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A Review of Computer Vision Applications in Concrete Crack Identification

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Abstract
In the field of concrete crack identification, computer vision technology is widely used to automate the process of detecting concrete cracks, which has a wide range of application prospects and can improve the accuracy and efficiency of concrete structure detection to further protect people's safety, lives, and property. In concrete crack identification, computer vision systems usually use image processing techniques to segment the image in order to find the location and shape of the cracks. This can be achieved by using various algorithms and tools, such as convolutional neural networks, support vector machines, and threshold-based segmentation algorithms. However, there are still some challenges in concrete structure detection, such as grayscale differences in concrete surfaces, light variations, and occlusions. To address these challenges, researchers have proposed some new approaches, such as deep learning-based methods and hybrid methods combining multiple algorithms. In this paper, the development history of computer vision in the field of concrete crack recognition will be reviewed, the mainstream algorithms for crack detection will be introduced in detail, traditional algorithms and deep learning algorithms will be compared. Comprehensive analysis shows that deep learning algorithms have obvious advantages over traditional algorithms in concrete crack recognition, with much higher accuracy and efficiency.

Keywords: *Computer vision, Crack detection, Deep learning, Review.*

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I. INTRODUCTION

Computer vision is an artificial intelligence technology that can automatically recognize and interpret digital images or videos. Concrete cracks are one of the most common defects in concrete structures. In infrastructure such as buildings, bridges, and roads, the presence of concrete cracks can have a serious impact on the strength and durability of the structure, and due to the inherent characteristics of the building material, most of the infrastructure is working with cracks during its service life[1]. Due to the nature of the building material, most of the infrastructures work with cracks during their service lives. Therefore, the timely and accurate identification and analysis of concrete cracks is of great importance. With the continuous development of computer vision technology, the research in the field of concrete crack identification has also been greatly developed, and computer vision technology has been widely used in the field of concrete crack identification, and many scholars[2-3]have used feature-based machine learning methods and traditional image processing techniques to extract and analyze structural cracks. In practical applications, cracks often appear in complex and variable environmental conditions, and the data obtained when using the above vision methods to detect cracks is often disturbed by a large amount of noise, which will seriously affect the reliability of the detection results. The research and development of highly accurate and robust crack detection methods has become a concern in the engineering field. Deep learning has demonstrated advantages that traditional methods do not have in several fields such as speech recognition, text translation, image processing[4] , and this artificial intelligence technique can help solve problems in crack detection, such as complex and variable environmental conditions and interference from large amounts of noise.

This paper mainly outlines the development history, research results and related applications of computer vision in the field of concrete crack recognition., as shown in Figure 1. Firstly, the image processing techniques and algorithms usually used in computer vision systems are introduced, such as threshold-based segmentation algorithms, morphology-based crack detection methods, and region-growth-based crack detection methods. Secondly, this paper reviews the research progress of crack detection based on deep learning in recent years, and provides an overview of the deep learning framework and deep learning algorithms. Finally, this paper summarizes the advantages and shortcomings of existing methods and provides an outlook on the future development trend of intelligent crack detection in the construction industry. In summary, this paper provides an exhaustive introduction to computer vision techniques and deep learning algorithms in the field of concrete crack recognition, which provides important references and references for related researchers.

