girder markers in Figure 5 was then calculated. The markers were located at positions generally corresponding to the stay cable and bridge deck anchor points, with equal spacing between each of the 12 markers (numbered 1 to 12 from left to right).

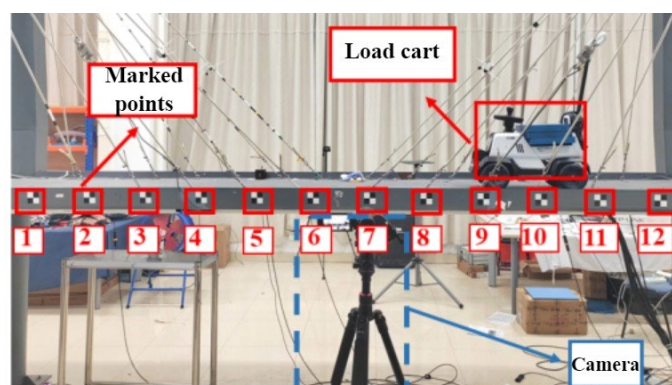


Figure 5. Layout of cable anomaly recognition test.

This experiment included two different conditions, as shown in Table 3. The study area was the mid-span section of the main girder. Since the measurement points were symmetrically arranged about the mid-span center, stay cables corresponding to main girder measurement points 3, 6 were loosened to make the study conditions more comprehensive. These points correspond to approximately the 1/4 and 1/2 positions of the main girder mid-span. To avoid coupling of the experimental results due to multiple variables, multiple repeated tests were conducted before and after the stay cables were loosened.

Table 3. Layout of cable anomaly recognition test.

Condition	Stay Cable Anomaly Position
B1	Main Girder Measurement Point 3
B2	Main Girder Measurement Point 6

2.4. WOA-Optimized Random Forest Model

The WOA simulates the hunting behavior of humpback whales. The hunting process can be divided into three main phases: encircling prey, bubble-net attacking, and

searching for prey. These phases are abstracted into mathematical models to achieve global optimization. The detailed steps of WOA are as follows.

Assume that the best individual in the current population represents the prey (i.e., the current optimal solution), and all other whale individuals update their positions by moving toward the optimal whale (or a randomly selected whale). This process is implemented using specific mathematical formulas that gradually bring each whale closer to the optimal solution. The position update formula is as follows:

$$\begin{cases} d = |CD * (\hat{k}) - D(\hat{k})| \\ D(\hat{k} + 1) = D * (\hat{k}) - Ud \\ U = 2a\hat{r} - a \\ V = 2\hat{r} \end{cases} \quad (16)$$

In Equation (16), d is the distance between the prey and the current whale, $D * (\hat{k})$ is the position of the optimal whale (i.e., the current optimal solution), and $\hat{k}$ is the current iteration number. C , U and V are correlation coefficients, $\hat{r}$ is a random number in $(0, 1)$, and a is a coefficient that decreases from 2 to 0.

The whale circles around the prey and performs the hunt, as described below:

$$\begin{cases} D(\hat{k} + 1) = D * (\hat{k}) + d_q e^{bl} \cos 2\pi l \\ d_q = |D * (\hat{k}) - D(\hat{k})| \end{cases} \quad (17)$$

In Equation (17), d_q is the distance between the whale and the prey, b is a constant, and l is a number in $[-1, 1]$.

The whale gradually approaches the prey (the current optimal solution) through a spiral model. This step is also implemented using a specific mathematical formula:

$$\begin{cases} D(\hat{k} + 1) = D * (\hat{k}) - Ud, & q < 0.5 \\ D(\hat{k} + 1) = D * (\hat{k}) + d_q e^{bt} \cos 2\pi l, & q \geq 0.5 \end{cases} \quad (18)$$

To search for more prey, the whale adopts a natural search method. This process can be expressed as:

$$\begin{cases} d = |CD_{\hat{r}} - D(\hat{k})| \\ D(\hat{k} + 1) = D_{\hat{r}} - Ud \end{cases} \quad (19)$$

In Equation (19), $D_{\hat{r}}$ is the position of a randomly selected whale.

After the position of a randomly selected whale is determined, the positions of other whales are updated. This effectively improves the global search ability of the algorithm. Applying the Whale Optimization Algorithm to the parameter search of the random forest algorithm can improve the parameter search efficiency of the random forest algorithm, thereby establishing a WOA-optimized random forest model.

Specifically, the classification prediction process based on WOA-optimized random forest model is as follows. First, the sample set is randomly divided into a training set and a test set according to a certain ratio. Then, the parameters of the Random Forest are initialized, and the upper and lower bounds of the parameters to be optimized are set. Similarly, the parameters of the WOA are initialized, and the population size of the whales is set. Next, the optimal search position is determined. By continuously updating the positions through iterations until the termination condition is met, the optimal set of hyperparameters is output. Based on this, the WOA-optimized random forest model is constructed. The WOA algorithm has strong global search ability because it simulates the hunting characteristics of whales. In this chapter, WOA is applied to optimize the

parameters of the random forest model. By combining the strengths of both, the sensitivity of the random forest model to parameter settings is overcome, and the model's predictive ability and generalization performance are improved.

3. Experimental Results and Discussion

3.1. Finite Element Simulation Verification of Anomaly Indicators

In the finite element model of the cable-stayed bridge, the main bridge adopts a double-tower, double-cable-plane, semi-floating, five-span continuous composite girder, which is a symmetrical structure. The study area selects the measurement points on the main girder corresponding to the 13 stay cables in the left half of the mid-span, as shown in Figure 6, with 25 measurement points arranged to ensure equal spacing. The model design vehicle speed is 100 km/h, and a 10-ton load passing the bridge deck at a uniform speed of 45 km/h is selected for analysis.

