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Overpass Bridge Inspection using Cascade Mask R-CNN with Hard Negative Sample Augmentation

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ABSTRACT

This paper proposes a novel framework for automated bridge inspection based on Cascade Mask R-CNN trained for detection of cracks. If the model is trained using only positive (crack) objects, some hard negative objects - visually similar objects to the positive objects, are not trained to be filtered and they are frequently detected by the trained model. Thus, the hard negative objects of cracks - such as joints, stains, and tree branches, are additionally sampled and used as another training samples after the augmentation using the positive objects. The Cascade Mask R-CNN is trained with two training image sets: one image set containing only positive crack objects, and the other set containing both positive crack objects and hard negative objects. Two Cascade Mask R-CNN models trained using both training image sets are implemented to find cracks on the images obtained using a UAV at a real overpass bridge in Korea. The performance of two models are evaluated using a metric based on the overlapped area of the detected objects and ground truth, and the model trained using both positive and hard negative samples resulted in lower false detection while keeping high detectability of positive crack objects. To alter the conventional bridge inspection procedure, a 3D model of the test bridge was organized using a Structure-from-Motion (SfM) software and 2D orthophotos are obtained for the bridge components. Then, the cracks are detected using the trained model on the orthophotos to generate a damage inspection map of the test bridge.

1. INTRODUCTION

Managing an increasing number of old civil structures is one of the most urgent and important social issues in most of highly developed countries. Among various types of concrete structures in many cities, overpasses are one of the most common and widely used structures in large cities. Since overpasses play a key role in reducing traffic congestion in large cities, blocking traffic due to poor overpass management inevitably

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incurs huge social costs. Therefore, it is important for facility administrators to efficiently manage numerous overpasses in cities. However, large volume and high height of overpasses are huge obstacles for efficient and safe management of overpasses. Although a bridge inspection vehicle is mostly used for overpass inspection, a bridge inspection vehicle is not suitable for efficient and safe overpass inspection since it is often overturned or causes traffic congestion.

To solve inefficiency that results from a bridge inspection vehicle, there are attempts to apply an unmanned aerial vehicle (UAV) for bridge inspection. Using an UAV for bridge inspection has two major advantages. First, there is no need to block traffic to set up a bridge inspection vehicle. Second, an UAV make it safe to acquire images of high-rise bridge piers. These advantages have recently led many civil researchers to study how to inspect the overpass using UAVs. For instance, Kim et al. (2017) have applied an UAV and image processing technique to detect cracks on a concrete wall and achieved error rate 7.3% for cracks that are narrower than 0.1mm. Even though there have been several researches that have tried to apply UAVs for a bridge or overpass inspection, there is no inspection example for a full structure of bridge of overpass at the best of the authors' knowledge. The reason for the small number of inspection cases for the entire structure is that it is difficult to distinguish cracks from objects similar to the various cracks found in the field.

Thus, this paper proposes a robust method to train a deep learning model for overpass inspection using hard negative sample augmentation to achieve high accuracy in a real-world environment and inspect the entire surface of a target overpass. Hard negative samples are negative examples that are determined as positive or ambiguous by a trained detector. In bridge inspection, water traces, cold joint or remaining of spider webs are hard negative samples (Jin et al., 2018). In this study, a state-of-the-art deep learning model Cascade Mask R-CNN (Cai et al., 2019) is trained with crack dataset enhanced with hard negative samples obtained from real structures in the field. The trained Cascade Mask R-CNN for crack detection is applied for overpass inspection and the crack detection result is compared with inspection results reported by bridge inspectors.

2. Overpass Inspection Crack Detection Deep Learning Model trained with Hard Negative Dataset.

This study presents an inspection scenario that maps the damage area detected by the deep learning model from the image captured using the drone to the bridge 3D model built using Structure from Motion (SfM) technology as shown in Fig. 1. The proposed inspection scenarios are: 1) damage dataset construction through internet and real structure shooting, 2) learning of deep learning models using collected dataset, 3) surface inspection of structures to be inspected using drones, 4) crack detection using SfM module The result consists of 4 steps of performing 3D model mapping.

