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A Crack Detection Method for Civil Engineering Bridges Based on Feature Extraction and Parametric Modeling of Point Cloud Data

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Accurate detection and analysis of cracks is critical for ensuring the safety and reliability of concrete bridges. Point cloud data (PCD) obtained from 3D scanning provides a promising avenue for automated crack assessment. However, processing the massive and unstructured PCD poses significant challenges in feature extraction and crack modeling. This paper proposes a novel method for bridge crack analysis by combining PCD feature extraction with a hierarchical neural network and Rodriguez rotation. The method first extracts crack features from PCD using outlier removal, denoising, and 3D coordinate conversion. A crack analysis model is then constructed by integrating multi-scale feature extraction and Rodriguez rotation into a hierarchical neural network, enabling the capture of both local and global crack patterns. Experiments on a benchmark data set demonstrate the effectiveness of the proposed approach, achieving 92.83% feature extraction accuracy, 95.73% parameter analysis accuracy, 93.51% recognition accuracy, and 0.91 F1 score. The method also shows improved efficiency compared to existing techniques. These results highlight the potential of the proposed PCD-based approach for accurate and efficient crack analysis in concrete bridges.

ACM CCS (2012) Classification: Artificial intelligence → Computer vision → Computer vision tasks

Keywords: Point cloud data, Bridge engineering, Cracks, Layered neural network, Analysis model

1. Introduction

According to statistics, there are about 1 million existing bridges worldwide and about 600,000 bridges in the U.S. Nearly 40% of these bridges are more than 50 years old. Aging and wear and tear of these bridge structures have led to increasing cracking problems, which not only affect the aesthetics of the bridges but more importantly, may threaten the structural safety of the bridges and increase the potential risk of accidents [1][2]. Therefore, improving the accuracy and reliability of bridge crack detection and analysis is of great significance to ensure the safe operation of bridges.

Ling *et al.* [3] monitored the moisture in concrete using sensors in order to effectively detect the generation of cracks in concrete. The results showed that climatic conditions had a significant relationship with the loss of moisture in concrete, and the loss of moisture mainly led to the generation of transverse cracks. Zhang *et al.* [4] utilized the visual image detection method to detect cracks in concrete bridge decks. The results showed that the accuracy of this method in the process of crack identification was 99.05%, 98.9%, and 99.25%, respectively. The detection accuracy and reliability of bridge deck cracks were greatly improved.

It can be seen that traditional crack detection methods, such as visual inspection and acoustic wave detection, although can detect cracks to a certain extent, are limited by the experience and skills of the inspectors, as well as the precision and efficiency of the inspection equipment, which often makes it difficult to carry out a comprehensive and accurate assessment of the cracks [5]. In contrast, point cloud data (PCD), as a new type of data source, has unique advantages such as high density, high precision, and non-contact measurement. Point cloud data is a collection of spatial 3D coordinate points acquired by 3D scanning equipment, which can realize 3D reconstruction and quantitative analysis of cracks [6][7]. At the same time, the information in point cloud data can be further explored through feature extraction and parameter analysis techniques, which can provide a scientific basis for the repair and reinforcement of bridge cracks.

Existing crack detection methods based on point cloud data have made some progress but still have some limitations. First, the vast, unstructured, and wireless nature of point cloud data poses great challenges in data processing and analysis. Second, current crack detection methods have limited accuracy in feature extraction and parameter analysis, making it difficult to fully capture the detailed features of cracks, especially in complex bridge structures. Based on this, the study innovates feature extraction of point cloud data and constructs a crack analysis model for bridge concrete structures using quantified parameters based on feature extraction.

The contribution of the study is to propose a new feature extraction method for point cloud data, which improves the quality and accuracy of point cloud data through step elimination and statistical filtering. An innovative crack analysis model is also designed to capture the characteristics of cracks in different directions more comprehensively. By solving the massive, unstructured nature of point cloud data, this paper provides strong technical support for the comprehensive and accurate detection and assessment of bridge cracks and provides an important reference for the safety assessment and maintenance management of bridge structures.

2. Related Work

In bridge engineering, concrete crack structures have always been an active and challenging research topic. Many scholars have carried out research on the detection, measurement, and analysis methods of bridge cracks. The research methods can be categorized into four main groups: sensor monitoring methods, visual image detection methods, laser scanning methods, and point cloud data based methods [8].

Regarding the sensor-based detection methods, Li *et al.* [9] concluded that noise interference and unclear bridge images make bridge safety maintenance still a challenging problem. The research team proposed a novel bridge crack detection model after combining short-term dense cascade networks and refinement networks, which achieved 97.54% detection accuracy and 37.0 images per second during detection, realizing real-time crack detection. The advantage of these methods is that the health status of bridge structures can be monitored in real time and continuously.

Among the detection methods utilizing visual images, Zhang *et al.* [10] proposed a lightweight bridge crack detection method using the YOLOv4 algorithm in order to further improve the performance of bridge crack detection methods by incorporating deep learning. The accuracy, recall, and F1 score of this method are 93.96%, 90.12%, and 92%, respectively. The primary advantage of visual image-based detection methods is their ability to quickly identify and locate cracks using image processing technology, making them ideal for large-scale bridge inspections. However, these methods are greatly affected by external factors such as ambient light and weather, making image acquisition challenging, and limiting detection accuracy and robustness.

Oytun *et al.* [11] used a terrestrial laser scanner to identify the bridge cracks by extracting point cloud data, solved the influence of different parameters on the quality of point cloud data, and obtained the range value of crack width under different scanning settings. The advantage of this method is that it can obtain the crack data on the bridge surface with high accuracy and without contact, but the laser scanning equipment is expensive, the data processing is complicated, and it requires skilled operators.

Among point cloud-based methods, Huang *et al.* [12] proposed a crack detection method based on the fusion of three transient point cloud attributes, which solved the problem of low recognition efficiency due to insufficient limited feature extraction of bridge cracks. The results showed that the average network accuracy of this method was improved by 5.4% to 87.78% over the initial network. The advantage of this method is that the point cloud data can realize the three-dimensional reconstruction and quantitative analysis of bridge cracks, which can more accurately assess the state and hazardous degree of cracks [13].

In summary, sensor monitoring methods, visual image detection methods, laser scanning methods, and methods based on point cloud data have achieved certain results but still have limitations in detection accuracy and effectiveness. Especially, the massive, wireless, and unstructured nature of point cloud data presents significant challenges in data processing and analysis. In particular, the robustness and efficiency of crack identification and localization in complex bridge structures still need to be improved, and these limitations restrict the effectiveness of point cloud data in bridge crack detection. To address these issues, this study innovatively improves the quality and accuracy of the point cloud data model through step elimination and statistical filtering, and also introduces a multi-range feature extraction method for optimization. The study aims to provide strong technical support for the comprehensive and accurate detection and assessment of bridge cracks and provides an important reference for the safety assessment and maintenance management of bridge structures.