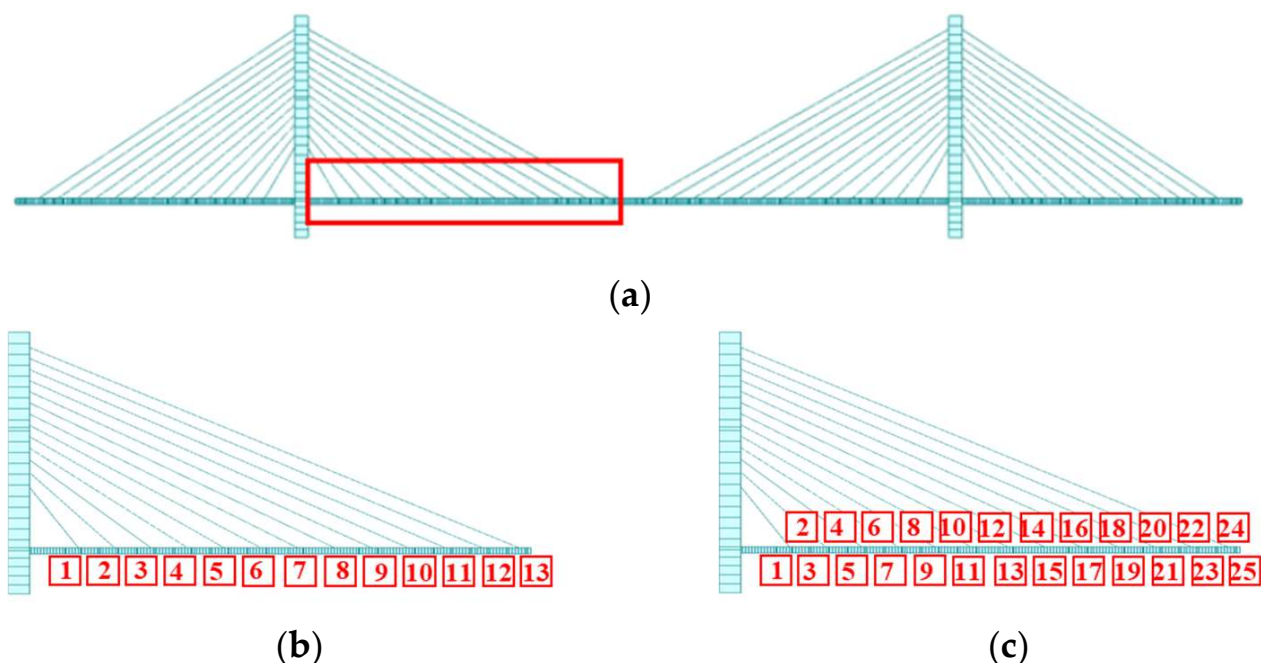


Figure 6. Layout of main beam and cable measurement points of cable-stayed bridge: (a) Selection of the study area of the cable-stayed bridge model; (b) Layout of corresponding stay cable measurement points in the study area; (c) Layout of corresponding main girder measurement points in the study area.

In the stay cable anomaly state, it is assumed that the elastic modulus of the stay cable is reduced by 30%. The condition settings are shown in Table 4, selecting stay cables at the 1/4, 1/2, and 3/4 positions of the study area for anomaly simulation. Figures 7 and 8 show the time-history displacement curves of the main girder under intact and anomalous states, where the displacement differences under the anomalous state are small, requiring judgment through stay cable anomaly identification indicators.

Table 4. Setting of abnormal conditions of the cable.

Condition	Stay Cable Anomaly Position
A1	Stay Cable 4 (Main Girder Measurement Point 7)
A2	Stay Cable 7 (Main Girder Measurement Point 13)
A3	Stay Cable 10 (Main Girder Measurement Point 19)

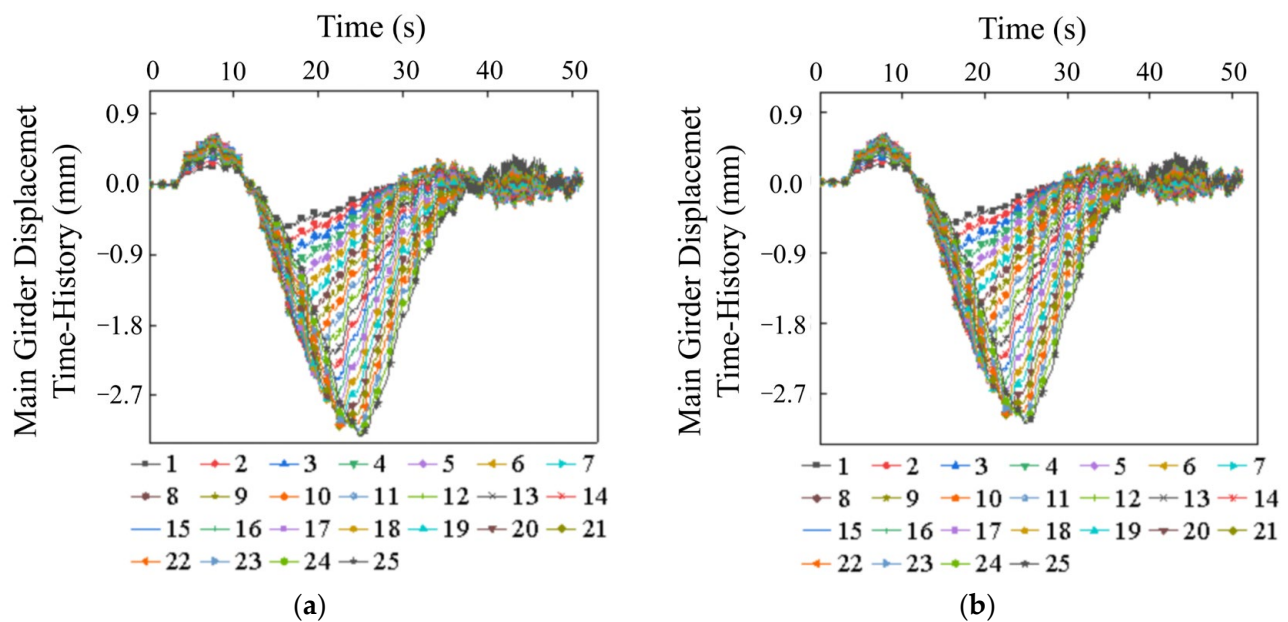


Figure 7. Time history displacement curve of a main beam measuring point when $v = 45$ km/h: (a) Intact stay cable state; (b) Stay Cable 7 anomaly.

