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Computer Vision Methods for Bridge Surface Damage Detection

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Abstract. After long-term service, bridges are prone to surface defects such as cracks, spalling, and corrosion. The timely identification and recording of these defects constitute an essential part of bridge inspection and maintenance. Conventional manual inspection relies on close-range visual observation and record keeping by inspectors; this approach carries safety risks when workers operate at height or beneath bridges, and its efficiency and consistency are readily affected by the experience of the personnel and by field conditions. In recent years, image-based computer vision (CV) methods have been increasingly applied to bridge surface damage detection. This paper adopts a literature review and a representative-study analysis to introduce bridge surface image data and commonly used CV methods, and to examine related research from three perspectives: crack detection and quantification, multi-type surface defect recognition, and CV-assisted bridge inspection. Existing studies show that CV can identify and localize common defects such as cracks, spalling, and corrosion, and can quantify the dimensions of certain defects when scale calibration is available. When combined with unmanned aerial vehicles (UAVs) and robots, CV reduces the need for close-range manual inspection and large-scale image screening. Nevertheless, detection performance remains affected by image quality, complex backgrounds, class imbalance, and shooting conditions, and the stability of models across different bridges and environments still has room for improvement. At present, CV is better suited as an auxiliary tool for bridge inspection, while significant defects and uncertain results still require confirmation by manual inspection.

Keywords: bridge surface damage, computer vision, crack detection, multi-type defect recognition, bridge inspection

1. Introduction

During long-term service, bridges are affected by material aging, vehicle loading, environmental attack, and temperature variation, so that the surfaces of concrete decks and members are prone to cracks, cover spalling, rebar corrosion, and rust-induced expansion. Although these defects do not necessarily reflect internal structural damage, they often serve as external signals of performance deterioration, and their location, extent, and development trend provide an important basis for maintenance authorities to formulate repair strategies. China has a very large stock of highway bridges, a considerable proportion of which have entered the middle-to-late stage of operation,

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making periodic inspection and maintenance extremely demanding. For a long time, bridge surface inspection has relied on inspectors who use climbing equipment or bridge inspection vehicles, or work on pylons to visually observe and manually record defects at close range. This approach involves obvious safety risks when inspectors work at height, close to members, or beneath bridges; it is also relatively slow, and different inspectors apply inconsistent criteria when judging and recording the same defect, so that the consistency and traceability of results are difficult to guarantee. With the widespread use of digital cameras, UAVs, and mobile terminals, image-based CV methods have gradually been introduced into bridge inspection, providing new means for the automatic identification, localization, and quantification of surface defects.

Existing research has focused on image acquisition and preprocessing, crack detection, multi-type defect recognition, defect segmentation and dimensional quantification, and UAV- and robot-assisted inspection [1]. Early methods relied heavily on edge detection, threshold segmentation, and hand-crafted features, and could identify some defects in images with relatively simple backgrounds, but were readily disturbed by shadows, stains, and member texture. With the development of convolutional neural networks (CNNs) and deep learning, bridge surface damage detection has gradually expanded from single-crack recognition to object detection and semantic segmentation of multiple defect types, including cracks, spalling, and corrosion [2-4]. In recent years, equipment such as UAVs and wall-climbing robots has also been combined with CV methods to acquire bridge surface images at locations that are difficult for inspectors to reach [5-9]. However, the data sources, defect category definitions, and evaluation metrics used in different studies are not consistent, and shadows, stains, occlusion, and varying shooting conditions in images also affect recognition performance. Whether a model can maintain stable performance across different bridges, shooting distances, and environmental conditions remains a concern in practical applications [1, 4].

This paper adopts a literature review and a representative-study analysis to introduce the main types of bridge surface defects, image data sources, and commonly used CV methods. On this basis, it examines the actual performance, applicable conditions, and limitations of existing research from three perspectives: crack detection and quantification, multi-type surface defect recognition, and CV-assisted bridge inspection. Finally, the paper analyzes the problems of current visual detection of bridge surface defects in terms of data quality, model generalization, and engineering application, and summarizes research directions that deserve further attention.

2. Data and methods for bridge surface damage detection

2.1. Defect types and image data

During long-term service, bridges are affected by vehicle loading, environmental attack, and material aging, so that decks, girders, and piers may develop various surface defects. Common defects include cracks, spalling, corrosion, and exposed rebar [1]. Cracks usually appear as linear or network patterns and vary widely in width; they are also a type of defect of particular concern in bridge surface inspection. Spalling mainly manifests as the detachment of surface concrete, with exposed aggregate visible in some cases. Corrosion generally appears in images as yellowish-brown or dark-red patches and abnormal texture. Exposed rebar usually occurs together with cover spalling and can appear in images as metallic strip-like regions [1]. These features primarily reflect visible abnormalities on the bridge surface; they cannot be used directly to judge whether internal structural damage exists or whether the load-bearing capacity has declined, and the structural safety state still requires comprehensive assessment together with other professional inspection methods [10].