3. Construction of a Bridge Crack Analysis Model Combining Point Cloud Data and Parameter Analysis

3.1. Crack Data Feature Extraction Based on Point Cloud Analysis

In bridge structure crack data collection, factors such as equipment errors and lighting can impact the accuracy and detail of point cloud data (PCD) [14][15]. To improve the analysis performance of bridge crack PCD, feature extraction, and localization are performed on the crack data. Firstly, the crack PCD processing aims to improve the stability of feature extraction. The PCD processing includes data step elimination and data denoising.

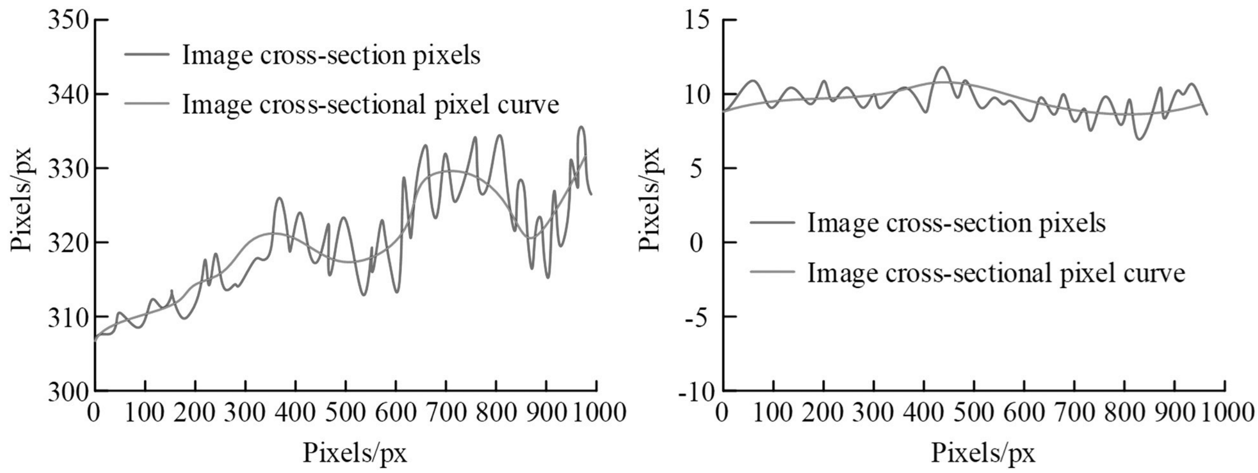
Point cloud data step elimination is the process of eliminating steps in the data by adjusting and fusing the depth averages of the left and right side point cloud data to improve data quality and accuracy. To determine if step elimination is necessary, first, the depth means on both sides of the PCD are calculated. Then, the left and right values are subtracted to obtain an absolute difference, and the absolute value is compared with the set value. If the absolute value exceeds the set value, a step is present and needs to be addressed. The data on the side with a lower mean is improved, and the processed PCD is fused to effectively eliminate the data step. The left and right PCD can be calculated using formula (1).

$$\begin{cases} I_L = \dfrac{1}{n^2}\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} I(i,j) \\ I_R = \dfrac{1}{n^2}\sum_{i=n}^{2n-1}\sum_{j=n}^{2n-1} I(i,j) \end{cases} \tag{1}$$

In formula (1), I_L represents the mean of the left PCD. I_R represents the mean of the right PCD. n represents the median of the PCD for bridge cracks. $I(i, j)$ signifies the depth value of the bridge crack PCD.

After completing the step elimination of PCD, data denoising operations can be carried out. The statistical filtering method is applied to denoise PCD. The goal of statistical filtering is to determine whether a point is an outlier by calculating the distance of each point from other points in its neighborhood. If the distance between a point and other points in its neighborhood exceeds a certain threshold, the point is considered to be an outlier and removed. Compared with other methods, the statistical filtering method can effectively remove isolated outliers and improve the quality and accuracy of point cloud data, especially for high-density and high-noise point cloud data.

During denoising, outliers are removed based on the density of the crack PCD. Eliminating these outliers can improve the clustering effect of PCD. After removing outliers, the average distance between PCD and cracks can be calculated, marked, and then denoised based on the average distance between points and cracks in all PCD. The average distance between a point and a crack is defined as the average distance from each point cloud data point to all points on the crack surface. The effect of PCD before and after filtering and denoising is shown in Figure 1.



(a) Data noise before filtering and denoising. *(b)* Data noise after filtering and denoising.

Figure 1. Processing results of point operation data before and after filtering and denoising.

After completing the step elimination and noise elimination of PCD, the features of bridge crack data can be extracted. To extract the features of PCD, the study utilizes calibration matrices and the center position coordinates of crack light strips to obtain the contour data of cracks. Most crack images are two-dimensional images. Therefore, during feature extraction, they need to be converted into three-dimensional images, which can be represented by formula (2).

$$S\begin{bmatrix} u \\ v \\ 1 \\ 0 \end{bmatrix} = R\begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} \tag{2}$$

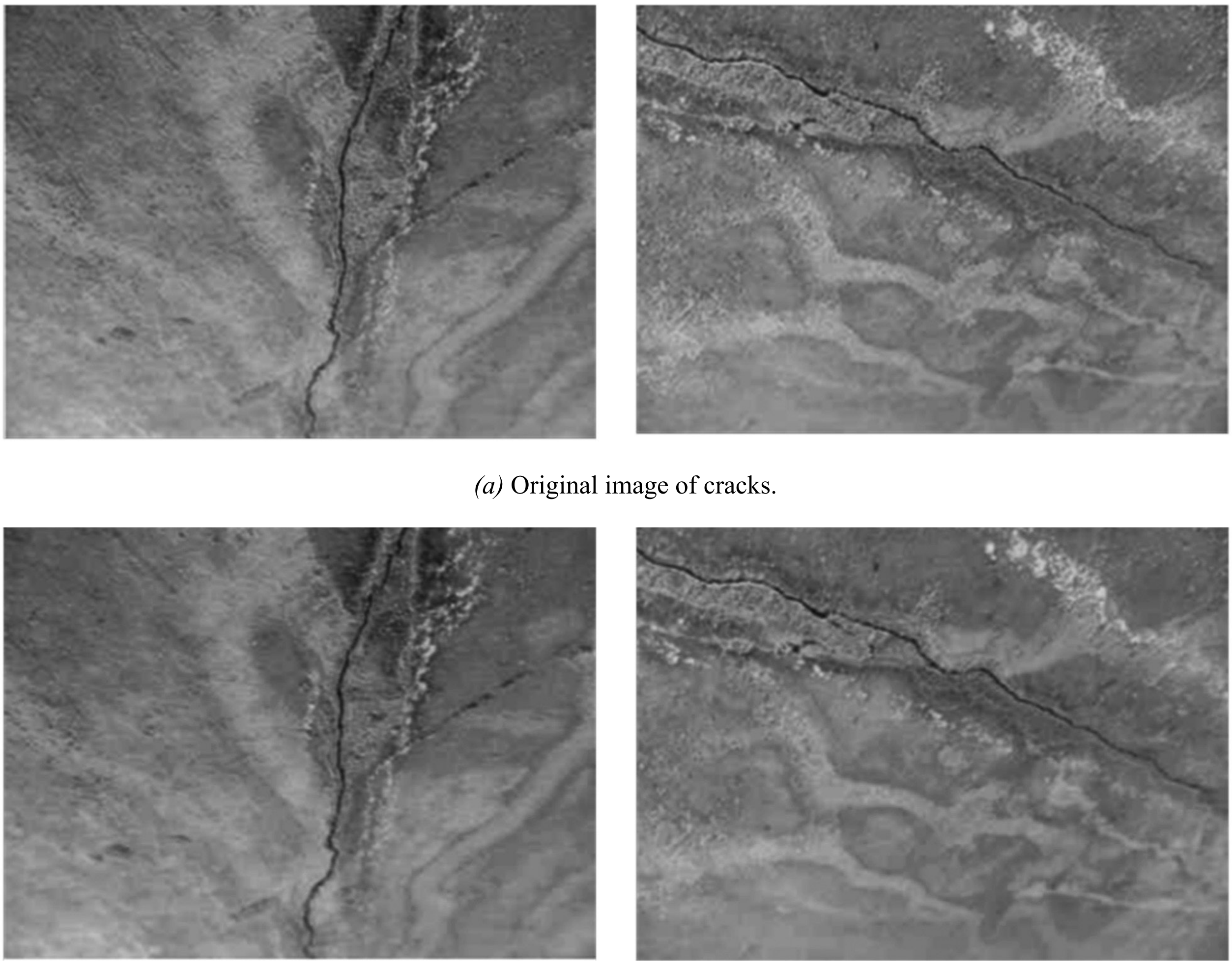
In formula (2), S represents a conversion factor in the point cloud image. (u, v, 1, 0) represents the homogeneous coordinates of the center image of the crack light strip. R represents the calibration matrix of PCD after planar calibration. (x_w, y_w, z_w, 1) represents the three-dimensional homogeneous coordinates after PCD conversion.