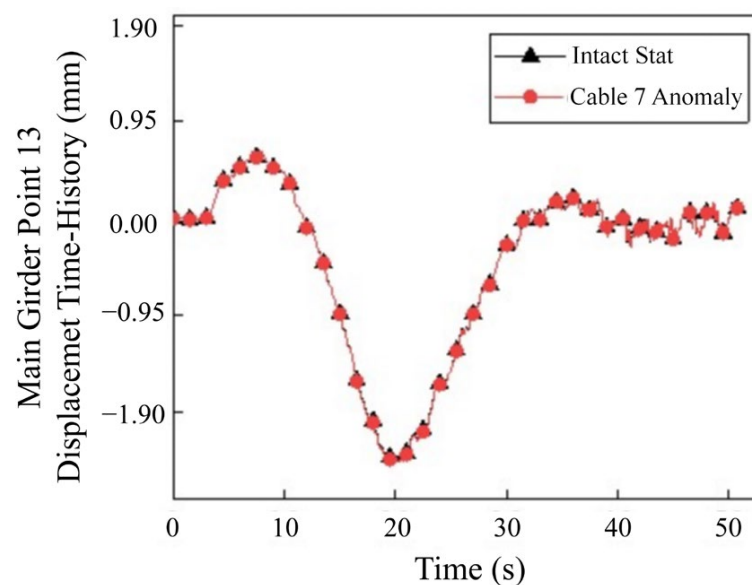


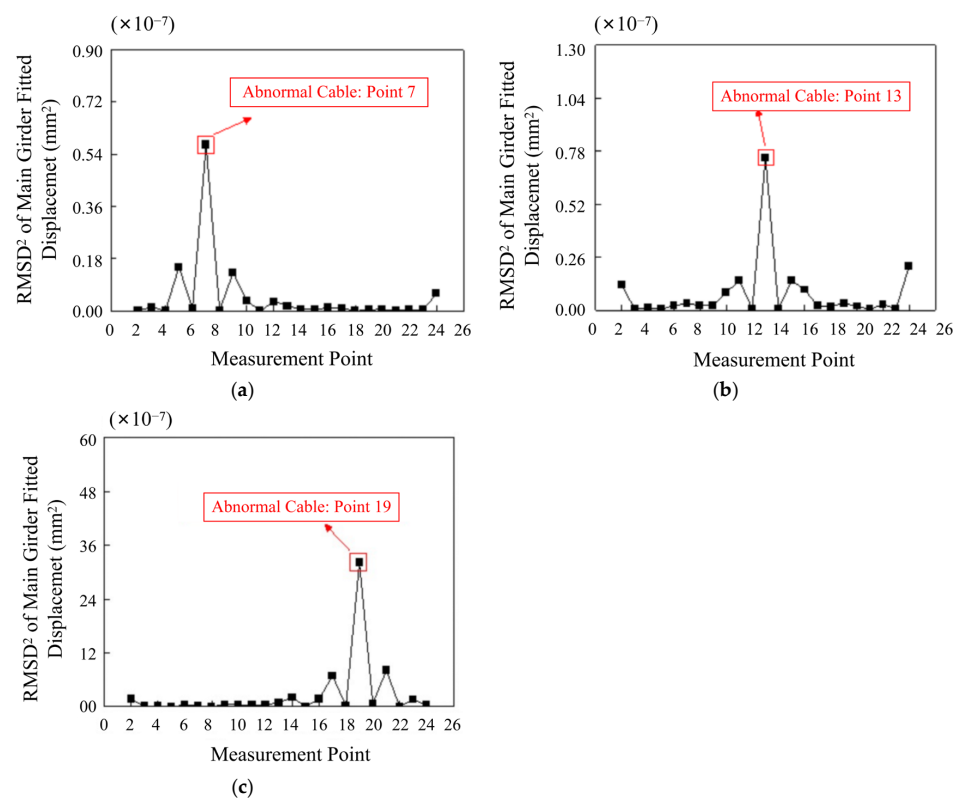
Figure 8. Time history displacement curve of measuring point 13 of the main beam when $v = 45$ km/h.

3.1.1. Calculation Results of Main Girder Fitted Displacement Indicator

Based on different fitting orders, the RMSE values of the fitted displacement of the main girder measurement points are calculated (see Table 5). When the fitting order is 1, the error is large, but as the order increases, the RMSE gradually decreases. At the 9th order, the RMSE is minimized, so a 9th-order polynomial is selected for fitting. The fitting error difference (RMSED2) is shown in Figure 9, which can effectively identify the stay cable anomaly position. The fitting results indicate that the fitting error is larger for measurement points near the endpoints, which may affect anomaly identification, suggesting the need to increase the number of measurement points.

Table 5. The fitting RMSE of the displacement at the measuring points of the main beam under different fitting orders when the cable is in good condition/mm ($\times 10^{-4}$).

Measurement Point \ Fitting Order	1st Order	2nd Order	3rd Order	4th Order	5th Order	6th Order	7th Order	8th Order	9th Order
Measurement Point 1	3454.81	1433.10	936.99	538.11	326.98	194.57	83.99	58.96	38.17
Measurement Point 2	2652.28	731.13	143.44	50.59	82.62	47.10	24.14	15.27	10.56
Measurement Point 3	1934.90	339.94	227.20	164.75	103.55	42.97	8.90	9.87	9.17
Measurement Point 4	1294.53	311.26	364.92	199.36	49.69	6.77	9.59	7.59	8.25
Measurement Point 5	789.21	466.60	397.21	167.57	31.08	29.18	12.25	6.37	5.62
Measurement Point 6	572.06	604.36	345.01	93.96	65.29	37.30	7.53	7.17	6.91
Measurement Point 7	771.01	701.72	248.39	59.13	76.58	29.47	8.63	7.91	7.33
Measurement Point 8	1111.26	747.60	158.90	120.25	61.97	10.17	10.16	6.85	6.56
Measurement Point 9	1420.93	746.40	177.67	173.92	38.47	19.21	9.96	6.52	6.51
Measurement Point 10	1682.83	688.72	257.70	195.89	33.37	33.77	6.73	6.17	5.56
Measurement Point 11	1862.42	583.02	315.70	177.57	51.38	34.50	6.56	6.28	5.58
Measurement Point 12	1981.72	445.31	342.20	125.58	65.38	25.01	9.34	6.53	6.04
Measurement Point 13	2019.94	328.78	328.78	62.78	62.78	9.19	9.19	5.67	5.67
Measurement Point 14	2003.66	342.08	294.37	88.05	51.66	21.03	8.03	6.52	6.07
Measurement Point 15	1912.89	471.00	244.51	154.62	35.99	33.98	6.21	6.36	5.43
Measurement Point 16	1769.77	633.11	206.70	200.41	36.69	35.98	7.24	5.32	4.72
Measurement Point 17	1552.26	752.88	195.45	204.07	50.88	24.34	8.85	5.00	5.00
Measurement Point 18	1284.52	821.58	224.20	166.04	60.96	8.33	8.33	5.62	4.73
Measurement Point 19	967.14	807.89	269.97	88.48	59.15	26.73	6.00	6.34	5.35
Measurement Point 20	717.81	724.57	312.58	65.92	45.53	40.28	7.22	5.61	5.30
Measurement Point 21	791.46	551.46	326.88	167.82	30.75	34.82	9.84	5.00	4.20
Measurement Point 22	1275.09	325.21	296.62	236.97	51.63	8.14	7.84	6.91	5.13
Measurement Point 23	1976.12	304.66	203.29	222.62	77.17	43.34	6.93	5.74	5.55
Measurement Point 24	2814.47	797.98	166.17	78.20	58.52	57.57	16.31	11.99	6.84
Measurement Point 25	3771.91	1643.88	781.93	671.95	249.98	221.84	64.01	51.36	26.36

**Figure 9.** The RMSED2 calculation result of the fitted displacement of the main beam measuring points: (a) Condition A1; (b) Condition A2; (c) Condition A3.

3.1.2. Calculation Results of Main Girder Effective Displacement Indicator

The effective displacement difference (EDD2) of the main girder measurement points is calculated and squared for intuitive identification of stay cable anomalies. Figure 10 shows that under conditions A1, A2, and A3, this method can accurately identify the anomaly position. The EDD2 of the main girder measurement points increases as the measurement points approach the mid-span, and even measurement points near the endpoints can effectively identify anomalies. Compared to fitted displacement, the effective displacement method does not require consideration of measurement point spacing, enabling more stable identification of anomaly positions and highlighting the impact of anomalies.