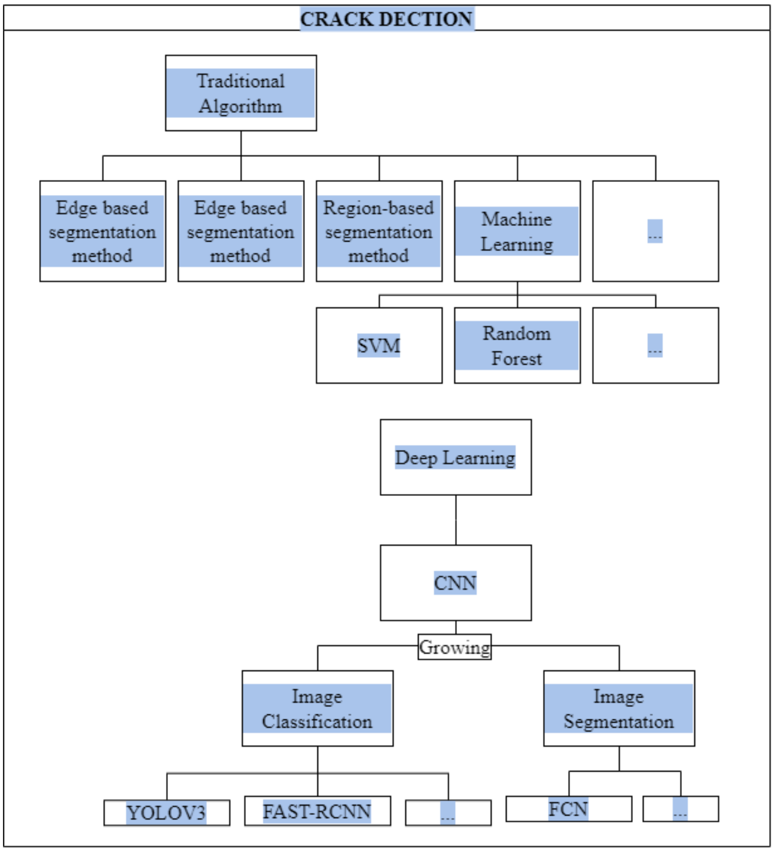

Figure 1: Brief Introduction of Crack Detection Algorithm

II. TRADITIONAL ALGORITHMS

Traditional surface defect detection algorithms usually obtain an image for easy detection by image pre-processing and then combine statistical machine learning methods to extract image features for defect detection. In defect detection, the commonly used edge detection methods (e.g., Prewitt, Sobel, and Canny operators) can simply and effectively locate defect regions in simple background detection environments. However, when faced with complex backgrounds or defects with low signal-to-noise ratios, the performance of the method is limited and also requires high imaging conditions. Therefore, frequency domain analysis can be an effective means to deal with these problems. Mutant defects often exhibit high-frequency characteristics in the frequency spectrum, and methods such as the Fourier transform, Gabor transform, and wavelet transform can be converted to the frequency domain to detect products with simple or periodic backgrounds. For large defects, statistical-based methods such as grayscale variation variability, grayscale histograms, and color characteristics can be used to characterize them, and traditional machine learning methods (e.g., SVM, random forest) can be used for classification to further improve the accuracy and robustness of defect detection. In the following, several common traditional algorithms applied in crack detection are described.

2.1 Crack Detection Method Based On Threshold Segmentation

The crack detection method based on threshold segmentation is a crack detection method based on image processing technology, whose basic idea is to binarize the image according to a certain threshold to separate the crack from the background, so as to achieve the detection and identification of cracks. The method is divided into two main steps.

The main steps of the method include.

i. Image pre-processing: including denoising, graying and other processing for subsequent threshold segmentation.
ii. Threshold segmentation: By setting a threshold value, the image is binarized to separate the cracks from the background, so that the features and shapes of the cracks can be extracted.

iii. Crack feature extraction: the shape, length, width and other features of the crack are extracted from the binary image of the crack.
iv. Crack determination: according to the shape, length, width and other characteristics of the crack, determine whether the crack is in line with the characteristics of the crack.
v. Crack Extraction: The areas that match the crack characteristics are extracted and the cracks are represented by shapes such as line segments or polygons.

Qiang et al[5] proposed a surface crack detection method based on the adaptive Canny algorithm and iterative threshold segmentation algorithm. During the image smoothing process, the adaptive Canny algorithm automatically calculates the difference between the current pixel gray value and the average gray value of the image within the filter window, and uses this difference as the spatial scale factor of Gaussian filtering. The Otsu method is applied to calculate the image gradient histogram to obtain the high and low threshold values, and the these new values are used to detect the edges of cracks. Finally, the crack-containing images are binarized based on an iterative threshold segmentation algorithm, and the broken points in the cracks and the voids within the cracks are removed by morphological expansion.

2.2 Morphology-Based Crack Detection Method

The morphology-based crack detection method uses mathematical morphology and curvature evaluation to detect crack-like models. The method defines a rectangular or other shaped structural element and performs operations such as erosion, expansion, open and closed operations on the concrete surface image, causing the edge information in the image that is not a crack to erode away, while filling the crack edges and then performing crack identification.