The three-dimensional image conversion can improve the accuracy of crack PCD recognition and provide reliable data support for crack recognition. After completing the feature extraction of the crack PCD, the crack can be located and processed [16]. To achieve crack recognition and localization based on PCD, the data relationship between the world coordinate system and the image coordinate system is set in three-dimensional images. Based on this, the corresponding coordinate values of the crack image in the coordinate system are calculated. The three-dimensional space of the crack PCD image can be defined using formula (3).

$$P_c = Q \times P_0 + T \tag{3}$$

In formula (3), P_c signifies the coordinate value of the crack PCD in the coordinate system. Q signifies the rotation vector value between the world coordinate system and the image coordinate system. P_0 represents the coordinate value of the crack PCD in the world coordinate system. T represents the corresponding movement vector between the two systems. It follows that the intuition for 3D coordinate conversion and localization lies in converting the crack information in the 2D image to a position in 3D space. Specifically, the center position of the light bar in the 2D crack image is converted to 3D point cloud data. The 2D image coordinates are converted to 3D chi-square coordinates using a calibration matrix, thus realizing 3D reconstruction of the cracks and thus more accurately describing the geometry and location of the cracks. The image before and after feature extraction from the bridge crack PCD is shown in Figure 2.

After completing the 3D spatial construction of the crack PCD, preliminary positioning of the cracks can be carried out. To ensure reli-



(a) Original image of cracks.

(b) Image after crack preprocessing.

Figure 2. Images before and after feature extraction of bridge crack point cloud data.

able positioning, the crack point can be used as the viewpoint for positioning, and the positioning algorithm is combined to analyze the bridge PCD. By extracting features from PCD, crack data is used as the corresponding spatial coordinates in the data, and then these data are adaptively adjusted to achieve crack location analysis.

3.2. Design of the Crack Analysis Model Combining Data Quantification and Parameter Analysis

After in-depth research on the characteristics of PCD for bridge cracks, simple feature extraction cannot meet the needs of comprehensive crack evaluation. To ensure the reliability of crack feature extraction and recognition, it is necessary to further reveal the deep information of cracks through parameter modeling analysis [17]. Due to the irregularity and disorder of PCD, this study integrates hierarchical neural networks and Rodriguez rotation to design an innovative crack analysis model. This model not only fully utilizes the advantages of neural networks in complex data processing, but also combines the Rodriguez rotation formula to perform precise rotation transformations on spatial data to better capture the characteristics of cracks in different directions. When designing the model, the properties of the bridge material itself are analyzed to ensure that the constructed analysis model is in accord with the characteristics of the bridge concrete. The stress variation curve of bridge concrete under compression is shown in Figure 3.

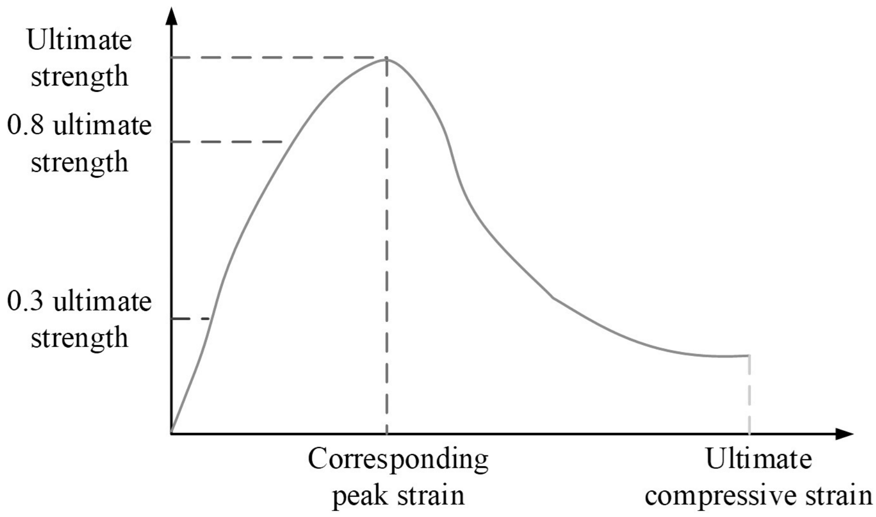


Figure 3. Stress variation curve of bridge concrete under compression.

After the concrete of the bridge is subjected to pressure and undergoes stress changes, the formation and evolution of cracks become a key indicator for evaluating the safety of the bridge structure. Traditional hierarchical neural networks may be affected by local deformation and crack complexity caused by stress changes when extracting local features from crack PCD, resulting in incomplete and inaccurate feature extraction [18][19]. Therefore, a multi-range feature extraction method is introduced.

The multi-range feature extraction method extracts features from crack PCD at multiple levels and scales by setting different range thresholds. This not only captures the local detailed features of cracks but also takes into account the overall performance of cracks at different scales. The hierarchical neural network contains several convolutional, pooling, and fully connected layers. The de-training process starts with the input layer receiving the processed point cloud data, followed by the convolutional layer extracting the local features of the cracks. Then the pooling layer performs feature dimensionality reduction to retain important information; the fully connected layer integrates the extracted features for classification and regression analysis. Finally, the recognition results of the cracks and parameter estimates are output by the output layer. The process uses mean square error and cross-entropy loss functions for regression and classification tasks, respectively, while minimizing the loss function with a dam optimization algorithm that continuously adjusts the network parameters through backpropagation [20][21]. By integrating and analyzing these multi-scale features, the morphology and characteristics of cracks can be described more comprehensively and accurately, providing strong data support for the construction of subsequent crack analysis models.