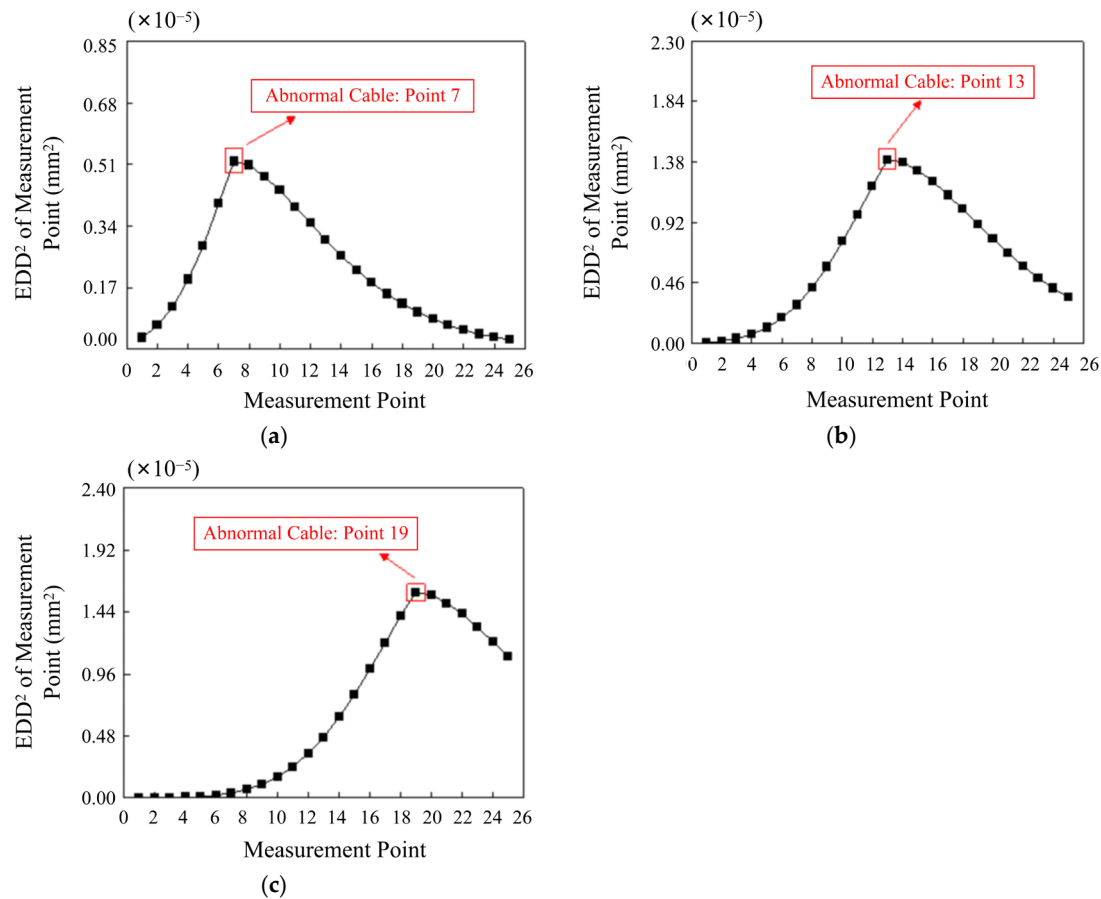


Figure 10. EDD2 calculation results of main beam measuring points: (a) Condition A1; (b) Condition A2; (c) Condition A3.

3.2. Verification of Multi-Point Displacement Identification of the Main Girder Using the Grayscale–Displacement Mapping Model

3.2.1. Image Motion Information Extraction Based on Dual-Threshold Segmentation Method

To extract precise displacement information from images, a dual-threshold segmentation method is adopted. First, edge detection technology is used to obtain the grayscale distribution of the image, followed by logical operations to achieve effective separation of the foreground and background. This method ensures clear differentiation of the foreground and background in complex environments, effectively eliminating noise interference in displacement calculations (Equation (20)).

$$\begin{cases} G_{\max} = (1 - \alpha)N_{ed} + \alpha M_{\max} \\ G_{\min} = (1 - \alpha)N_{ed} + \alpha M_{\min} \end{cases} \quad (20)$$

In Equation (20), the thresholds $G_{\max}$ and $G_{\min}$ can be adjusted as the background and foreground thresholds based on the actual measurement scenario, N_{ed} is the average grayscale value of the edge, $M_{\max}$ and $M_{\min}$ are the maximum and minimum grayscale values in the subregion, respectively, and α is the scaling factor, with a default value of 0.5, which can be dynamically adjusted during the foreground-background segmentation process. In practical applications, the dual-threshold segmentation method can handle grayscale fluctuations in images and provide accurate input data for subsequent displacement calculations. Through laboratory tests and validation with actual bridge models, the dual-threshold segmentation method can stably separate the foreground and background in multiple scenarios, particularly in dynamic environments, with high accuracy in distinguishing the foreground and background. Compared to traditional edge detection methods, this approach can effectively handle complex backgrounds in images, improving the stability and accuracy of image displacement extraction.

3.2.2. Image Motion Information Extraction Based on Statistical Methods

In addition to the dual-threshold segmentation method, this paper introduces a grayscale information extraction technique based on statistical methods. This method statistically analyzes the distribution of grayscale values in the image, calculates the statistical probability within the grayscale range, and processes the grayscale range based on a set reduction ratio (Equation (21)).

$$v = 2^{\lfloor \log_2 c \rfloor} \quad (21)$$

In Equation (21), c is the continuity detection result of the image grayscale distribution, defined as the minimum grayscale range length where the statistical probability of the grayscale range is $[0, 255]$ continuously non-zero, and $\lfloor \log_2 c \rfloor$ denotes the floor function. This method can reduce computational complexity without losing important information, particularly in cases with large images or limited computational resources, effectively improving processing efficiency. The advantage of the statistical method lies in its flexibility and adaptability. As the grayscale distribution in the image varies unevenly, this method can automatically adjust the processing strategy for the grayscale range, optimizing the extraction results. Experimental validation shows that this method provides high identification accuracy in various complex environments, demonstrating strong stability and rapid response capabilities, especially in dynamic monitoring and high-frequency data extraction.

3.2.3. Conversion of Pixel Displacement to Actual Displacement

After obtaining pixel displacement, the next step is to convert it into actual physical displacement. To this end, the time baseline parallax method is adopted. This method requires the camera to remain stationary during shooting and ensures that the image plane is parallel to the target being measured. By capturing two images with a time interval, the parallax value of the object in the image pair is calculated to obtain the displacement as shown in the Figure 11.