The main steps of the method include.

i. Image pre-processing: including denoising, graying and other processing for subsequent morphological processing.
ii. Morphological transformation: morphological transformation operations such as opening, closing, expansion, and erosion make the crack region and the background region separated and extract the edge features of the cracks.
iii. Crack feature extraction: The shape, length, width and other features of the crack are extracted through the extraction and analysis of the crack edge.
iv. Crack determination: according to the shape, length, width and other characteristics of the cracks, determine whether the cracks are in line with the characteristics of the cracks.
v. Crack extraction: The areas that match the characteristics of cracks are extracted and the cracks are represented by shapes such as line segments or polygons.

The method can effectively utilize the shape properties, connectivity, curvature and other features of cracks, and is suitable for crack detection in concrete surface images with complex backgrounds, and is widely used in crack detection research. It should be noted that the parameter settings for image pre-processing and morphological transformation operations are more sensitive, while factors such as crack shape, color and background may also affect the crack detection, so multiple experiments and processing are required to improve the accuracy and reliability of crack detection.

Young-Ro et al[6] proposed a concrete crack detection method using shape characteristics based on morphological algorithms and crack features, assuming that the input image is contaminated with various noises, using morphological operators and extracting crack patterns.

2.3 Crack Detection Method Based On Area Growth

The crack detection method based on region growing is a crack detection method based on image processing technology. The basic idea is to divide the image into several similar regions and grow the crack regions by calculating the similarity and connectivity of each region, so as to achieve the detection and identification of cracks.

The main steps of the method include.

i. Image pre-processing: including denoising, sharpening, graying and other processing to facilitate subsequent area growth.
ii. Region initialization: the image is divided into several small regions and the similarity of each region is calculated.
iii. Region growth: Start from the region with the highest similarity, calculate the similarity and connectivity of other regions adjacent to the region, and merge the regions with similarity above a certain threshold and connectivity into the current region to form a new region.
iv. Crack determination: determine whether the area conforms to the shape and characteristics of the crack, such as narrow shape, darker color, etc.

v. Crack extraction: The areas that match the crack characteristics are extracted and the cracks are represented by shapes such as line segments or polygons.

It should be noted that the region growth method requires high technical requirements such as image segmentation and similarity calculation, while factors such as the shape, color and

background of the cracks may also affect the detection of cracks, so multiple experiments and processing are required to improve the accuracy and reliability of crack detection.

In crack detection, the region growing algorithm can be used to zone the crack image and find the seed regions, and then vectorize the crack regions and connect them with the seed regions according to the similar properties between the crack regions, iterating continuously until all the crack regions are connected. This algorithm can realize the connection of fractured cracks, but the computational effort and the presence of noisy regions may lead to some noisy regions being misconnected, which affects the accuracy of crack detection.

To solve the problem of computationally intensive region growing algorithms, some improvement methods based on optimization algorithms have been proposed. For example, some optimization algorithms based on GPU acceleration and parallel computing have been proposed, which can effectively improve the running speed of the algorithm. In addition, some deep learning-based crack detection methods have been proposed to detect and segment cracks using techniques such as convolutional neural networks, which usually have higher accuracy and shorter computation time.

Song et al[7] A crack detection algorithm based on multi-scale pyramid and improved region growth is implemented for PV image crack detection problem, filtering the image, extracting the fracture features of different scale PV images using multi-scale pyramid, and introducing an improved directed region growth algorithm to complement the detected cracks.

2.4 Machine Learning Algorithms

Shi et al[8] proposed CrackForest, a new random structured forest-based road crack detection framework that applies integral channel features to redefine the markers that constitute cracks, introduces random structured forests to generate high-performance crack detectors that can identify arbitrarily complex cracks, and proposes a new crack descriptor to characterize cracks and effectively distinguish them from noise.