The multi-scale feature extraction method performs multi-level and multi-scale feature extraction on crack point cloud data by setting different scale thresholds. For example, 5-10 points are local scale for extracting the local detail features of the cracks; 10-20 points are medium scale for capturing the medium range features of the cracks; and 20-30 points are overall scale for extracting the overall morphology of the cracks. By integrating and analyzing these features at different scales, the morphology and characteristics of the cracks can be fully described [22][23].

After completing multi-scale bridge crack detection analysis, some box girder bridges also need to consider the internal structure of their bridge body when conducting crack analysis. To ensure the adaptability of the detection model, the study introduces Rodriguez rotation to reconstruct the internal structure of the box girder bridge, thereby constructing the analysis model. Compared to standard neural networks, Rodriguez rotation is able to accurately handle rotational transformations of point cloud data in different directions to avoid information loss. For example, it can align a diagonal crack with the model's orientation, making it easier for the neural network to extract its features and improve the recognition accuracy of the model [24][25]. When reconstructing the internal structure, the internal structure drawings are projected and registered to ensure adaptive adjustment between the drawings and the solid model space. Drawing registration first projects the vertical axis, which can be represented by formula (4).

$$V_2 = \sin\theta K \times V_1 + \cos\theta V_1 + (1 - \cos\theta) \tag{4}$$

In formula (4), V_2 represents the unit vector of the entity's Z-axis. θ represents the Z-axis angle value between the drawing and the entity. K represents the vector product between the Z-axis of the drawing and the entity. V_1 represents the unit vector of the Z-axis of the drawing. To improve the performance of the analysis model in drawing mapping and crack correspondence analysis, a rotation matrix for Rodriguez rotation is constructed, which can be represented by formula (5).

$$R_w = \sin\theta \begin{bmatrix} 0 & -k_z & k_y \\ k_z & 0 & -k_z \\ -k_y & k_x & 0 \end{bmatrix} + E\cos\theta + (1-\cos\theta)(k_x, k_y, k_z) \tag{5}$$

In formula (5), R_w represents the rotation matrix. k_x, k_y and k_z represent the components of the vector product on the x, y, and z axes. E represents the identity matrix of the rotational mean. Once the rotation matrix is constructed, automatic mapping is used to complete the corresponding analysis of cracks. The process of automatic mapping can be represented by formula (6).

$$F_2 = F_1 \cdot R_{w1} \cdot R_{w2} + T \tag{6}$$

In formula (6), F_2 signifies the set of coordinate points where the crack automatically maps to the projection plane. F_1 signifies the set of coordinate points for the internal structure in the drawing. R_{w1} and R_{w2} represent the values after the rotation of the x-axis and y-axis in the rotation matrix. Through the above operations, effective detection and analysis of bridge cracks can be completed. Figure 4 shows the analysis process of concrete crack structure in bridge engineering by combining PCD feature extraction and parameter analysis.

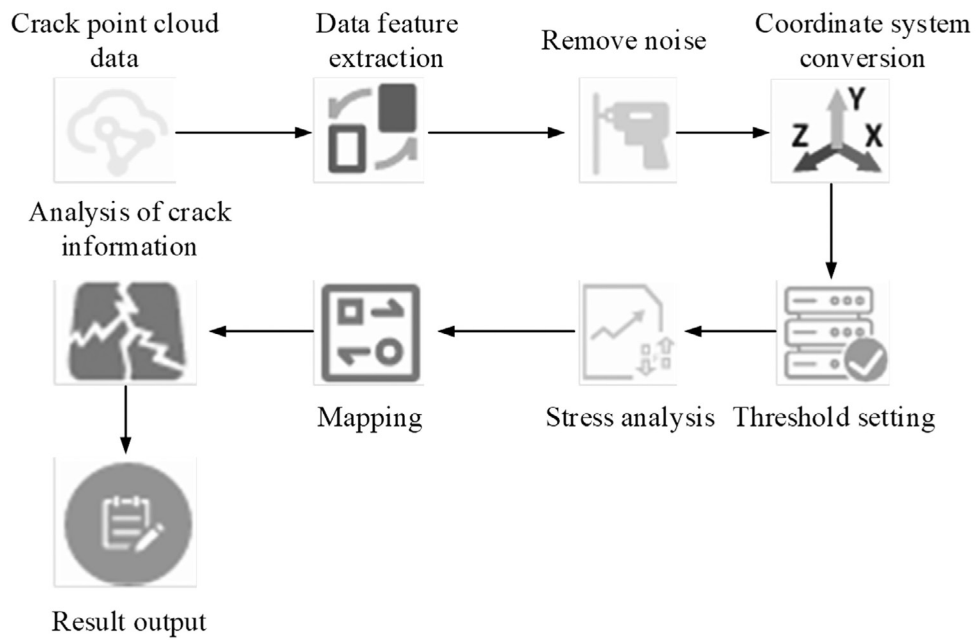


Figure 4. Flow chart of bridge engineering concrete crack structure analysis combining point cloud data feature extraction and parameter analysis.

4. Performance Analysis of Crack Analysis Model for Bridge Structures

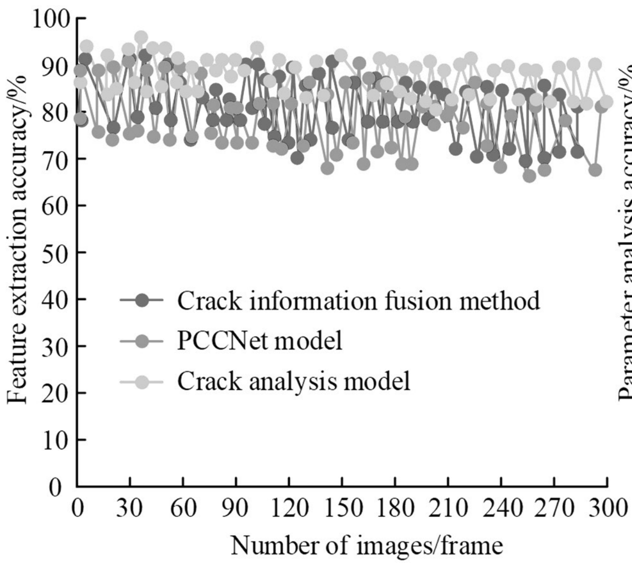
4.1. Performance Analysis of Data Processing in Crack Analysis Model

To evaluate the performance of the crack analysis model for bridge structures, the study uses the common crack data CFD as a dataset for simulation experiments. The dataset contains about 5000 crack images, each with a resolution of 1024x768 pixels. They include various types of fine cracks, wide cracks, transverse cracks, and longitudinal cracks, with crack widths ranging from 0.1 mm to 5 mm. All images were standardized and processed, including grayscaling, noise filtering, contrast enhancement, and other operations to ensure data consistency and quality.