When the monitoring point moves from the initial position B to a new position B', the deformation in the vertical direction is denoted as ΔZ , and the deformation in the horizontal direction is denoted as ΔX . These two deformation components represent the displacement changes of the monitoring point in two mutually perpendicular directions and are key parameters for describing the overall displacement state of the monitoring point. The deformations in the horizontal and vertical directions can be expressed as:

$$\begin{cases} \Delta X = \frac{\hat{Y}}{\hat{f}} \Delta P_x = \zeta \Delta P_x \\ \Delta Z = \frac{\hat{Y}}{\hat{f}} \Delta P_z = \zeta \Delta P_z \end{cases} \quad (22)$$

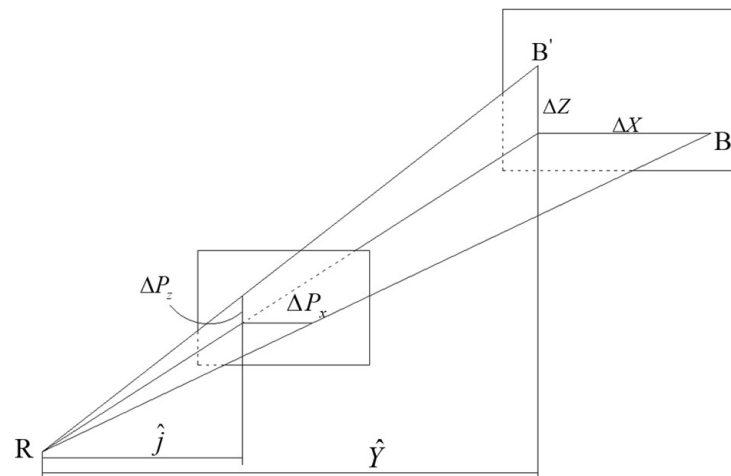


Figure 11. Geometric relationship of point imaging of target object.

In Equation (22), $\hat{Y}$ is the distance from the optical center to the object plane, $\hat{f}$ is the focal length of the camera, and ΔP_x and ΔP_z represent the disparities in the horizontal and vertical directions, respectively.

We set two points on the image as a' and b' , corresponding to points a and b on the surface of the actual target object, as shown in the Figure 12.

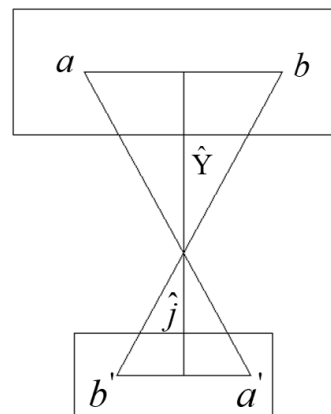


Figure 12. Schematic diagram of photographic scale.

The actual distance between points a and b in real space is denoted as L_{ab} , and the pixel distance between a' and b' on the image is denoted as $L_{a'b'}$. Based on the proportional relationship between these two distances, the photographic scale can be calculated as shown in Equation (23):

$$\zeta = \frac{\hat{Y}}{\hat{f}} = \frac{L_{ab}}{L_{a'b'}} \quad (23)$$

When the image plane is parallel to the object plane, the coefficient ζ can be obtained given the linear distance between any two points on the object plane and the corresponding distance d on the image plane. However, in practical applications, it is rare for the object plane and image plane to be absolutely parallel. Therefore, the handling method for non-parallel cases needs to be discussed.

As shown in Figure 13, the plane O_1 represents the object plane where the target object is located, and another plane O_2 is obtained by horizontally rotating O_1 by a certain angle γ so that O_2 is perpendicular to the main optical axis. Clearly, the CCD plane and Π_2 are parallel to each other, satisfying the basic conditions of the time baseline parallax method, where the displacements on the two planes are linearly related according to the photographic scale. Therefore, calculations only need to consider the relationship between the displacements on the original object plane and the reference object plane.

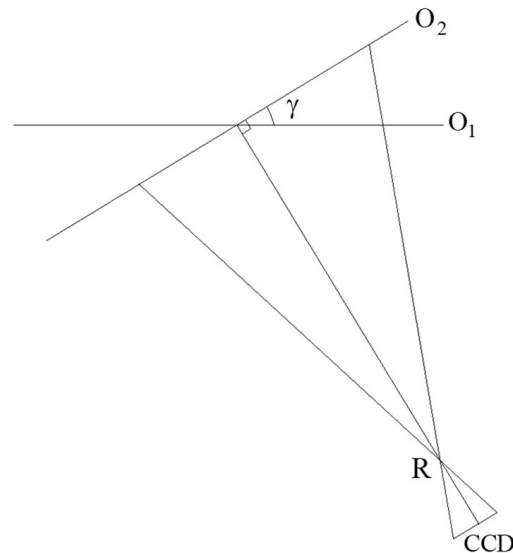


Figure 13. Schematic diagram of camera tilt photography.

As shown in Figure 14, the reference object plane can be expressed as $O_2: z = Z_p$, and the original object plane as $O_1: z + x \cdot \tan \gamma = 0$. The optical center point is $R(0, 0, z_0)$. Let a point on the reference object plane O_2 be $P_1(x_1, y_1, 0)$, and the intersection of the line connecting P and the optical center point R with the original object plane O_1 be $P'_1(x'_1, y'_1, z'_1)$. The expression for the line segment RP_1 is:

$$\frac{x - x_1}{-x_1} = \frac{y - y_1}{-y_1} = \frac{z}{z_0} \quad (24)$$

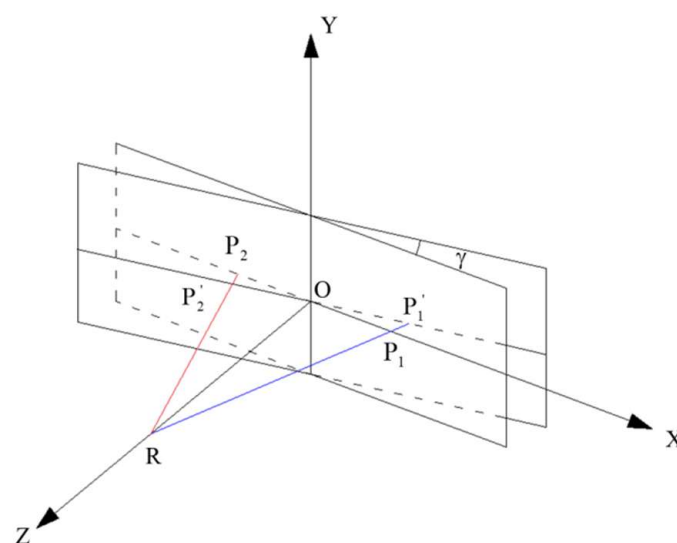


Figure 14. Schematic diagram of the relationship between the two planes.