2.5 Summary of Traditional Algorithms

In addition to the above algorithms, there are some other algorithms belonging to this category, such as: image segmentation methods based on cluster analysis, segmentation methods based on wavelet transform, methods based on genetic algorithms, etc. Since cracks in reality often exist in complex and changing environmental conditions with complicated structures, the crack detection data obtained using the above vision methods often contain a lot of noise during the detection process, which will seriously affect the usability of the

detection results. And the above algorithms are noise sensitive and very slow, which is not conducive to application in practical engineering. Therefore, deep learning methods are introduced in the field of crack vision detection to replace traditional image processing techniques and feature-based machine learning techniques to achieve high accuracy detection of cracks in construction facilities in multiple scenes[9].

III. STATUS OF RESEARCH ON DEEP LEARNING-BASED CRACK DETECTION

At present, deep learning-based defect detection has been applied to many fields such as metal firmware, cloth and silk fabrics, construction cracks, steel cracks, etc., and has achieved good results. The following will introduce its implementation method with specific cases. Changes in the appearance of building materials (such as cracks or corrosion) are inseparable from the safety of their building structures, and the effectiveness of relying on visual inspection by inspectors is limited, compared to the more reliable and convenient structural damage detection based on computer vision.

Deep learning, a branch of machine learning, has attracted much attention in recent years due to its outstanding performance in target detection and semantic segmentation[10]. The successful application of deep learning algorithms in medical vision detection has inspired researchers to explore in other fields as well. For example, Zhang et al[11] applied deep convolutional neural networks to crack detection task for the first time in 2016 to classify the crack images taken by smartphones, which provided a new idea for intelligent detection of cracks. Deep learning-based crack detection algorithms can be divided into two major categories, i.e., crack image classification and pixel-based crack image segmentation.

3.1 Crack Image Classification

Cui et al[12] established a deep learning dataset through concrete erosion tests to achieve accurate identification of concrete erosion damage, and proposed an improved YOLO-v3 algorithm model with accuracy, precision and MAP of 96.32 %, 95.68 % and 75.68 %, respectively, which verified the applicability of deep learning for concrete erosion damage research.

Kang et al[13] developed a crack detection, localization and quantification method for realistic and practical problems with various complex backgrounds under different environmental conditions. The Faster-R-CNN based method provides a bounding box level crack detection.

Cha et al[14] proposed a vision method based on convolutional neural networks (CNNs) deep architecture for detecting concrete cracks without computing defect features. The designed CNN was trained on 40 K images with 256 × 256 pixel resolution and finally obtained an accuracy of about 98 %.The trained CNN was combined with a sliding window technique to scan any image larger than 256 × 256 pixel resolution, the robustness and adaptability of the proposed method was tested on 55 images (5888 × 3584 pixel resolution) with different structures, which were not used for the training and validation process under various conditions. The performance of CNNs using conventional Canny and Sobel edge detection methods is investigated in comparison, and the results show that the proposed method has better performance and is able to detect concrete cracks in practical situations.

3.2 Pixel-Based Crack Image Segmentation

Pixel-level Segmentation, also known as Semantic Segmentation, is an important task in the field of computer vision, whose goal is to classify each pixel in an image to determine the class of objects or objects to which it belongs[15]. Pixel-level segmentation has a wide range of applications in many computer vision tasks, such as autonomous driving, medical image analysis, aerial photography of drones, image enhancement, etc. The goal is to classify each pixel in an image to determine the class of objects or objects to which it belongs. Unlike Object Detection, pixel-level segmentation requires not only detecting objects in an image, but also segmenting them at the precise pixel level, i.e., labeling each pixel with the class of the object or object to which it belongs. This makes pixel-level segmentation more detailed and precise than target detection. Common pixel-level segmentation methods include traditional machine learning-based methods and deep learning methods. Traditional methods mainly include graph theory-based, energy function-based methods and methods based on image segmentation algorithms. In contrast, deep learning methods include Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs), etc.

Kang et al[13] integrated three independent computer vision algorithms: crack detection using a regionally proposed convolutional neural network (Faster R-CNN) with faster bounding box aspect; crack detection using modified tubular flow field (TuFF)[16] for pixel-level crack segmentation; and an improved distance transformation method (DTM) for damage quantification, which calculates crack thickness and length from segmented cracks recorded by modified TuFF and optimizes them to improve the performance of this paper's method for crack segmentation under thickness and length measurements, overcoming the limitations of traditional crack segmentation methods based only on deep learning.