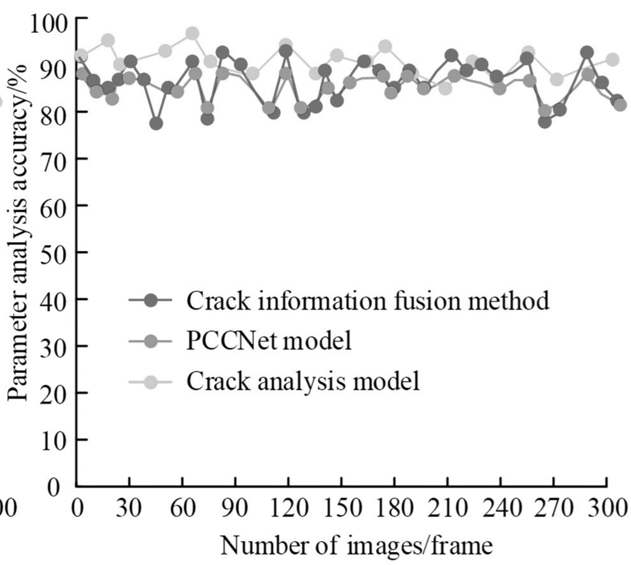
The experiments are conducted on a system running Windows 10 operating system, equipped with an Intel Core i9 series CPU, an NVIDIA GeForce RTX 30 GPU, 64GB DDR4 ECC RAM, and 1TB of storage.

For performance comparison, the crack information fusion algorithm and the Point Cloud Context Network (PCCNet) model are used. The crack information fusion algorithm is a fusion method based on multiple features, such as color, texture, shape, *etc.*, which improves the accuracy and robustness of crack detection by integrating the advantages of different features. PCCNet is a contextual network designed for point cloud data, which improves the accuracy and efficiency of crack detection by capturing spatial relationship and contextual information of point cloud data.

Compared with other methods, these two methods are representative in the field of crack detection and show good results in different types of bridge crack detection. By comparing our model with these methods, the performance advantages of the proposed methods can be evaluated more comprehensively. To prove the performance of the crack analysis model in crack feature extraction, the study uses feature extraction accuracy and parameter analysis accuracy as validation indicators. The feature extraction accuracy and parameter analysis accuracy are displayed in Figure 5.



(a) Comparison results of feature extraction accuracy among three methods.



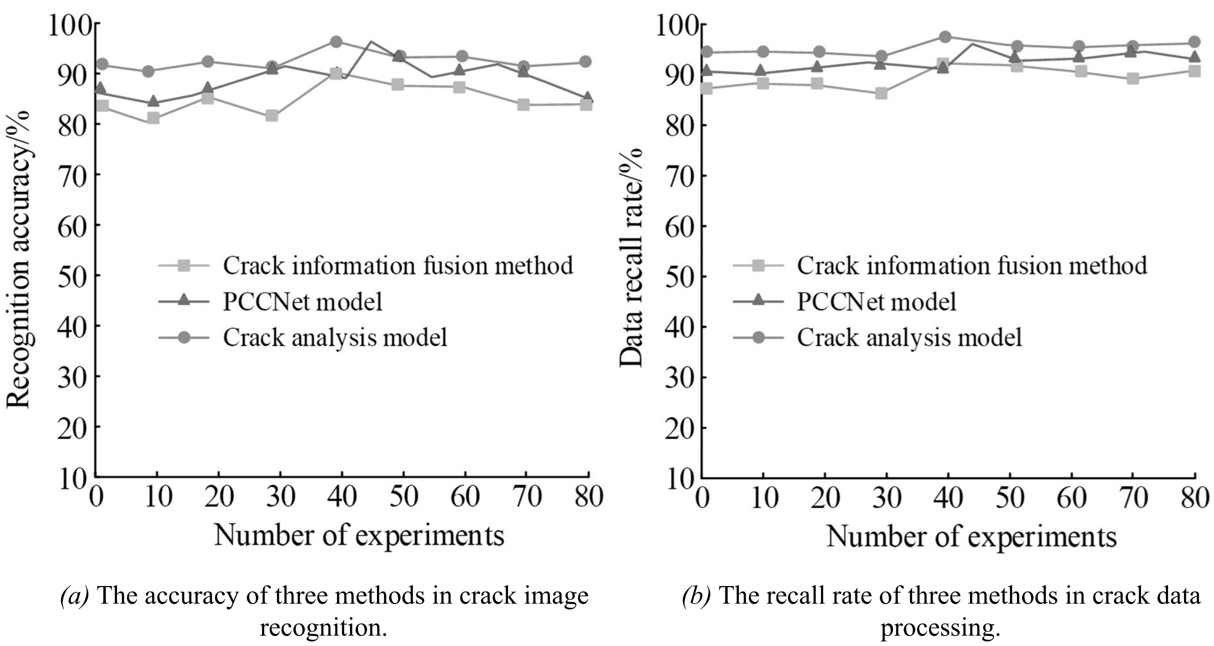
(b) Comparison results of parameter analysis accuracy of three methods.

Figure 5. Feature extraction accuracy and parameter analysis accuracy.

According to Figure 5 (a), the accuracy of feature extraction for the crack analysis model, PCCNet model, and crack information fusion method was 92.83%, 86.15%, and 84.29%, respectively. According to Figure 5 (b), the accuracy of the crack analysis model in the parameter analysis process was 95.73%, while the parameter analysis accuracy of the PCCNet model and crack information fusion method were 88.95% and 86.07%, respectively. This indicates that the crack analysis model constructed in the study has shown high accuracy and precision in feature extraction and parameter analysis. To demonstrate the performance of the crack analysis model in the data analysis process, the identification accuracy and data recall of crack data are studied as validation indicators for performance testing. The accuracy and recall comparison results of these three methods in crack image data recognition are shown in Figure 6.

In Figure 6 (a), the recognition accuracy of the crack analysis model, PCCNet model, and crack information fusion method in crack image data recognition were 93.51%, 90.08%, and 88.25%, respectively. According to Figure 6 (b), the data recall rates of the crack analysis model, PCCNet model, and crack information fusion method in the data processing process were 96.07%, 92.49%, and 89.81%, respectively. This indicates that the crack analysis model has shown high performance in crack image data recognition and data processing, with better recognition accuracy and data recall than the PCCNet model and crack information fusion method, demonstrating the effectiveness and superiority of the model in bridge crack detection. In Figure 7, the F1 values and Intersection over Union (IoU) of three methods during crack treatment are compared.