Based on the equations of the original plane O_1 and reference object plane O_2 , the coordinates of point P'_1 can be obtained as:

$$\begin{cases} x'_1 = \frac{z_0 x_1}{z_0 - x_1 \tan \gamma} \\ y'_1 = y_1 \left(\frac{x_1 \tan \gamma}{x_1 (z_0 - x_1 \tan \gamma)} + 1 \right) \\ z'_1 = \frac{-z_0 x_1 \tan \gamma}{z_0 - x_1 \tan \gamma} \end{cases} \quad (25)$$

When solving for the coordinates of point P'_1 , the horizontal angle γ between the camera's main optical axis and the object plane, as well as the distance z_0 from the optical center to the object plane, need to be known. In practical engineering applications, the distance from the lens to the monitoring point is usually much larger than the coordinate values x_1 and y_1 on the reference object plane, so the coordinate transformation formula can be reasonably approximated to simplify the calculation process and improve computational efficiency. Thus:

$$\begin{cases} x'_1 = x_1 \\ y'_1 = y_1 \\ z'_1 = -x_1 \tan \gamma \end{cases} \quad (26)$$

Similarly, the coordinates of point P'_2 can be obtained from Equation (27); then the relationship between the length L of the segment $P_1 P_2$ on the reference plane and the length L' of the segment $P'_1 P'_2$ on the original object plane can be expressed as:

$$L' = \sqrt{L^2 + \tan^2 \gamma (x_1 - x_2)^2} \quad (27)$$

From Equation (27), when the angle θ is small, the effect of the angle between the original object plane and the reference object plane on the time baseline parallax method can be neglected. In summary, since this study focuses on the relative displacement of the bridge in the vertical direction, the time baseline parallax method remains applicable.

The advantage of the time baseline parallax method is that it can achieve high-precision displacement measurement without relying on complex equipment or conditions. For tilted photography, the actual displacement of the object can still be accurately calculated through coordinate transformation formulas. This method is widely used in bridge health monitoring systems, especially for real-time dynamic monitoring of large-span structures. Experiments show that this method can effectively convert pixel displacement into actual physical displacement, with high accuracy and robustness.

3.3. Multi-Point Displacement Data-Driven Stay Cable Anomaly Identification Results

3.3.1. Stay Cable Anomaly Identification Based on Main Girder Fitted Displacement Indicator

In the experiment, polynomial fitting of the displacement data of the main girder measurement points was used, and the fitting error (RMSE) was employed to detect the anomalous state of the stay cable. By fitting polynomials of different orders, it was found that low-order polynomials provided better fitting results, while high-order fittings might lead to unstable results. In experimental condition B2, measurement point 6 corresponds to the stay cable anomaly position, and when the stay cable anomaly occurs, the fitting error shows significant changes (Figure 15).

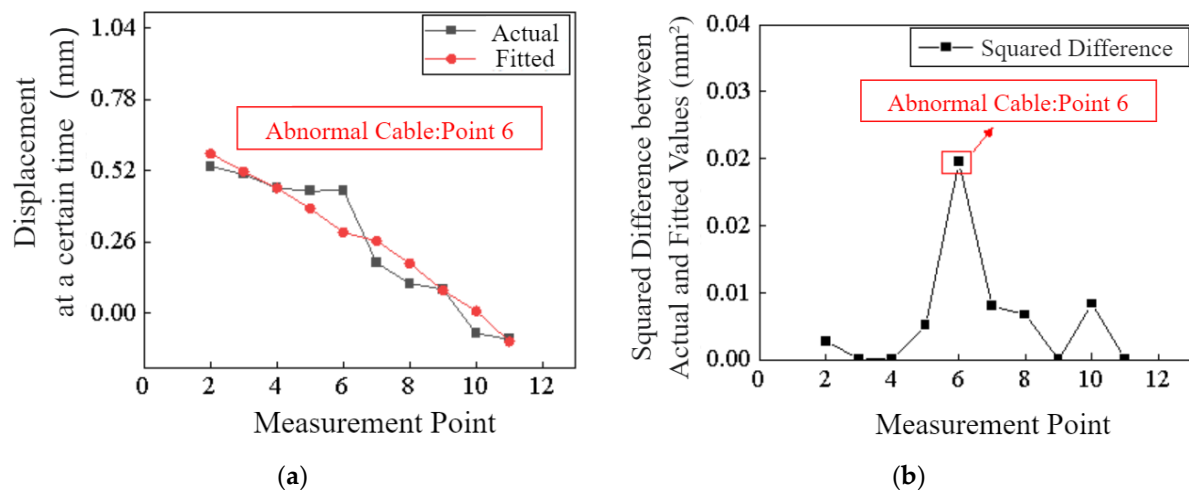


Figure 15. Fitting effect of measuring point displacement of main beam at a certain time in working condition B2: (a) Displacement values of main girder measurement points at a certain time; (b) Squared fitting difference of main girder measurement point displacement at a certain time.

By calculating the root mean square error difference (RMSED2) of the fitting error, the anomaly position can be accurately identified, and the effectiveness of this method was verified through repeated calculations in multiple experiments. The experiments show that changes in the stay cable position significantly affect the fitting error of the main girder measurement points in both normal and anomalous states, enabling accurate anomaly localization (Table 6).

Table 6. The fitting RMSE value of the main beam measurement point displacement under the intact stay cable condition in working condition B1/mm ($\times 10^{-2}$).

Measurement Point	Fitting Order	1st Order	2nd Order	3rd Order	4th Order	5th Order	6th Order	7th Order	8th Order	9th Order
	Measurement Point	Order	Order	Order	Order	Order	Order	Order	Order	Order
Measurement Point 2		16.20	7.66	7.69	7.77	9.54	10.47	15.89	40.82	84.16
Measurement Point 3		4.79	4.68	4.85	6.00	6.49	6.25	7.52	13.54	21.84
Measurement Point 4		6.79	5.93	6.40	6.82	7.92	7.85	7.75	8.69	10.30
Measurement Point 5		18.94	6.93	7.49	7.77	7.53	7.88	7.85	8.89	8.37
Measurement Point 6		16.93	3.44	3.35	3.61	4.06	5.20	6.34	6.84	10.72
Measurement Point 7		18.85	4.24	4.35	4.89	5.36	4.86	5.64	6.38	10.66
Measurement Point 8		10.79	6.84	7.59	7.60	7.64	7.46	7.67	9.17	8.27
Measurement Point 9		12.70	5.86	5.88	6.03	6.70	8.99	8.79	9.52	10.16
Measurement Point 10		5.02	4.89	4.72	5.19	5.77	5.76	8.57	14.82	21.59
Measurement Point 11		12.16	6.78	6.72	7.01	6.69	8.59	17.63	44.17	83.33

3.3.2. Stay Cable Anomaly Identification Based on Main Girder Effective Displacement Indicator

To enhance the stability and reliability of the results, a statistical averaging method was used to process multiple sets of repeated experimental data. By squaring the difference in effective displacement (EDD2) before and after the stay cable anomaly, the changes under the anomalous state can be effectively enhanced, further highlighting the fluctuations caused by the anomaly (Figures 16 and 17).