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Bridge surface images are mainly acquired by handheld cameras, bridge inspection vehicles, fixed cameras, and UAVs [1, 5]. Handheld cameras are flexible and suitable for close-range capture of local details, but their use at some positions requires inspectors to work at height or close to members, which involves certain safety risks. Bridge inspection vehicles can deliver personnel and equipment to locations that are not directly accessible, such as girder bottoms and piers, and cover a relatively large area; however, equipment deployment is costly and is constrained by clearances beneath the bridge. Fixed cameras can be installed near critical members for long-term monitoring, but their viewing angles are relatively fixed and their coverage is limited. UAVs are highly maneuverable and efficient, and can quickly acquire bridge surface images over a large area, which makes them particularly suitable for long-span bridges and high-pier structures [5, 8]. Previous studies have noted that UAV-based bridge inspection is shifting from purely image acquisition toward automatic route planning and intelligent defect recognition, although the overall automation level still has room for improvement [1].

Image quality directly affects subsequent detection results. During actual acquisition, illumination variation, shadow occlusion, shooting angle, shooting distance, vegetation or member occlusion, complex backgrounds, and image resolution may all alter the appearance of defects in the image and thereby affect the accuracy and stability of detection algorithms [6]. In constructing a crack dataset with complex backgrounds, one study selected images containing interfering factors such as shadows, artificial markings, and weeds to test the recognition capability of algorithms under complex conditions [6]. Another study acquired a total of 169,621 images from ten long-span bridges and found that images obtained from different bridges and at different times showed marked differences in illumination and contrast [7]. Without necessary data filtering and enhancement, model performance may deteriorate across scenes. Therefore, image data quality is an important factor affecting the effectiveness of visual detection of bridge surface defects.

2.2. Image processing and computer vision methods

Before entering a detection model, bridge surface images usually require preprocessing. Common methods include lens distortion correction, image denoising, contrast enhancement, image mosaicking, and scale calibration. Lens distortion correction is mainly used to reduce geometric distortion caused by camera imaging, while denoising can reduce the influence of random noise on the recognition of fine defects. Contrast enhancement often uses methods such as histogram equalization to make the difference between defect regions and the background more pronounced. Image mosaicking combines multiple local images into a larger member image to facilitate observation of the overall distribution of defects. Scale calibration uses reference objects of known size or camera parameters to establish the correspondence between pixel dimensions and actual dimensions, providing a basis for calculating parameters such as crack length and width [1, 9]. By combining image mosaicking with scale quantification, one study achieved crack detection over a width range of 0.1 to 3.3 mm, with a maximum error in crack width quantification below 10% [9].

Methods for bridge surface damage detection have gradually developed from traditional image processing to machine learning and deep learning. Traditional methods mainly use threshold segmentation, edge detection, and texture feature extraction, and rely heavily on manually specified features and rules. When the background is relatively simple and defect features are conspicuous, such methods can achieve certain results, but they are readily disturbed under complex backgrounds and multi-type defect conditions [7]. Deep learning methods can learn defect features from annotated data, and common tasks include image classification, object detection, and semantic segmentation. Image classification mainly determines whether a defect exists in an image, object

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detection can identify the defect category and its location, and semantic segmentation can further obtain pixel-level results of defect regions [5]. In recent years, the You Only Look Once (YOLO) series of object detection algorithms and semantic segmentation methods such as U-Net, SegFormer, and DeepLabv3+ have been applied to bridge surface damage detection. An improved SegFormer-SP method achieved favorable recognition performance in the segmentation of surface defects on concrete bridges, while maintaining a small model size and fast inference speed [5]. Another study separately constructed detection networks for block-like defects and cracks and tested them on image data from multiple bridges, with a comprehensive detection accuracy exceeding 95% [7].

Model performance cannot be judged by a single metric alone. Precision mainly reflects false detections among the results, whereas recall indicates whether actual defects are sufficiently identified. The F1 score considers both precision and recall and can be used to evaluate overall recognition performance. The Intersection over Union (IoU) is commonly used in object detection and semantic segmentation to measure the overlap between predicted regions and ground-truth annotations. For practical bridge inspection, it is also necessary to consider the inference speed and storage capacity of a model to determine whether it is suitable for running on field equipment [6, 7]. Previous research on bridge crack detection reported that an improved YOLOv8s model achieved a recall of 0.829 and a model size of 11.14 MB, controlling the model size while maintaining good detection performance [6]. Because the datasets, defect categories, and evaluation metrics adopted by different studies differ, detection results reported in the literature should not be directly compared in a simplistic manner.