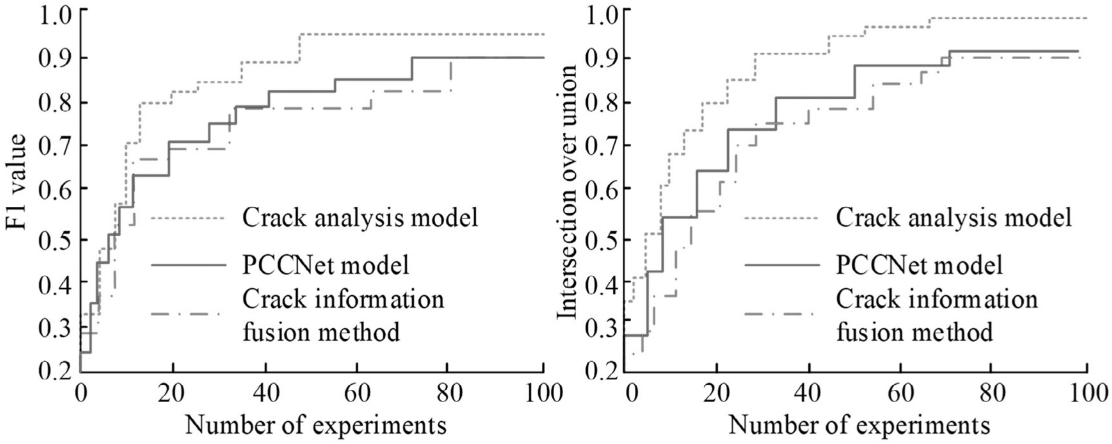
According to Figure 7 (a), during the processing of crack image data, the F1 value of the crack analysis model was the highest, which was 0.91. The F1 values of the PCCNet model and crack information fusion method were 0.85 and 0.82, respectively. As shown in Figure 7 (b), in the comparison of IoU, the IoU of the crack analysis model, PCCNet model, and crack information fusion method was 0.95, 0.90, and 0.87, respectively. This further proves the effectiveness and superiority of the crack analysis model in bridge crack detection, which can provide more reliable data support for the safety assessment and repair reinforcement of bridge structures.



(a) The accuracy of three methods in crack image recognition.

(b) The recall rate of three methods in crack data processing.

Figure 6. Comparison results of accuracy and recall of three methods in crack image data recognition.



(a) Comparison results of F1 values for three methods. *(b)* Comparison results of intersection over union.

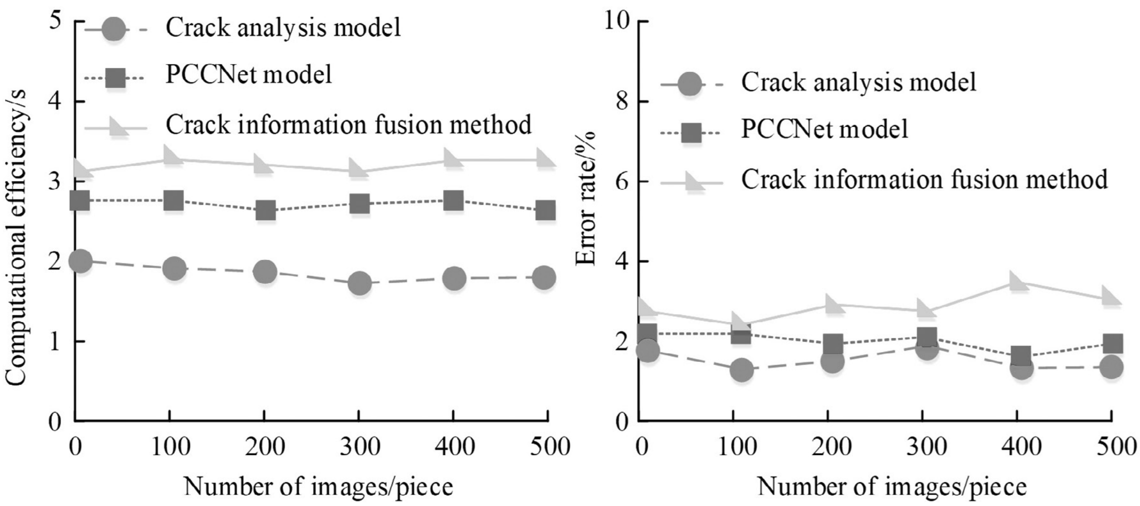
Figure 7. Comparison results of F1 value and IoU of three methods in crack treatment process.

4.2. Simulation Experiment Effect of Crack Analysis Model

To present the application effect of the bridge crack analysis model, simulation experiments are carried out on the dataset. The comparison results of computational efficiency and error rate of three methods in crack identification process are shown in Figure 8.

As shown in Figure 8 (a), with the increase in the number of test samples, the calculation time of each model tends to stabilize. The calculation time of the crack analysis model is 2.13s, the calculation time of the PCCNet model is 2.81s, and the calculation time of the crack information fusion method is 3.25s.

As shown in Figure 8 (b), for the error rates in crack image recognition, the error rates of crack analysis model, PCCNet model, and crack information fusion method were 2.05%, 2.73%, and 3.51%, respectively. This indicates the practicality and superiority of crack analy-



(a) Comparison of computational efficiency among three methods in the test set. *(b)* Comparison of error rates among three methods in experimental sets.

Figure 8. Comparison of computational efficiency and error rate of three methods in crack identification process.

sis models in bridge crack detection. It can not only complete crack identification tasks in the short run but also provide more stable and reliable identification results.

In order to evaluate the runtime and performance variation of the crack analysis model under different data volumes, taking into account the effects of different lighting, camera angles, and crack appearance variations on the model performance, the study tested the runtime for a fixed number of images after incorporating these factors and analyzed the effect of increasing data volumes on the runtime.

According to Table 1, the shortest detection time for the crack analysis model was 2.17 seconds for 100 images, 21.31 seconds for 1,000 images, and 106.53 seconds for 5,000 images. The detection time increases with the number of image samples to be detected, but the time of fixed image detection is lower than the other two types of methods. In addition, the detection accuracy of the crack analysis model was 93.51%, 90.35%, and 91.47% in normal light, low light, and high light environments, respectively. The accuracy is also significantly higher than the other two types of models. It can be seen that the proposed model of the study can show superior application performance under different test sample environments and has significant value for use.

To prove the performance of the crack analysis model in the bridge crack treatment, experiments are conducted using 10 crack images. The predicted values of the crack analysis model are compared with the actual values. Table 2 displays the detection time, accuracy, and stability between the two methods.

Table 1. Comparison results of runtime and accuracy for different number of images and environments.

Number of images/conditions	**Crack information fusion method**		**PCCNet model**		**Crack analysis model**	
	Running time/s	**Detection accuracy/%**	**Running time/s**	**Detection accuracy/%**	**Running time/s**	**Detection accuracy/%**
100	3.25	/	2.81	/	2.17	/
500	16.25	/	14.05	/	10.65	/
1000	32.5	/	28.12	/	21.31	/
2000	65.07	/	56.28	/	42.68	/
5000	162.57	/	140.55	/	106.53	/
Normal light	/	88.25	/	90.08	/	93.51
Low light	/	83.11	/	85.62	/	90.35
High light	/	84.53	/	86.79	/	91.47
Camera angle change	/	87.01	/	89.27	/	92.83
Changes in crack appearance	/	85.34	/	87.55	/	91.95

Table 2. Comparison results of detection time, accuracy, and stability between two methods.