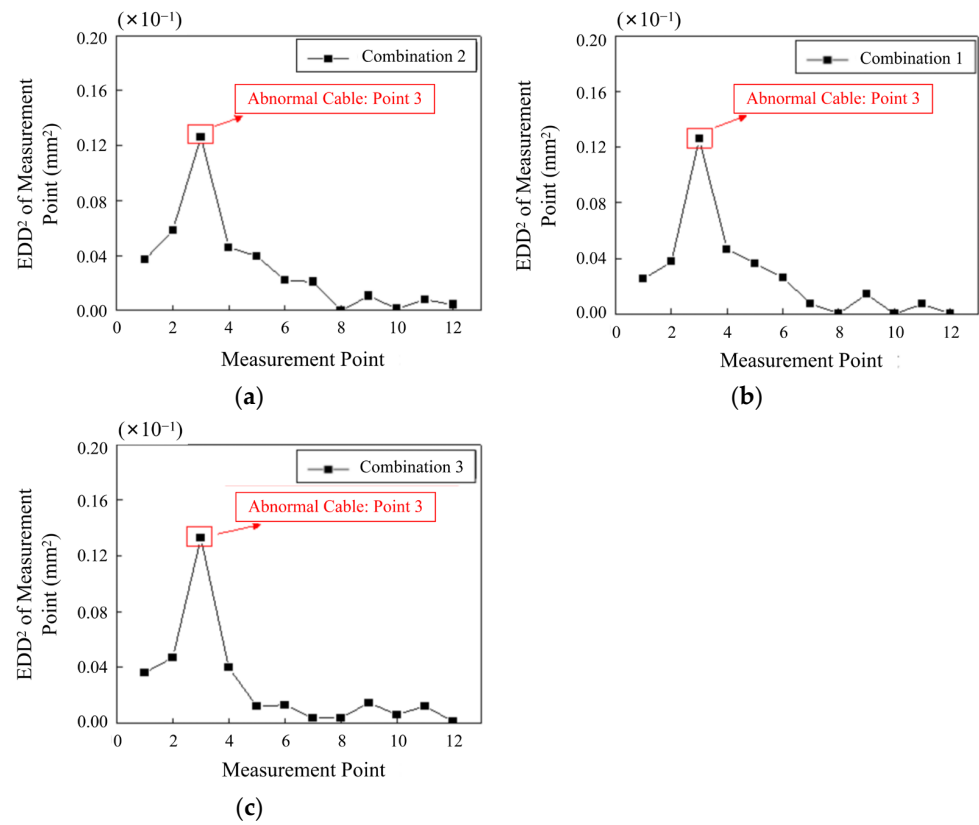


Figure 16. EDD2 calculation results of main beam measuring points under condition B1: (a) Combination 1; (b) Combination 2; (c) Combination 3.

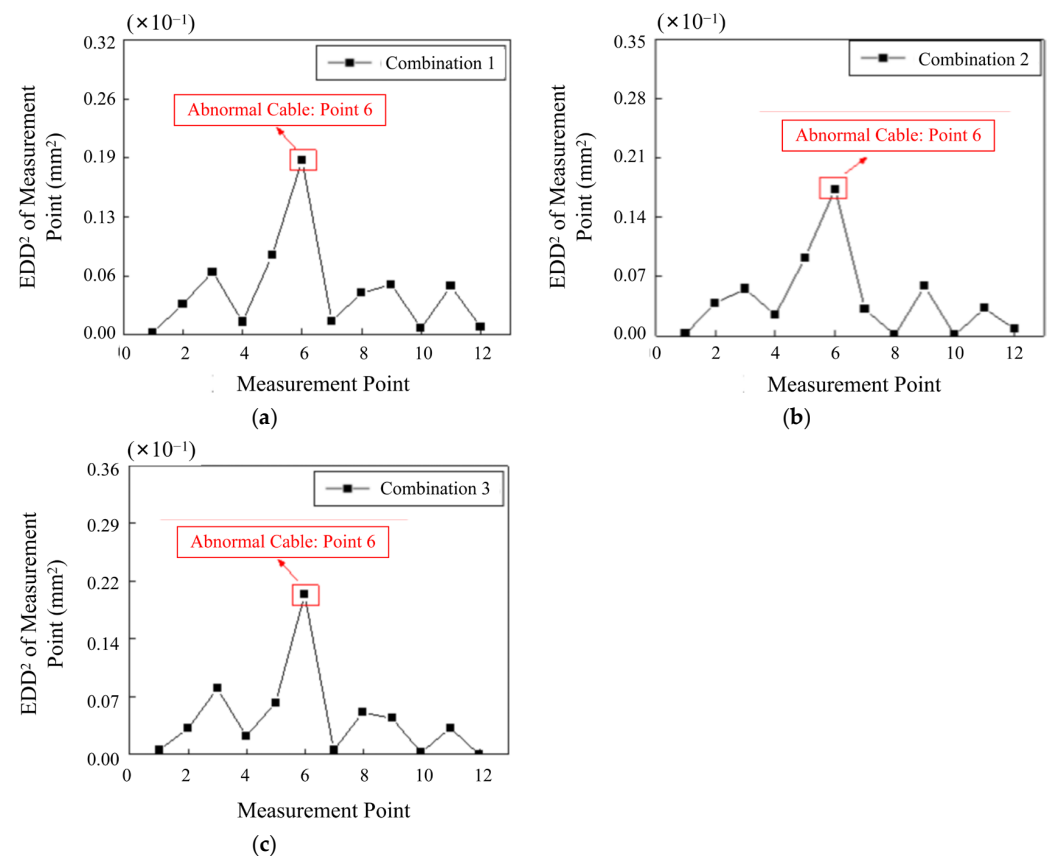


Figure 17. EDD2 calculation results of main beam measuring points under condition B2: (a) Combination 1; (b) Combination 2; (c) Combination 3.

The results show that under each condition, when a stay cable anomaly occurs, the EDD2 value of the main girder measurement points reaches a peak and is fully consistent with the preset anomaly position, proving the accuracy and reliability of the stay cable anomaly identification method based on the main girder effective displacement in practical applications.

3.4. Stay Cable Anomaly Classification and Prediction Results Based on WOA-Optimized Random Forest Model

3.4.1. Comparison of Prediction Results of Three Neural Network Models

To investigate the feasibility of WOA-optimized hyperparameters and the predictive performance of the WOA-optimized random forest model, the identification results of a single cable anomaly condition using WOA-optimized random forest model is compared with that using the random forest and back propagation neural network algorithm. The mid-span position of the main girder, approximately at 1/2 of its length, is taken as the research object. To ensure the feasibility of training three neural networks, the occurrence of a cable anomaly at this mid-span position is set as sample category 2, while other conditions are set as sample category 1. Thus, two sample categories, 1 and 2, are obtained.

