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Research on Pavement Crack Detection Based on Deep Learning and UAV Aerial Images

Yong shun Zhao[1]
1College of Civil Engineering, Chongqing Jiaotong University, Chongqing, China

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ABSTRACT:
Pavement distress detection forms a fundamental part of highway maintenance, among which cracks are the most common type of defect. Cracks not only compromise the structural integrity and aesthetic appearance of the pavement, but may also pose serious risks to driving safety. Traditional inspection methods often suffer from low efficiency, high labor costs, insufficient accuracy, and potential disruptions to traffic flow, highlighting the urgent need for more advanced alternatives. With the rapid advancement of computer vision and deep learning technologies, automated approaches based on object detection have been widely adopted in pavement distress inspection. Simultaneously, unmanned aerial vehicles (UAVs) have demonstrated significant potential in pavement image acquisition due to their high mobility, low cost, and ease of operation. This paper proposes a novel pavement crack detection method that integrates deep learning algorithms with UAV aerial imagery, aiming to achieve automated crack identification and precise localization. The proposed approach significantly improves detection efficiency and accuracy, offering strong engineering adaptability and promising potential for widespread application. It provides an effective technical foundation for the intelligent development of road maintenance.

Keywords: highway pavement, crack detection, deep learning, convolutional neural network, UAV aerial image.

I. INTRODUCTION

With the continuous expansion of highway mileage, the task of road maintenance has become increasingly demanding [1]. As one of the most prevalent types of pavement distress, cracks, if not repaired in a timely manner, may lead to severe consequences such as subgrade instability and pavement collapse. These issues can significantly shorten the service life of roads and pose serious threats to traffic safety. Therefore, timely detection and maintenance of pavement cracks are crucial not only for preventing the further propagation of damage, but also for substantially reducing road maintenance costs and the incidence of traffic accidents. Ultimately, this contributes to enhanced road safety and overall transportation efficiency [2].

At present, pavement distress detection primarily relies on traditional methods such as manual inspection. In this approach, inspectors typically collect data on the geographic location, crack types, and quantities directly on-site through a combination of visual observation and manual measurements. Although this method offers a certain degree of intuitiveness and operational flexibility, it suffers from several significant limitations. First, the random distribution and wide spatial coverage of cracks make the inspection process time-consuming and labor-intensive. Second, manual inspections often require occupying roadways, which can easily lead to traffic congestion and may even compromise the safety of inspection personnel. Third, the results of manual detection are heavily influenced by subjective human judgment, making the process prone to both false detections and omissions, and lacking consistency and generalizability [3].

In recent years, the advancement of deep learning and unmanned aerial vehicle (UAV) technologies has opened up new avenues for pavement crack detection. The rapid progress in computer vision has enabled deep learning to achieve remarkable breakthroughs in image processing, demonstrating strong capabilities in object detection. At the same time, UAVs—due to their small size, low cost, high maneuverability, and broad field of view—have shown great potential in road inspection applications. Therefore, this study integrates deep learning techniques with UAV-acquired aerial imagery and proposes a pavement crack detection method based on this combination. The proposed approach not only significantly enhances the accuracy and efficiency of crack detection but also

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greatly reduces the need for manual intervention and lowers maintenance costs. This method provides a robust technical foundation for achieving intelligent and automated road inspection.

II. DEVELOPMENT OF PAVEMENT CRACK DETECTION METHODS

2.1 Traditional Detection Methods

Traditional pavement crack detection primarily relies on manual inspection, wherein inspectors visually observe and manually measure pavement damage and crack locations. This approach is not only inefficient and labor-intensive, but also increasingly inadequate in coping with the rapidly expanding highway network. Moreover, manual inspections pose significant safety risks, as the personal safety of inspectors cannot be effectively guaranteed during field operations. Due to its reliance on subjective judgment, manual inspection is prone to false positives and missed detections, resulting in low accuracy and poor consistency. As such, it fails to meet the demands of large-scale, high-efficiency detection. Instead of facilitating maintenance and crack repair, this method can, to some extent, impose additional burdens on the transportation system.