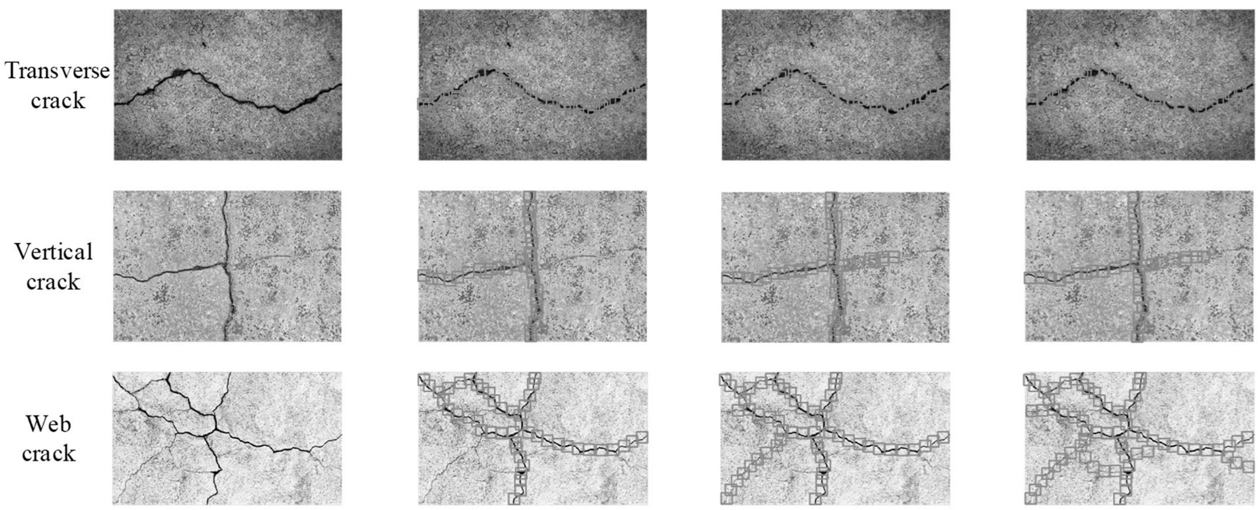
Crack image number	**Prediction value of crack analysis model**			**True value**		
1	Detection time/s	Accuracy/%	Stability/%	Detection time/s	Accuracy/%	Stability/%
2	2.89	90.86	91.28	2.38	93.18	94.37
3	2.91	91.02	92.04	2.36	92.95	94.26
4	2.85	90.88	91.67	2.41	93.02	94.11
5	2.96	91.57	91.53	2.31	93.07	94.25
6	2.78	92.03	92.07	2.25	92.88	94.37
7	2.88	91.37	91.66	2.19	92.73	94.22
8	2.79	90.48	91.16	2.27	92.48	93.89
9	2.91	90.05	91.34	2.31	92.69	93.47
10	2.86	89.95	91.29	2.23	92.77	93.88

According to Table 2, in the comparison of detection time, accuracy, and stability of 10 bridge cracks, the optimal values of the crack analysis model were 2.78 s, 92.03%, and 92.07%, respectively. The actual optimal values were 2.19 s, 93.18%, and 94.37%, respectively. The difference between the two was 0.59 s, 1.15%, and 2.30%, indicating that the designed model has shown good performance in bridge crack detection. To further verify the performance of the crack analysis model, the calculated measurement values of the analysis model are compared with the actual measurement values, as displayed in Table 3.

According to Table 3, the calculated measurement results of the crack analysis model were all smaller than the actual measurement results, which may be related to image detail processing. Although there was a certain gap, the overall difference was very small, with a maximum error of only 4.045 mm. At the same time, the relative error difference was also very small. It indicates that the crack analysis model has high accuracy and precision in measuring the width of bridge cracks, which can meet the needs of practical applications. In the final study, horizontal cracks, vertical cracks, and mesh cracks were used as test objects to compare the three methods for real detection, and the results are shown in Figure 9.

Table 3. Comparison results of measurement values between two methods.

Crack image number	Calculates measurement results/mm	Actual measurement result/mm	Error/mm	Relative error/%
1	186.375	190.025	3.65	1.92
2	56.381	60.278	3.897	6.47
3	127.286	130.695	3.409	2.61
4	100.287	103.556	3.269	3.16
5	91.269	93.871	2.602	2.77
6	75.663	78.962	3.299	4.18
7	85.371	88.954	3.583	4.03
8	115.693	118.375	2.682	2.27
9	118.631	121.059	2.428	2.01
10	69.582	73.627	4.045	5.49



(a) Original image. *(b)* Crack information fusion method. *(c)* PCCNet model. *(d)* Crack analysis model.

Figure 9. Crack detection results under different methods.

The original transverse, vertical, and mesh crack images are shown from top to bottom in Figure 9(a), while Figure 9(b) shows the detection results under the crack information fusion method, Figure 9(c) shows the crack detection results under the PCCNet method, and Figure 9(d) shows the crack detection results under the crack analysis model. As can be seen from Figure 9, in transverse crack detection, all three methods have comparable detection results. However, in vertical crack detection, the crack information fusion method fails to detect the presence of fine cracks in time resulting in lower accuracy. For mesh cracks, the proposed crack analysis model demonstrates superior performance by effectively identifying and detecting all visible cracks in the image, displaying high detection effectiveness and feasibility. This highlights the proposed model's value and advantages over the other methods.

5. Conclusion

This paper proposed a novel method for analyzing concrete cracks in bridges using point cloud data (PCD). The key innovations are a PCD feature extraction approach that combines outlier removal, denoising, and 3D coordinate transformation, and a crack analysis model that integrates multi-scale feature extraction and Rodriguez rotation into a hierarchical neural network.

Experiments on a benchmark dataset showed that the proposed method achieves high accuracy in crack detection and localization, with 92.83% feature extraction accuracy, 95.73% parameter analysis accuracy, and 0.91 F1 score. It also demonstrates improved efficiency compared to existing methods. The main advantage of the proposed approach is its ability to automatically extract relevant crack features from the unstructured and noisy PCD and accurately model both local and global crack patterns using a hierarchical neural network. The integration of Rodriguez rotation enables the capture of crack orientation information, which is important for assessing crack severity.

However, there are several limitations that need to be addressed in future work. The current method has only been tested on a single dataset and its performance on more diverse real-world data needs to be evaluated. The integration of mechanical models for crack growth prediction and severity assessment is also an important direction to explore. Finally, deploying the system on actual bridges for continuous monitoring and testing its long-term reliability and scalability are necessary steps for practical adoption.

In summary, this paper demonstrates the potential of PCD-based methods for automated crack analysis in concrete bridges. The proposed approach advances the state of the art in terms of feature extraction and crack modeling and lays the foundation for further research on this important problem. With further development and real-world validation, this methodology could have a significant impact on improving the safety and reliability of transportation infrastructure.