The fitted displacement of the main girder can reflect cable anomalies to some extent. The fitted displacement at the measuring point corresponding to the anomalous cable location will differ from the fitted displacements at other locations at the same time. Therefore, a cable anomaly sample library is constructed based on the fitted displacements of 12 measuring points on the main girder. The fitted displacements of the 12 measuring points at each time step are used as inputs, and corresponding feature labels are sequentially assigned to them. Categories 1 and 2 are used as outputs. Finally, a total of 3348 samples are obtained, with 1674 samples in category 1 and 1674 samples in category 2. The total samples are randomly divided into a training set and a test set at a ratio of 8:2. The fitted displacements of the 12 measuring points are input into the WOA-optimized random forest, random forest and back propagation models for training, and then the test set is input into the models to obtain the prediction results of the test set. To further ensure the accuracy of the trained models and improve their generalization performance, new experimental data under the conditions of category 1 and category 2 are respectively selected as a validation set for validation. Finally, the prediction results of the training set, test set, and validation set are obtained.

To analyze the training results of the three neural network models more intuitively, their classification performance metrics, namely precision (Pre), recall (Re), and the weighted average of precision and recall (F1-score), are compared based on the confusion matrices of the training set, test set, and validation set, and are ranked accordingly, as shown in Table 7.

During neural network model training, the prediction results of the training set are critical, as they ensure the accuracy and reliability of subsequent predictions. It can be clearly seen from Table 7 that after optimizing the random forest algorithm using WOA, the Pre, Re, and F1-score of the model's prediction results are significantly improved. This indicates that WOA can achieve hyperparameter optimization of the random forest algorithm and enhance model performance. In contrast, the training results of the back propagation neural network are relatively poor, which is the reason why this study selects the random forest algorithm as the base and uses WOA to optimize it.

Table 7. The classification performance indicators and rankings of different sample set categories for three types of neural network models.

		P_{re}	P_{re} Rank	R_e	R_e Rank	$F_{1-score}$	$F_{1-score}$ Rank	All Score
Training set	WOA-optimized random forest	1	1	1	1	1	1	3
	Random forest	1	1	0.997	2	0.998	2	5
	Back propagation	0.508	2	0.691	3	0.586	3	8
Test set	WOA-optimized random forestF	0.912	1	0.893	1	0.902	1	3
	Random forest	0.465	3	0.423	3	0.443	3	9
	Back propagation	0.484	2	0.687	2	0.568	2	6
Validation set	WOA-optimized random forest	0.874	1	0.947	1	0.909	1	3
	Random forest	0.535	2	0.516	3	0.525	3	8
	Back propagation	0.52	3	0.596	2	0.555	2	7

3.4.2. Stay Cable Anomaly Identification Based on Main Girder Fitted Displacement and WOA-Optimized Random Forest Model

The experimental results show that the WOA-optimized random forest model can successfully identify the stay cable anomaly position. On the training set, the model's prediction accuracy reached 100%, while on the test set and validation set, the prediction accuracies were 84.76% and 94.04%, respectively. This indicates that the model not only has high accuracy during training but also possesses good generalization ability. Based on the confusion matrix analysis, although the prediction results on the test set are slightly less ideal, the overall classification performance remains good, particularly in the validation set, where the model can accurately identify the anomaly positions of all categories. Additionally, classification performance indicators (such as accuracy, precision, recall, and F1-score) also show that the WOA-optimized random forest model outperforms other models (Table 8).

Table 8. Performance indicators of different categories.

Category		Pre	Re	F1-Score
Category 1	Test Set	0.839	0.856	0.847
	Validation Set	0.945	0.965	0.955
Category 2	Test Set	0.901	0.853	0.876
	Validation Set	0.97	0.912	0.940
Category 3	Test Set	0.804	0.835	0.819
	Validation Set	0.909	0.944	0.926

Specifically, Category 2 shows relatively good prediction performance on both the test set and validation set, while Category 1 demonstrates high stability. Overall, the WOA-optimized random forest model exhibits the best performance in stay cable anomaly identification, with significant recognition capabilities.

3.4.3. Experimental Results: Stay Cable Anomaly Identification Based on Main Girder Effective Displacement and WOA-Optimized Random Forest Model

Similar to the results based on fitted displacement, the experimental results based on the main girder effective displacement also show that the WOA-optimized random forest model performs excellently in stay cable anomaly identification. The prediction accuracy on the training set and test set both reached 100%, and the validation set achieved an accuracy of 92.5%. Among the classification performance indicators for different categories,

Category 1 (located at approximately the 1/4 position of the mid-span) shows the best classification performance, while the other two categories also exhibit good prediction results (Table 9).

Table 9. Performance indicators of different categories.

Category		Pre	Re	F1-Score
Category 1	Test Set	1	1	1.000
	Validation Set	1	1	1.000
Category 2	Test Set	0.971	1	0.985
	Validation Set	0.947	0.900	0.923
Category 3	Test Set	1	0.977	0.988
	Validation Set	0.905	0.950	0.927

These experimental results indicate that the WOA-optimized random forest model can achieve high accuracy in stay cable anomaly identification based on the main girder effective displacement, with strong generalization ability across multiple conditions, effectively addressing errors caused by environmental factors during the experiment.

4. Conclusions

Based on a river-crossing cable-stayed bridge project, this paper integrates finite element modeling, machine vision technology, and optimized neural network algorithms to propose a stay cable anomaly identification method based on multi-point displacement measurements of the main girder. The main conclusions are as follows:

Through finite element simulation, two identification indicators—“fitted displacement” and “effective displacement” of the main girder—are proposed, both of which can accurately reflect the location and degree of stay cable anomalies, demonstrating good sensitivity and stability.

Based on the Eulerian perspective, a grayscale–displacement mapping model is established to achieve non-contact, efficient, and real-time measurement of multi-point displacement on the main girder. Experiments show that this method achieves a precision of 0.04 mm, with frequency domain errors controlled within 1%, offering measurement performance comparable to traditional contact methods while being more efficient.

The WOA-optimized random forest model, enabling accurate classification of various stay cable anomaly conditions. The model demonstrates excellent identification and generalization capabilities across the training set, test set, and validation set, outperforming traditional random forest neural network models.

In summary, the stay cable anomaly identification system proposed in this paper, which integrates displacement identification indicators, vision measurement technology, and an optimized classification model, effectively improves identification accuracy and practicality. Although the research findings presented herein are primarily at the laboratory validation stage, they still offer significant guidance for practical engineering applications. Future research may further optimize the environmental adaptability of the vision system, expand the applicability of the identification algorithm under complex conditions, and promote the development of intelligent health monitoring technologies for cable-stayed bridges.

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