2.2 Deep Learning-Based Detection Methods

In recent years, deep learning-based detection methods have emerged as a research hotspot in pavement crack detection. By leveraging deep learning algorithms such as convolutional neural networks (CNNs), cracks can be automatically identified and localized from pavement images. Compared with traditional image processing and machine learning approaches, deep learning demonstrates superior robustness and generalization capability in handling complex backgrounds and multi-scale targets. This leads to significant improvements in both detection accuracy and processing efficiency.

At present, deep learning has not only advanced the application of computer vision techniques in pavement distress detection but also facilitated the practical implementation and broader adoption of related engineering technologies [4]. Its successful application in crack detection signifies a gradual transition of detection technologies toward automation and intelligence, effectively enhancing the generalizability, accuracy, and efficiency of inspection processes.

III. APPLICATION OF UAV PHOTOGRAMMETRY IN PAVEMENT CRACK DETECTION

3.1 Basic Components of a UAV Aerial Imaging System

The UAV photogrammetry system is an efficient platform for spatial data acquisition and has been widely applied in fields such as surveying and mapping, geographic information systems (GIS), land management, and environmental monitoring. Its application in pavement crack detection relies on several key components, which can be categorized as follows.

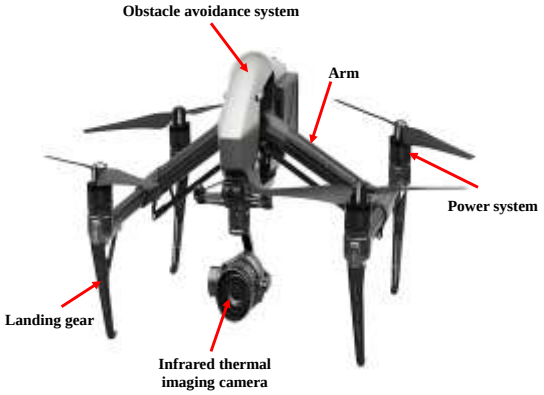

Fig.1 UAV-mounted equipment.

(1) UAV Platform

A dedicated left-turn waiting area is a designated space at an intersection for vehicles waiting to make a left turn. This area should be designed based on road conditions and traffic volume. The main purposes of setting up a left-turn waiting area are: to reduce the waiting time for left-turning vehicles; to separate left-turning vehicles from through traffic; and to enhance the safety of intersection traffic

(2) Imaging Equipment

Image acquisition typically relies on high-resolution RGB cameras, infrared cameras, or LiDAR (Light Detection and Ranging) sensors, depending on the specific technical requirements of the detection task. For instance, RGB cameras are suitable for visual crack detection, while infrared and LiDAR systems are more effective for image acquisition under nighttime conditions or in complex terrain environments.

(3) GNSS and INS Positioning System

The integration of the Global Navigation Satellite System (GNSS) and Inertial Navigation

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System (INS) provides the UAV with high-precision positioning and attitude information. This ensures the accuracy of flight paths and the spatial precision of image geolocation.

(4) Autonomous Flight Control System

The autopilot system enables functionalities such as flight path planning, waypoint navigation, and automated takeoff and landing. These features significantly enhance the level of automation and operational safety.

(5) Power Supply System

Batteries or other power systems provide essential energy support for both the UAV and its onboard payloads, serving as a critical component for ensuring continuous operation.

3.2 Advantages of UAV Photogrammetry in Pavement Crack Detection

UAV aerial imagery integrates the strengths of UAV platforms with modern photogrammetric technologies [5]. Owing to the UAV's high maneuverability and ease of operation, the system is capable of capturing large-scale, multi-angle, high-resolution ground images. When equipped with infrared imaging devices, UAVs can operate under all-weather and all-day conditions, unaffected by time or climate constraints. Compared with traditional inspection methods, UAV-based systems offer several significant advantages:

First, their operation does not interfere with normal traffic flow, thereby reducing traffic management pressure.

Second, UAVs can cover broader lane areas and acquire higher-precision image data, greatly enhancing spatial resolution and overall data quality.

Finally, UAVs exhibit strong adaptability and stability even in complex or harsh environments, improving overall operational efficiency and flexibility.

Fig.2 UAV-Based Pavement Crack Inspection Scene.

IV. APPLICATION OF DEEP LEARNING IN PAVEMENT CRACK DETECTION

4.1 Convolutional Neural Network

With the widespread application of deep learning in the field of computer vision, defect detection has increasingly benefited from these advancements. The Convolutional Neural Network (CNN), as one of the most commonly used algorithms for defect detection, offers the advantage of learning features directly from data [6]. This capability not only enhances model adaptability and detection performance but also enables strong performance across diverse application scenarios.

