Crack Detection in Asphalt-Paved Top Surface of River Embankments Using Unmanned Aerial Vehicles and Computer Vision Algorithms

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1. INTRODUCTION

Crack monitoring is crucial in assessing the degradation of riverine infrastructures such as river embankments and hydraulic structures. From a management perspective, it is necessary to measure and analyze changes in the size, shape, and orientation of cracks over time. This survey is commonly time-consuming and requires professional-expertise. Accordingly, automatic data collection and related analysis for such work are expected to be put into practical use, when considering the dwindling civil engineering workforce in Japan. In recent years, unmanned aerial vehicles (UAVs) have been increasingly incorporated in infrastructure maintenance work in terms of their cost-effectiveness and work safety improvement. However, subsequent visual check is still cumbersome for the vast amount of UAV images in river embankment inspections. Also, human errors might occur more frequently, compared with earlier on-site visual inspections.

As a screening tool in the management process, this study proposes a new automated method to detect the area including cracks in riparian asphalt pavements, using the UAV images with a computer vision algorithm. For such a trial, this study adopted the object detection algorithm named You Only Look Once version 7 (YOLOv7) for crack detection, and then examined the accuracy of the present method, compared with the visual inspection result.

2. METHODOLOGY

The YOLOv7 is a state-of-the-art object detection model that utilizes a single convolutional neural network to perform object detection and classification on an input image[1)]. This model leverages the latest advancements in computer vision researches with the deep learning method to deliver accurate and fast object detection results. In order to provide a more comprehensive assessment of asphalt pavements, this study provides two trained models derived from two individual datasets annotated by different methods: custom dataset with bounding boxes of multiple uniform sizes (i.e., 20-, 30-, 100-pixel) for crack annotation; public (or crack species-based) dataset prepared for the classification of the damage types of asphalt-paved road surface based on in-vehicle camera images (i.e., Road Damage Dataset 2019, RDD2019)[2)].

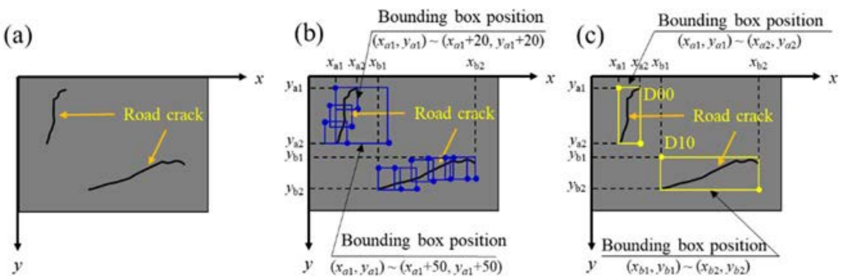

Fig. 1 (a) Raw UAV image, (b) Crack annotation method with bounding boxes of multiple uniform sizes, (c) Crack annotation method based on damage types of asphalt-paved road surface.

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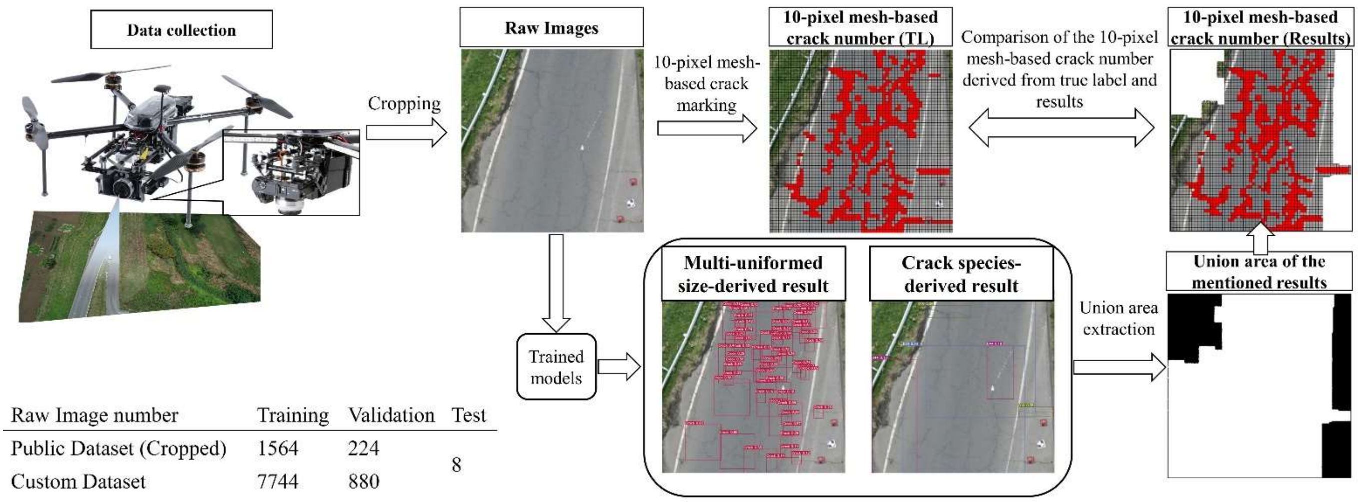

Raw Image number	Training	Validation	Test
Public Dataset (Cropped)	1564	224	8
Custom Dataset	7744	880	

Fig. 2 Flowchart of processes of crack detection, and model performance evaluation with the mesh-based crack number.

Fig. 1 shows an example of a raw UAV image and related bounding boxes marked by the two models. For instance, every annotation in **Fig. 1(c)** is classified into one of the predesignated types (e.g., D00, longitudinal crack) based on the road surface damage database[2].

Fig. 2 shows a flowchart of the processes of the crack detection and model accuracy evaluation. For dataset of training and inference processes, this study used the UAV images over a river embankment with the space resolution of 2.5 cm per pixel, then cropped the several raw images with the size of 600 pixels × 600 pixels. Cracks were checked visually, identified using a unit of 10-pixel red-colored square mesh, and total number of segmented crack areas was counted as “true crack number”. Additionally, the region that are likely to contain cracks (i.e., white area, **Fig. 2**) was determined from the union area of the annotations inferred by the two models. Then, the “inferred crack number” were estimated by counting the red segmented crack area within the white area. Lastly, the accuracy of the present method was checked by comparison of true crack numbers to inferred ones.

3. RESULTS AND DISCUSSION

Results demonstrated that the present method averagely covers more than 90% of the cracks marked visually in the test dataset. In addition, the performance of the present model improved by 13 % compared to the model using the custom dataset only. Especially, alligator cracks were difficult to be identified for the model trained using the custom dataset. By contrast, the trained model derived from the crack species-based dataset detected such sort of crack more effectively. This discrepancy is attributable to the present custom dataset containing less variety of crack for training. Therefore, the resultant accuracy might be greatly dependent on the quality as well as the quantity of the dataset.

4. CONCLUSION

The present study provided a new deep learning approach of improving the ability of the crack area detection in the riverine asphalt pavement, using additional dataset without increasing the complexity of the neural network architecture. Considering the maintenance perspective, quantification of individual crack widths will be undertaken in our future work.

REFERENCE

1) Wang, C. Y., Bochkovskiy, A., & Liao, H. Y. M. (2022). YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. *arXiv preprint arXiv:2207.02696*. https://doi.org/10.48550/arXiv.2207.02696

2) Road Damage Detector, https://github.com/sekilab/RoadDamageDetector.