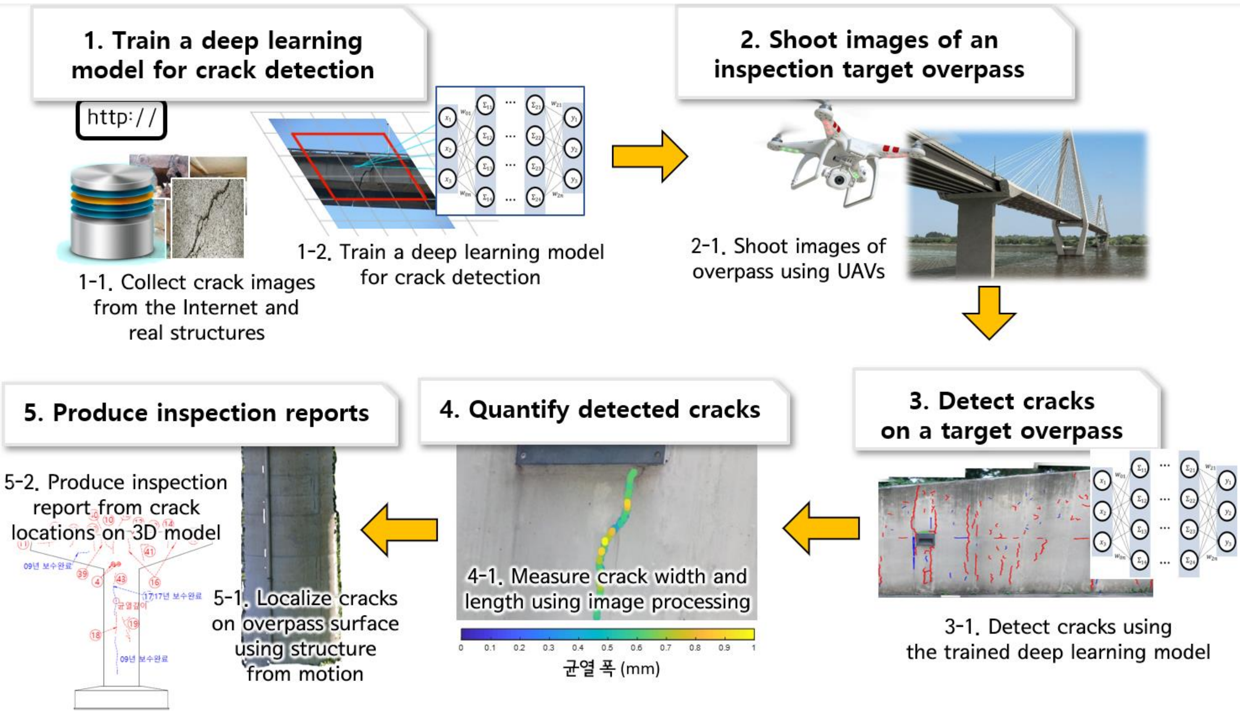


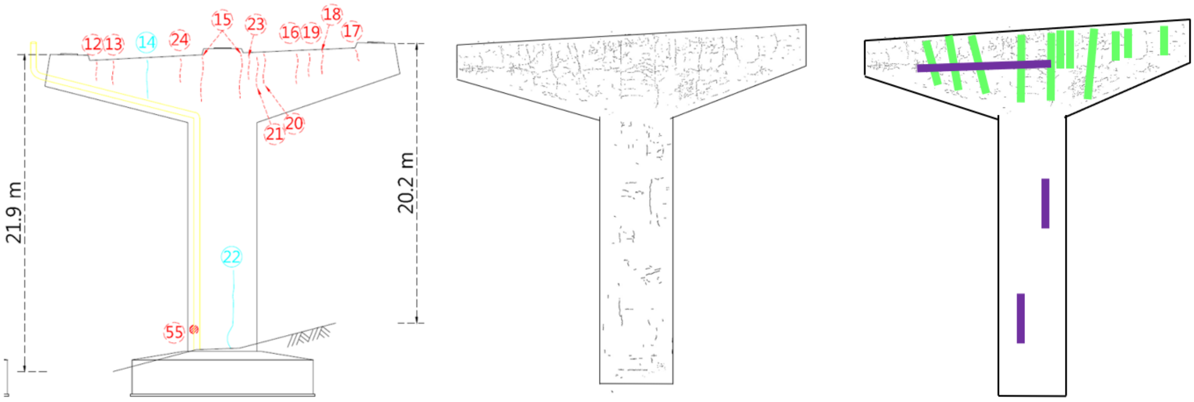
Fig. 1 Overall crack detection framework using deep learning technique

In this study, first, in order to train a deep learning model for crack detection, 825 crack images were collected from the Internet and real structures, and the cracks of each image were labeled in pixels. To enhance the collected crack dataset with hard negative examples such as spider webs or water trace running down on a structure surface, we collected 2415 hard negative images from real structures and the Internet. The 2415 hard negative images were merged with clean crack images as shown in Fig. 2. By merging the clean crack images with the hard negatives, deep learning model avoid class imbalance problem and achieve higher accuracy in crack detection. The labeled dataset was used to train Cascade Mask R-CNN, one of the state-of-the-art instance segmentation models. In order to verify the performance of the learned crack detection Cascade Mask R-CNN, exterior shots were taken on three spans of a real overpass bridge located in Gangnam-gu, Seoul. At this time, surface images were acquired using commercial drones DJI Mavic Pro and Intel Falcon 8. After shooting, a 3D model of an overpass was constructed from the bridge and bottom plate images collected using a commercial SfM program, Metashape. The orthogonal images of the front, back, left, and right sides were obtained from the 3D model, and crack detection was performed using the learned Cascade Mask R-CNN for the orthogonal images of each side. Fig. 3 is an example of the crack detection result of the pier surface using Cascade Mask R-CNN, and Fig. 4 is an example of an orthogonal image of a 3D model of a deck constructed using SfM. Fig. 5 is a comparison result between the trained crack detection model and human inspectors. The comparison conducted on No. 37 pier of Tancheon overpass only for the cracks that are longer than 50cm. Deep learning models and visual inspection results were consistent with 21 cracks. Among the cracks detected by the deep learning model, 8 cracks were not reported in the visual inspection. The deep learning model missed 3 cracks on the pier surface.

Fig. 2 An example of hard negative images merged with a clean crack image.

Fig. 3 An Example of Crack Detection Result by the trained Cascade Mask R-CNN

Fig. 4 Slab Orthomosaic Image of Tancheon Overpass



(a) (b) (c)

Fig. 5. An Example of Comparison between Inspection Result by Human Inspectors and the trained Cascade Mask R-CNN : (a) An Inspection Result reported by Human Inspectors, (b) A Binary Image of Crack Detection Result by the trained Cascade Mask R-CNN and (c) Comparison Results (Green line denotes crack detection where both the inspectors and the trained model reported the same result. Purple line denotes cracks that are found by the trained model but not by the inspectors.)

3. CONCLUSIONS

This paper proposed a robust framework for crack detection on real structures in the field using state-of-the-art deep learning model, Cascade Mask R-CNN and hard negative training data such as spider webs or water traces. The detection results are compared with the visual inspection results and showed reliable crack detection performance but also showed the small number of false positives. In the further research, it is required to evaluate the performance of the deep learning models on the extended numbers of test beds and accelerate the crack detection process.

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