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Based on an Overview of Crack Detection

Jinglong Wei

School of Environment and Architecture, University of Shanghai for Science and Technology, Shanghai 200093, China

Abstract

This Crack detection, as an important part of concrete structural health monitoring, aims to reflect the stress state and damage degree of the structure. Traditional concrete crack detection mainly relies on manual visual identification, which has low detection efficiency and accuracy. In addition, manual visual detection has problems such as being greatly affected by lighting conditions, being unable to cover overhead locations such as bridge towers and high piers, and being highly subjective. In recent years, in order to solve the above problems, researchers at home and abroad have developed concrete crack detection equipment based on digital image technology, such as inspection vehicles equipped with high-resolution cameras, unmanned aerial vehicles, crawling robots, and so on. Meanwhile, efficient and accurate crack detection algorithms are the basis for realizing accurate crack identification. How to balance the detection speed and accuracy has been the focus of academic attention. This paper reviews the research progress of concrete crack detection equipment based on digital image technology at home and abroad in recent years, including camera platform, calibration method, preprocessing, traditional and deep learning algorithms, crack feature extraction, image stitching, and 3D representation and monitoring of cracks. In addition, the deficiencies in the research are summarized.

Keywords

Crack Detection; Digital Imaging Technology; Deep Learning; Crack Detection Algorithms.

1. Introduction

Concrete cracks, as a key index of concrete stress performance test, play a crucial role in the degree of damage and early manifestation of structural diseases in concrete structures. The presence of cracks directly affects the durability and stability of concrete structures, which may lead to serious structural damage and cause great harm to the safety performance of the structure. Regular crack detection and crack tracking monitoring are of great significance in the field of concrete structures, which can reveal the force mechanism of concrete structures and assess the loss of stiffness and residual bearing capacity of concrete structures.

However, traditional crack detection mainly relies on manual detection, but the efficiency and accuracy of manual detection are low. The detection results are affected by factors such as inspectors and inspection instruments, resulting in results varying from person to person. In addition, human eye recognition has problems such as large influence of light, inability to detect high altitude position, easy to miss detection, etc. It is difficult to visually represent the detection data and cannot meet the requirements of large-scale concrete structure crack detection.

In recent years, with the development of computer technology, scholars began to use image processing and machine learning algorithms to detect the damage of concrete structures. The rapid development of deep learning technology has been introduced into the field of bridge crack detection, which significantly improves the detection accuracy and simplifies the detection process. Inspection methods based on digital image technology are more accurate, efficient, and capable of quantifying crack detection results. The introduction of high-altitude inspection using a camera mounted on a drone has greatly improved the safety and economic benefits of inspection.

Therefore, the purpose of this thesis is to comprehensively review the concrete crack detection methods based on digital image technology in recent years and discuss their advantages in terms of quantification of crack detection results, safety and economy. At the same time, it summarizes the shortcomings of the existing technology and looks forward to the future development direction in the field of bridge crack detection.

2. Crack Detection Methods

Computer vision techniques are widely recognized as an efficient method in the implementation of image-based crack detection automation. However, the application of computer vision techniques within this field has been facing many challenges over the past decades [1]. The key step in crack detection is to extract features with crack sensitivity, a task that can be realized by image processing techniques or deep learning frameworks. As a result, research on image-based crack detection has been divided into two main categories: traditional image processing methods and automated methods based on deep learning

2.1. Image Processing Methods

Image processing plays an important role in automatic crack identification algorithms, and its process usually includes three key steps: image preprocessing, image segmentation and feature extraction. As one of the foundations of crack detection algorithms, image preprocessing aims to effectively reduce the amount of image data and improve problems such as uneven illumination and noise during picture taking and transmission, where common operations include image compression, image denoising and image enhancement [2]. It has been reported that image compression can be achieved by means of grayscaling and downsampling to reduce the number of images and improve processing efficiency. In the field of crack detection, for the variability between different grayscaling methods, it has been pointed out that they have less impact on the image of concrete structures [3]. In addition, the purpose of image denoising and image enhancement is to improve the image quality and highlight the difference between the cracked part and the background in order to promote the accuracy of subsequent segmentation and feature extraction [4].

Image segmentation techniques are key aspects of crack detection algorithms and are used to categorize pixels in an image to form a binary image that contains only cracks and background. Commonly used image segmentation methods include threshold segmentation, of which the method proposed by Ohtsu et al. to calculate the threshold value is widely used[5]. However, for threshold selection of crack images, studies have shown that the threshold calculated by the regression method is better, but its adaptive ability is poor [6].