References

[1] H. Fu *et al.*, "Crack Segmentation Based on Improved YOLACT++ Algorithm", in *Proceedings of the 2021 Chinese Intelligent Automation Conference, Springer Singapore*, 2022, pp.425–432. http://dx.doi.org/10.1007/978-981-16-6372-7_48

[2] T. S. Tran *et al.*, "Advanced Crack Detection and Segmentation on Bridge Decks Using Deep Learning", *Construction and Building Materials*, vol. 400, no. 12, pp. 1–13, 2023. http://dx.doi.org/10.1016/j.conbuildmat.2023.132839

[3] Y. Ling *et al.*, "Monitoring of Bridge Overlay Using Shrinkage-modified High Performance Concrete Based on Strain and Moisture Evolution", *Structural Monitoring and Maintenance*, vol. 10, no. 2, pp. 155–174, 2023. http://dx.doi.org/10.12989/smm.2023.10.2.155

[4] Q. Zhang *et al.*, "Real-time Detection of Cracks on Concrete Bridge Decks Using Deep Learning in the Frequency Domain", *Engineering*, vol. 7, no. 12, pp. 1786–1796, 2021. http://dx.doi.org/10.1016/j.eng.2020.07.026

[5] J. Liu *et al.*, "A Hierarchical Semantic Segmentation Framework for Computer Vision-based Bridge Damage Detection", *Smart structures and Systems*, vol. 31, no. 4, pp. 325–334, 2023. http://dx.doi.org/10.12989/sss.2023.31.4.325

[6] Y. Wei *et al.*, "Methodology for Quantifying Features of Early-age Concrete Cracking from Laser Scanned 3D Data", *Journal of Materials in Civil Engineering*, vol. 33, no. 7, pp. 1–12, 2021. http://dx.doi.org/10.1061/(ASCE)MT.1943-5533.0003774

[7] X. Li *et al.*, "A Local Feature Aggregation PointNet++ Network Based on Graph Network", in *Proceedings of the 2021 4th International Conference on Image and Graphics Processing*, 2021 pp. 169–174. http://dx.doi.org/10.1145/3447587.3447612

[8] C. A. Putri *et al.*, "Failure Probability for Fatigue Crack in Web Plate of Bridge Girder", *International Journal of Steel Structures*, vol. 22, no. 1, pp. 42–55, 2022. http://dx.doi.org/10.1007/s13296-021-00559-x

[9] [9]G. Li, T. Liu, and Z. Fang, "Automatic bridge crack detection using boundary refinement based on real-time segmentation network", *Structural Control and Health Monitoring*, vol. 29, no. 9, pp. 2991–2992, 2022. http://dx.doi.org/10.1002/stc.2991

[10] J. Zhang *et al.*, "Automated Bridge Crack Detection Method Based on Lightweight Vision Models", *Complex & Intelligent Systems*, vol. 9, no. 2, pp. 1639–1652, 2023. http://dx.doi.org/10.1007/s40747-022-00876-6

[11] M. Oytun and G. Atasoy, "Effect of Terrestrial Laser Scanning (TLS) Parameters on the Accuracy of Crack Measurement in Building Materials", *Automation in Construction*, 144, pp. 1–12, 2022. http://dx.doi.org/10.1016/j.autcon.2022.104590

[12] H. Huang *et al.*, "Automated Detection of Through-cracks in Pavement Using Three-instantaneous Attributes Fusion and Swin Transformer Network", *Automation in Construction*, vol. 158, no. 6, pp. 1–16, 2024. http://dx.doi.org/10.1016/j.autcon.2023.105179

[13] Y. Yu *et al.*, "Multi-image-feature-based Hierarchical Concrete Crack Identification Framework Using Optimized SVM Multi-classifiers and D–S Fusion Algorithm for Bridge Structures", *Remote Sensing*, vol. 13, no. 2, pp. 1–28, 2021. http://dx.doi.org/10.3390/rs13020240

[14] K. Yu *et al.*, "Automated Finite Element Modeling and Analysis of Cracked Reinforced Concrete Beams from Three Dimensional Point Cloud", *Structural Concrete*, vol. 22, no. 6, pp. 3213–3227, 2021. http://dx.doi.org/10.1002/suco.202100194

[15] P. Stałowska *et al.*, "Crack Detection in Building Walls Based on Geometric and Radiometric Point Cloud Information", *Automation in Construction*, vol. 134, no. 5, pp. 1–19, 2022. http://dx.doi.org/10.1002/suco.202100194

[16] Y. Umehara *et al.*, "Research on Identification of Road Features from Point Cloud Data Using Deep Learning", *International Journal of Automation Technology*, vol. 15, no. 3, pp. 274–289, 2021. http://dx.doi.org/10.20965/ijat.2021.p0274

[17] Y. Zhang *et al.*, "Double-tensioned Steel Strands Vertical Prestress System on the Webs of Long-span PC Box-girder Bridges", *Journal of Bridge Engineering*, vol. 26, no. 6, pp. 1–11, 2021. http://dx.doi.org/10.1061/(ASCE)BE.1943-5592.0001715

[18] C. G. Guo and J. Li, "A Unified Stochastic Damage Model for Concrete Based on Multi-scale Energy Dissipation Analysis", *Science China Technological Sciences*, vol. 67, no. 3, pp. 1–15, 2024. https://dx.doi.org/10.1007/s11431-023-2443-8

[19] H. Chu *et al.*, "Tiny-Crack-Net: A Multiscale Feature Fusion Network with Attention Mechanisms for Segmentation of Tiny Cracks", *Computer-Aided Civil and Infrastructure Engineering*, vol. 37, no. 14, pp. 1914–1931, 2022. http://dx.doi.org/10.1111/mice.12881

[20] S. M. Ahmed *et al.*, "EPN: Edge-aware PointNet for Object Recognition from Multi-view 2.5 D Point Clouds in 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)", *IEEE*, vol. 12, no. 6, pp. 3445–3450, 2019. http://dx.doi.org10.1109/IROS40897.2019.8967705

[21] A. Mirzazade *et al.*, "Semi-autonomous Inspection for Concrete Structures Using Digital Models and a Hybrid Approach Based on Deep Learning and Photogrammetry", *Journal of Civil Structural Health Monitoring*, vol. 13, no. 8, pp. 1633–1652, 2023. http://dx.doi.org/10.1007/s13349-023-00680-x

[22] H. Zhang *et al.*, "Detection of RC Spalling Damage and Quantification of Its Key Properties from 3D Point Cloud", *KSCE Journal of Civil Engineering*, vol. 26, no. 5, pp. 2023–2035, 2022. http://dx.doi.org/10.1007/s12205-022-0890-y

[23] M. Artus *et al.*, "BIM Based Framework for Damage Segmentation, Modeling, and Visualization Using IFC", *Applied Sciences*, vol. 12, no. 6, pp. 2772–2773, 2022. https://dx.doi.org/10.3390/app12062772

[24] W. Ye *et al.*, "Automatic Pixel-level Crack Detection with Multi-scale Feature Fusion for Slab Tracks", *Computer-Aided Civil and Infrastructure Engineering*, vol. 38, no. 18, pp. 2648–2665, 2023. https://dx.doi.org/10.1111/mice.12984

[25] T. Mizutani *et al.*, "Automatic Detection of Delamination on Tunnel Lining Surfaces from Laser 3D Point Cloud Data by 3D Features and a Support Vector Machine", *Journal of Civil Structural Health Monitoring*, vol. 14, no. 1, pp. 209–221, 2024. https://dx.doi.org/10.1007/s13349-023-00731-3

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