3. Main applications of computer vision in bridge surface damage detection

3.1. Crack detection and quantification

Cracks are a relatively common type of surface defect in concrete bridges and have been studied extensively in CV detection. Crack detection requires first identifying cracks from bridge surface images and determining their location and extent. With scale reference information or after camera calibration, the correspondence between image pixels and actual dimensions can also be established to estimate crack length, width, and distribution. Without scale information, detection results usually only represent the pixel range of cracks in the image and cannot be directly converted into actual width or length [1, 9]. Existing studies show that deep learning methods can already perform crack recognition reasonably well, but accurate quantification of fine cracks and continuous monitoring of long-term crack development still present certain difficulties [10].

In actual bridge images, background information such as shadows, artificial markings, and weeds interferes with crack recognition. One study selected images from bridge inspection reports that contained fine and blurry cracks, shadows, artificial markings, and weeds, and formed 2,140 training images through manual annotation and data augmentation [6]. Based on YOLOv8s, this study improved the feature extraction capability of the model and its recognition performance under complex backgrounds. The study also measured crack length and width, so that the detection results not only reflected crack location but also supported crack size recording. Another study used a negative-pressure wall-climbing robot equipped with a high-definition camera to acquire images of concrete bridge tower surfaces, and combined a Transformer segmentation network with scale quantification for crack detection [9]. This method identified multi-scale cracks and was applied to crack detection on the main tower of a sea-crossing bridge [9]. Combining image detection results with scale quantification allows crack recognition to be further used for size recording and subsequent inspection.

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Computer vision can improve the screening efficiency of bridge crack images and facilitate consistent recording of crack location and distribution, reducing the manual workload of inspecting images one by one [1, 10]. Pixel-level detection results can also be used for subsequent review and for comparison between inspection results obtained at different times. In actual detection, cracks with small widths or inconspicuous features may still be missed, and shadows, construction joints, water stains, and stains may be falsely identified as cracks [6, 7]. When a model is applied to different bridges or shooting conditions, its detection performance may also vary. At present, such methods are better suited as auxiliary tools for bridge crack screening and defect recording, and suspicious regions detected still require manual confirmation.

3.2. Multi-type surface defect recognition

Compared with single-crack detection, multi-type defect recognition must handle bridge surfaces that often simultaneously contain multiple defects such as cracks, spalling, corrosion, and exposed rebar. The detection task must not only determine whether a defect exists but also further identify its category and location or extent. Different defect types have different features in shape, color, texture, and scale. Cracks usually appear as slender linear features, spalling appears as irregularly bounded patch-like regions, corrosion is often accompanied by reddish-brown or yellowish-brown color and texture changes, and exposed rebar may occur together with cover spalling [1, 5]. In actual images, defect features are not always clearly separable; background information such as water stains, oil stains, shadows, and surface color differences may resemble some defects, and fine cracks may be confused with member texture in low-resolution images. These factors all increase the difficulty of multi-type defect recognition.

Cha et al. used Faster Region-Based Convolutional Neural Network (Faster R-CNN) to build a multi-type damage detection model and constructed a dataset of 2,366 images to identify multiple categories of damage, including concrete cracks, steel corrosion, bolt corrosion, and steel delamination [2]. This method could identify multiple defects within the same image and provide their categories and locations, demonstrating that object detection methods can be used for multi-type surface defect recognition on bridges [2]. The detection performance of different defect categories is not entirely consistent, which is related to defect scale, sample quantity, and visual similarity among categories. Therefore, overall detection accuracy alone cannot fully reflect the model's recognition ability for each category, and the results for individual categories must also be analyzed.

Multi-type defect recognition is sensitive to the quantity and distribution of training data. When sample numbers differ greatly across categories, the model may learn insufficiently from minor categories, and its recognition performance is usually lower than that for categories with more samples [2, 5]. At the same time, bridges differ in material, surface aging, illumination, and shooting environment, and when a model is applied to a new bridge or a new shooting scene, its detection performance may decline [1, 4]. At present, automatic multi-type recognition is better suited for preliminary screening and category indication of bridge defects. For suspected defects with unclear boundaries, weak features, or complex member regions, inspectors still need to confirm them in the field.

3.3. Computer vision-assisted bridge inspection

Computer vision detection results must be combined with actual bridge inspection procedures to fulfill their practical role. After bridge surface images are processed by detection, suspected defect

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regions with defect category, location, and extent information can be obtained. Associating these results with bridge members, inspection batches, and historical defect records can form standardized defect records and provide a basis for subsequent review. Inspectors can prioritize suspected defect regions according to the detection results, reducing the workload of screening large numbers of images one by one. For the same member, changes in defect location and extent can also be observed by combining detection results from different periods, providing a reference for subsequent inspection and maintenance [1].