A CNN is primarily composed of the following fundamental components: the input layer, convolutional layers, pooling layers, activation function layers, fully connected layers, and the output layer. The use of multiple convolutional layers for feature extraction significantly improves detection accuracy and greatly enhances the model's robustness in complex environments, resulting in more precise image processing and classification.

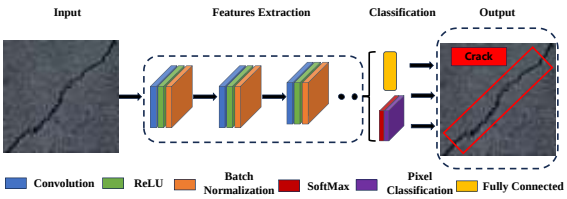

Fig.3 Structure of Convolutional Neural Network.

4.2 Deep Learning-Based Object Detection Algorithms

Deep learning-based object detection algorithms are primarily categorized into two-stage and one-stage detection frameworks. Each category offers distinct advantages in terms of detection pipeline and performance emphasis, and both have been widely applied in various visual recognition tasks, including pavement crack detection.

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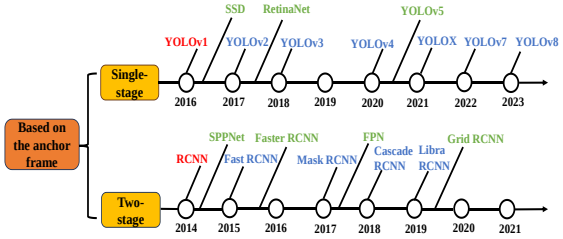

Fig.4 Development of the target detection algorithm.

4.2.1 Two-Stage Object Detection Algorithms

Two-stage detection methods first generate a set of region proposals from the input image using a region proposal generator, and then perform feature extraction, classification, and bounding box regression on these candidate regions. A representative family of such algorithms is the Region Proposal Convolutional Neural Network (R-CNN) series [7], including Fast R-CNN, Faster R-CNN, and Mask R-CNN.

Overall, two-stage object detection algorithms offer high detection accuracy and are particularly suitable for tasks involving complex object shapes and demanding precision requirements. However, due to their more intricate detection pipeline and slower inference speed, they are generally not ideal for real-time applications.

4.2.2 One-Stage Object Detection Algorithms

One-stage detection methods bypass the region proposal step and directly perform object localization and classification on the original image using an end-to-end processing framework. This significantly simplifies the detection pipeline and improves computational efficiency. The main representatives of one-stage detection algorithms are the YOLO (You Only Look Once) [8] and SSD (Single Shot MultiBox Detector) [9] series.

YOLO formulates object detection as a regression problem by dividing the input image into a grid and predicting bounding box coordinates, confidence scores, and class probabilities within each grid cell. It offers advantages such as high inference speed and compact architecture, making it well-suited for real-time applications. However, its detection accuracy may decline when dealing with small objects or complex backgrounds.

SSD, on the other hand, performs simultaneous bounding box regression and classification on multiple feature maps of different resolutions. By introducing anchor boxes and a multi-scale detection mechanism, SSD achieves a balanced trade-off between speed and accuracy, making it suitable for tasks involving multiple objects and varying object scales.

V. PAVEMENT CRACK DETECTION METHOD BASED ON DEEP LEARNING AND UAV AERIAL IMAGERY

The integration of deep learning and UAV technology offers a novel approach for achieving efficient and intelligent pavement crack detection. This paper proposes a pavement crack detection method that combines deep learning algorithms with UAV-acquired aerial imagery. The proposed method consists of the following three key steps:

5.1 Crack Image Data Acquisition

The quality and diversity of crack image data are critical factors influencing subsequent model training and detection accuracy. To obtain high-quality crack images, this study utilizes a UAV equipped with a high-resolution camera to perform low-altitude aerial photography within predefined road inspection areas. The UAV follows a pre-planned flight path at a stable speed and altitude, ensuring consistency in image acquisition and completeness in area coverage.