The feature extraction technique is a key part of the crack detection algorithm, and its main task is to determine whether a segmented image is a crack by extracting its characteristic parameters. Aiming at the problem that the image foreground may contain interfering objects in practical applications, the commonly used feature parameters are designed around the geometrical shape of the crack, such as the aspect ratio of the outer rectangle and the degree of roundness. Related studies have shown that when the roundness of the target is less than 0.08 pixels, the aspect ratio is greater than 30 pixels, and the perimeter is greater than 40 pixels, it has a higher probability of being a crack[7]. Other studies have proposed a series of feature parameter and edge similarity methods based on the crack skeleton to distinguish cracks from interferences [8].

2.2. Deep Learning Based Algorithm for Automatic Crack Detection

The introduction of deep learning has brought about a significant change in the field of imaging. Convolutional neural networks began to make their presence felt in the field of imaging since the term deep learning was introduced to machine learning in 1986 and AlexNet won the ILSVRC classification task in 2012. Deep learning models consist of multiple layers to learn data features with multiple levels of abstraction, and unlike traditional methods, deep learning does not require preprocessing operations on images, but automatically extracts target features from a large number of learning samples. Deep learning based crack detection algorithms are mainly categorized into image classification algorithms, target detection algorithms and image segmentation algorithms. These methods first extract features through convolutional layers, and then combine classification, recognition or segmentation modules with them to clarify the specific tasks of the model.

For example, Han Xiaojian et al[11] used a local threshold segmentation neural network to extract cracks, while Meng Shijiao[12] used a Deeplab-based convolutional neural network model to achieve pixel-level semantic segmentation of the crack region, which improves the recognition accuracy of the model. In addition, Jiewen Yang et al[13] proposed a deep learning algorithm combining U-Net and Haar-like, which proved its effectiveness. Su Renya et al[14] proposed a pixel-level crack detection method based on U-Net convolutional network, which solved the problems of losing detail information and difficulty in obtaining width information in the previous crack detection by superimposing a shallow network and a deep network. Yu Gayong et al[15] introduced Mask R-CNN network and scanned the concrete surface image through a sliding window to realize the automated detection of cracks. And Yu Gayong et al[16] also proposed an integrated bridge crack intelligent detection method combining YOLOv5 and UNet3+ algorithms. In addition, Tan Guojin et al[17] improved the DeepLabv3+ model by adding the YOLOF module and ResNet module to improve the accuracy of the model. Zhang Zhenhai et al[18], on the other hand, combined deep learning and traditional methods to achieve accurate identification of cracks by filter processing and image segmentation using an improved Mobile-NetV2-based model.

Although image classification and target detection algorithms have achieved some success in crack recognition, they cannot directly extract cracks from images, and still need to be combined with image segmentation algorithms to complete the extraction of cracks. Full convolutional neural network can realize pixel-level image segmentation and has been widely used in the field of crack recognition. With the improvement of cameras and other hardware devices, the pixel-level segmentation of cracks has become the future development trend of crack recognition[19].

3. Conclusion

With the continuous progress of science and technology, various quasi-distributed monitoring techniques for concrete cracks have been significantly developed and matured, and these techniques play a crucial role in actual projects. The new monitoring technology can overcome the problems of limited monitoring range and difficulty in capturing the timing of crack appearance, providing a more comprehensive, flexible and accurate solution for engineering monitoring. Comprehensively, the concrete gap detection technology based on digital image processing is in line with the general trend of the development of seismic artificial intelligence, and is considered to be one of the important development directions for bridge gap detection in the future. Thus based on the traditional manual detection methods, the technology has fire advantages, as described below:

(1) High-precision detection and quantitative management: digital image processing technology shows superior performance in bridge crack detection, which is characterized by

high precision, low cost, high efficiency and high safety. The technology is capable of accurate quantitative management of cracks, automatic calculation of the geometric characteristics of cracks, and marking of cracks of different widths and different directions.

(2) The superiority of deep learning crack recognition algorithm: the deep learning-based crack recognition algorithm can still maintain high accuracy under complex backgrounds. In particular, the pixel-level segmentation algorithm can reduce the complexity of image preprocessing steps and directly realize the accurate segmentation of cracks.

(3) Three-dimensional visualization output and tracking monitoring: digital image processing technology can accurately locate the position of cracks on bridges and realize three-dimensional visualization output and tracking monitoring of cracks. This method can help engineers better understand the distribution of cracks and take corresponding repair and maintenance measures in time, thus improving the safety and stability of bridges.

(4) Various image-acquisition platforms mainly rely on manual identification and measurement of appearance lesions in the later stage. However, due to the limited range of expression of pictures, large concrete structures require hundreds of thousands or even millions of pictures, so the workload of manual identification is very large. This situation leads to a bottleneck that makes it difficult to popularize the application of this detection technology on a large scale.

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