Kim et al[17] proposed a new crack evaluation framework for concrete structures using a mask and a region-based convolutional neural network (Mask R-CNN) to detect cracks and quantify cracks by performing morphological operations on the detected crack masks. The 376 concrete images were annotated with cracks using the VGG annotator and a Mask R-CNN was trained for crack detection. The trained model was tested and successfully detected most of the cracks 0.3 mm or wider and quantified the crack width using image processing techniques. In a field test, the trained network was used to scan large concrete walls to detect cracks and quantify the crack widths. The results show that the trained network is suitable for the detection of real structures, while this paper demonstrates the potential of deep learning in automated structural detection.

Konig et al[18] propose an automated annotation approach for semantic segmentation of surface cracks by using a fully convolutional U-Net-based architecture that allows a patch-based training process using small datasets. The architecture exploits the residual connectivity within the convolutional blocks and introduces an attention-based gating mechanism between the encoder and decoder parts for further propagation of only the relevant activations. Using this architecture, this paper achieves the latest best results on two different cracked datasets and outperforms the previous best results in both metrics. The architecture is robust and applicable to various crack segmentation datasets.

IV. CRACK DETECTION APPLICATION STATUS

The traditional image acquisition method requires professionals to hold the acquisition equipment for close range photography, which is not conducive to detecting and evaluating structural cracks in hard-to-reach areas. To solve these problems, an increasingly intelligent, flexible and mobile crack image acquisition equipment needs to be built. Such equipment can improve the efficiency of crack image acquisition and reduce operational hazards, meeting the current and future development needs of the construction industry. As shows in Figure 2.

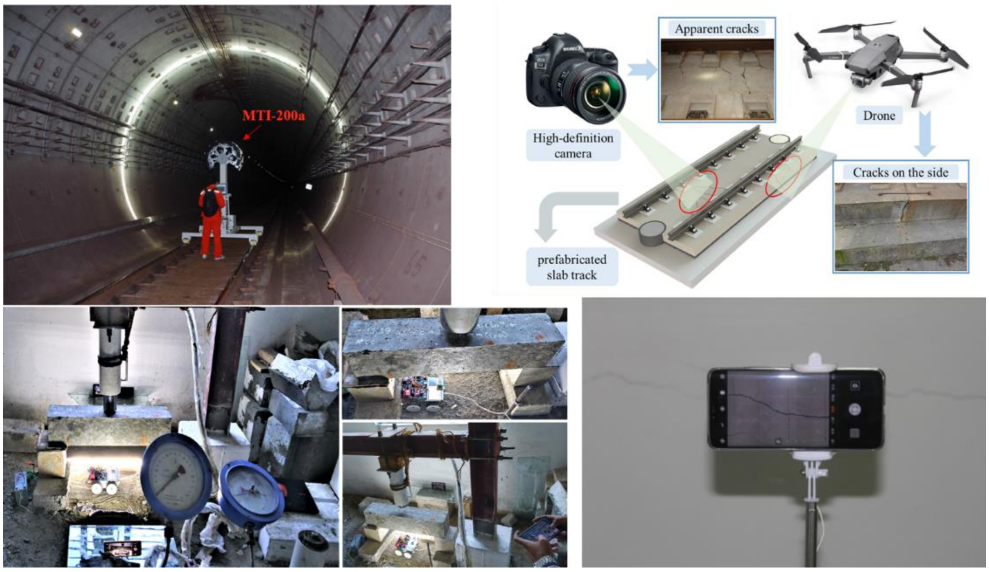

Figure2: The self-developed image acquisition equipment named Metro Tunnel Inspection(upper left)[19]; Schematic diagram of apparent cracks collection in concrete for slab tracks(upper right)[20];Experimental set up for beam testing(lower left)[21];Working map of smartphone APP(bottom right)[22]

In recent years, several researchers have developed machine vision-based crack detection robot platforms for different types of civil engineering infrastructures to explore and apply.