This aerial imaging approach effectively overcomes the limitations of traditional manual inspection methods, such as high labor costs, low data collection efficiency, and difficulty accessing complex terrain. Additionally, by integrating GPS with the UAV's flight control system, precise geolocation information for each captured image can be recorded. This enables accurate spatial mapping of crack locations, supporting visualized crack management and seamless integration with Geographic Information Systems (GIS).

During the data acquisition process, the camera must possess high resolution and imaging stability to clearly capture cracks of various sizes, shapes, and orientations. After image collection, an initial screening process is conducted to eliminate blurred, overexposed, or invalid images, thereby ensuring the validity and representativeness of the dataset.

The final standardized pavement crack image dataset includes various crack types (e.g., transverse, longitudinal, and alligator cracks) under different lighting and surface material conditions. This dataset provides a solid foundation for training and testing deep learning models, and offers a scientific basis for performance evaluation and comparative analysis of crack detection algorithms.

5.2 Image Preprocessing and Augmentation

After the construction of the dataset, a series of systematic preprocessing and enhancement operations are required to improve image usability and enhance the model’s ability to recognize crack

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features. First, denoising techniques such as Gaussian filtering and median filtering are applied to eliminate random noise in the images, thereby improving image clarity and the signal-to-noise ratio. Next, image enhancement techniques—including histogram equalization, contrast stretching, and edge enhancement—are used to emphasize detailed features in crack regions and strengthen key structural information in the images.

To standardize input image size and format, cropping and resizing are commonly performed. Additionally, regions of interest (ROIs) can be selectively cropped based on crack distribution to improve training efficiency. Converting color images to grayscale can reduce computational complexity and highlight grayscale differences associated with cracks, which is beneficial for subsequent feature extraction.

To address data scarcity and enhance the model's generalization capability, data augmentation strategies are widely employed. These include operations such as image flipping, rotation, translation, scaling, brightness adjustment, and the addition of simulated noise to generate diverse training samples. These techniques not only enrich the dataset but also improve the model's robustness to various crack shapes, scales, and lighting conditions.

5.3 Deep Learning Model Selection and Training

Given the characteristics of pavement crack detection tasks, it is essential to select a deep learning object detection model that offers high accuracy, strong robustness, and good real-time performance as the core framework. Among mainstream detection models, YOLOv8 stands out for its lightweight architecture, end-to-end inference speed, and strong localization capability, making it well-suited for real-time applications. In contrast, Faster R-CNN, as a representative two-stage detection algorithm, delivers higher recognition accuracy and is particularly effective in handling complex backgrounds and fine-grained crack detection tasks.

The model training process is conducted using supervised learning. The preprocessed image dataset is first divided into training, validation, and test sets. Each image is annotated with bounding boxes and class labels corresponding to crack instances. The annotated data are then used to train the selected model by optimizing objective functions such as IoU Loss, Focal Loss, or Cross-Entropy Loss, iteratively adjusting model parameters to minimize the error between predicted and actual values.

During training, various strategies are employed to improve model generalization and prevent overfitting, including data augmentation, learning rate scheduling, batch normalization, and regularization techniques. Furthermore, transfer learning can be leveraged by initializing the model with weights pre-trained on large-scale general-purpose datasets, thereby accelerating convergence and enhancing performance on limited crack-specific datasets.

Upon completion of training, the model is quantitatively evaluated on an independent test set. Common performance metrics include mean Average Precision (mAP), Precision, Recall, and F1-score, which together provide a comprehensive assessment of the model's accuracy and stability in real-world crack detection scenarios. The model with the best overall performance is then selected for deployment and inference, enabling automated crack identification and precise localization in actual pavement images.

VI. CONCLUSION

With the continuous expansion of highway networks, relying solely on manual inspection and maintenance is no longer sufficient to meet the efficiency and safety demands of modern transportation systems. Moreover, this approach entails significant economic and labor costs. As a result, the automation and intelligence of road inspection have become an inevitable development trend.

Pavement crack detection technologies based on deep learning and UAV aerial imagery are emerging as a key research direction in the field of pavement distress detection, owing to their advantages in accuracy, efficiency, and adaptability. This approach not only improves the precision and operational efficiency of crack identification but also provides more scientific and effective technical support for road maintenance and management. In the future, it is expected to play an increasingly critical role in the intelligent maintenance of transportation infrastructure and the enhancement of road safety.

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