UAVs and specialized robots can further extend the application of CV to bridge inspection, especially at bridge locations that are difficult for personnel to reach. Feng et al. used a UAV equipped with a camera to acquire surface images of suspension bridge main cables and used a few-shot learning method to identify main cable surface defects, thereby reducing the need for close-range inspection work at high-altitude locations such as main cables [8]. Ding et al. used a negative-pressure wall-climbing robot to acquire images of concrete bridge tower surfaces and used a Transformer model for crack recognition and localization [9]. These two studies used different acquisition platforms, but both combined automated image acquisition with CV detection. In this way, locations that are difficult for personnel to inspect directly can be preliminarily screened through images, providing new technical means for bridge inspection.

According to existing studies, CV-assisted inspection can mainly reduce the manual screening of large numbers of images, reduce the need for some high-altitude and close-range inspection work, and make the recording of defect location and category more standardized [1, 8, 9]. However, detection performance is still affected by image clarity, occlusion, illumination, and shooting distance, and false detections and missed detections cannot be completely avoided. Image detection mainly reflects visible defects on the bridge surface and cannot be used directly to judge internal structural damage and load-bearing capacity [1, 10]. Therefore, at the present stage, CV is better suited as an auxiliary tool for bridge inspection, used for preliminary defect screening and information recording. For significant defects, uncertain recognition results, or cases requiring judgment of structural safety, further confirmation by manual inspection and other professional testing methods is still necessary.

4. Existing problems and future directions

At present, the data used for visual detection of bridge surface defects still differ considerably across studies. Datasets used by different studies are not unified in bridge type, member scope, defect categories, and annotation methods; some data come from laboratories or relatively ideal shooting environments, while others come from actual bridges or public images, so that results from different studies are difficult to compare directly [1, 4]. Actual bridge surfaces are also affected by shadows, rain stains, oil stains, moss, coating aging, and member texture, and changes in shooting distance and angle alter the appearance of defects in images. At the same time, the sample numbers of different defects are often imbalanced. Crack images are relatively easy to acquire, whereas samples of exposed rebar, local spalling, and some corrosion types are fewer, which affects the model's recognition of minor categories. Even when a model achieves high accuracy on an existing test set, its detection performance may decline when applied to a new bridge or shooting environment.

When a model is transferred from experimental datasets to actual inspection environments, it must cope with more field constraints. Fine cracks, early corrosion, and spalling edges have weak features in images and are readily disturbed by resolution and background information. When bridge materials, shooting equipment, illumination, and viewing angle change, the original recognition capability of the model may also be affected. For models deployed on UAVs, mobile terminals, and

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field inspection equipment, computational capacity and operating speed must also be considered. If a model is too large, it may be difficult to meet field inspection requirements even with high recognition accuracy. Therefore, practical use requires a reasonable trade-off among detection performance, operating speed, and equipment conditions. At present, automatic recognition results cannot replace the comprehensive judgment of inspectors regarding the structural state of the bridge, and manual review remains an important part of field inspection.

Future research can further improve data diversity and model adaptability across different scenes. Datasets should cover different bridge types, members, defect categories, and shooting conditions as far as possible, and defect classification and annotation methods should be gradually unified to improve comparability across studies. For defects with few samples, data augmentation and few-shot learning can be used to alleviate insufficient training data. Model research should consider not only detection accuracy but also lightweight design and field operating efficiency, so that models are better suited for UAVs, robots, and mobile devices. Multi-view images and the cooperation of different detection methods can also help reduce occlusion and information loss caused by a single viewpoint. Compared with testing only on fixed datasets, future research needs continuous validation in real bridge environments to further understand model stability across different times, bridges, and shooting conditions.

5. Conclusion

This paper reviews the image data, CV methods, and detection process for bridge surface defects, with a focus on three aspects: crack detection and quantification, multi-type surface defect recognition, and CV-assisted bridge inspection. Existing studies show that CV methods can already identify common defects such as cracks, spalling, and corrosion from bridge surface images and determine their locations. When scale calibration is available, the dimensions of certain defects can be further quantified. When combined with UAVs and robots, CV also reduces the need for close-range manual inspection and large-scale image screening. In addition, associating detection results with bridge members, inspection batches, and historical records can form standardized defect records and support subsequent review and maintenance. At present, the practical effectiveness of automatic detection of bridge surface defects is still affected by image quality, complex backgrounds, sample quantity, and shooting conditions. The recognition performance of a model may vary across different bridges and environments, and automatic detection results cannot directly reflect internal bridge damage and structural safety state. Therefore, at present, CV is better suited as an auxiliary tool for bridge inspection, used for preliminary defect screening, localization, and recording, while significant defects and uncertain recognition results still require confirmation by manual inspection and other professional testing methods. Future research should further improve data diversity and model adaptability across scenes, gradually unify defect classification and annotation methods to improve comparability across studies, and consider lightweight model design for UAVs, robots, and mobile devices. Continuous validation in real bridge environments is also needed to improve the stability and reliability of model performance in practical inspection.

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