Ye et al[20] collected concrete crack images from railroad operation sites and school slab track test platforms using UAVs and high-definition cameras, and resampled concrete crack images from public databases to establish a database containing 48,000 images for detecting apparent concrete cracks in slab tracks, and proposed a method for rapid detection of apparent concrete cracks in slab tracks, extracting concrete crack areas , whose edges are closed and continuous.

Das et al[21] conducted an experimental and numerical study of the flexural cracking performance of reinforced concrete beam members to investigate the effect of bending cracks by varying the percentage of tensile reinforcement in the beam cross-section, and developed and validated a computer vision-based data-driven numerical tool for crack characterization and quantification based on real-time spatio-temporal video monitoring data from beam flexural tests.

Ni et al[22] investigated the measurement and analysis of concrete crack characteristics of smartphone APP based on digital image processing technology under Android system, and the results showed that the size of single pixel point has a good linear relationship with the shooting distance of the base lens without magnification, and the relationship between SSPP and magnification of all zoom lenses at the same shooting distance follows the law of exponential function, and the use of The accuracy of measuring concrete cracks by smartphone zoom lens or shortening the shooting distance can meet the requirements of engineering inspection.

V. CONCLUSION AND OUTLOOK

The current status of research and development of computer vision in the field of concrete crack detection can be summarized as follows.

Traditional image processing algorithms: Traditional image processing algorithms usually extract features from images by processing them first, and then classify them by some classifiers. In the field of concrete crack detection, the common traditional image processing algorithms include edge detection algorithm, morphology algorithm, region growth algorithm, etc. Although these algorithms can detect some cracks, it is often difficult to detect some small cracks due to the complex and variable texture of the concrete surface.

Traditional machine learning algorithms: Traditional machine learning algorithms usually require hand-designed features and classification by some classifiers. In the field of concrete crack detection, common traditional machine learning algorithms include support vector machine (SVM), decision tree, random forest, etc.. These algorithms are capable of detecting more cracks, but for cases where the shape and size of the cracks vary greatly, it is often necessary to redesign the features, increasing the complexity of the algorithm.

Deep learning algorithms: Deep learning algorithms usually do not require hand-designed features, and learn features directly from raw data and perform classification by some deep neural network models. In the field of concrete crack detection, common deep learning algorithms include convolutional neural network (CNN), recurrent neural network (RNN), convolutional recurrent neural network (CRNN), etc. These algorithms can automatically learn the features of images, which are better for crack detection and can be adaptive to different scales of cracks.

The main advantages of deep learning on the field of concrete crack detection include:

Adaptive: Deep learning algorithms are capable of adapting to different scales and shapes of cracks.

Automation: Deep learning algorithms do not need to design features manually and are able to learn features of images automatically.

Robustness: Deep learning algorithms are more robust to some noise and disturbances.

The main shortcomings of the current deep learning in the field of concrete crack detection include:

Insufficient datasets: Due to the complex and variable textures of concrete surfaces, there are currently fewer datasets available for deep learning training, and there are some problems with quality and diversity, which can affect the generalization ability of deep learning models.

Manual labeling is difficult: the texture of the concrete surface is complex, and there are huge variations in the shape, size, direction and depth of cracks, making the cost of manual labeling data integration higher, and the labeling results may be inconsistent and inaccurate.

Insufficient model interpretability: Deep learning models are usually strongly black-boxed, making it difficult to explain how the models make classification decisions, which poses certain security risks in some critical areas.

Future research in the field of concrete crack detection can be carried out in the following areas:

Increase the dataset: build a larger, more comprehensive and accurate concrete surface crack dataset to improve the generalization ability of the deep learning model.

Improving annotation efficiency: Using automated techniques (e.g., semi-supervised learning, weakly supervised learning, etc.) to reduce manual annotation costs and improve annotation efficiency.

Model interpretability research: To study how to improve the interpretability of deep learning models and provide more reliable interpretation and evaluation for the application of deep learning models.

Joint multi-source data research: Integrate multiple data sources (e.g. ground measurements, UAV images, satellite remote sensing, etc.) for concrete crack detection research to improve detection accuracy.

Incorporating domain knowledge: Incorporating domain knowledge into deep learning models to improve the accuracy and interpretability of the models.

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