Title	Sub-dataset Generation and Selection Methods for Convolutional-Neural-Network-based Crack Detection in Structural Maintenance
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Summary of Dissertation

Since the appearance of cracks is understood as an initial sign of the deterioration of structures such as concrete and brick walls, crack detection plays an important role in structural maintenance to ensure the safety and durability of structures. Conventionally, a maintenance engineer performs crack detection manually, which is laborious and time consuming. Therefore, the development of systematic methods to automatically detect cracks has become an important research topic in structural maintenance.

Although various crack detection methods have been proposed, in general, methods based on the use of Convolutional Neural Networks (CNNs) have exhibited the best performance. However, CNN-based methods fail to detect cracks under varied environmental conditions such as shadows, colors, and noise. Furthermore, CNN-based methods fail to detect cracks when small datasets are used for training CNN. The performance of such methods also depends on labeling images of the training datasets. Therefore, the generation of training datasets comprising images with accurate labeling is important in CNN-based crack detection.

In this dissertation, two methods are proposed to improve the performance of CNN-based crack detection in structural maintenance.

First, sub-dataset generation and selection methods are proposed for CNN-based crack detection under various environmental conditions. Sub-datasets are generated from a large dataset based on the image attributes. CNN learning is performed with each sub-dataset. Then, crack detection of input images is performed using a learned CNN selected by the proposed selection method, which selects the proper learned CNN by matching the attributes of the input images with those of the sub-datasets used for learning. The results of numerical experiments show that the proposed methods improved the performance of CNN-based crack detection methods under varied environmental conditions, where shadow and color are considered as the key factors affecting the crack detection on concrete walls and brick walls, respectively.

Second, an image-augmentation method, referred to as crack cropping, is proposed for the generation of training datasets for each maintenance target. The proposed method generates crack datasets by discarding non-crack images using an edge-detection technique. The results of numerical experiments show that the proposed method is able to generate training datasets with proper labeling from the images of target structures.

This dissertation consists of five chapters including an introduction, literature review, two proposed methods, and a conclusion. The outline of each chapter is as follows:

In Chapter 1, Introduction, the background, objectives, novelty, benefits, and effect on society of this dissertation are explained.

In Chapter 2, various papers related to crack detection in structural maintenance are reviewed comprehensively. Namely, the papers on techniques of crack detection including physical methods, vision-based methods, image processing methods, and so on are reviewed. In addition, image augmentation methods to generate datasets for crack detection in CNN are reviewed.

In Chapter 3, sub-dataset generation and selection methods have been proposed to improve the performance of crack detection using CNN-based methods.

With the proposed method, a large dataset of images is divided into sub-datasets using the proposed sub-dataset generation algorithm based on the attributes of the images. Subsequently, CNN learning is conducted using each sub-dataset generated through the proposed method. The proposed methods are applied to two kinds of structures, i.e., the concrete walls and the brick walls. For the concrete walls, two sub-datasets are manually generated: one for non-shadowed images and the other for shadowed images. For the brick walls, a sub-dataset generation method that generates sub-datasets using the color information as the image attribute is proposed. The generated sub-datasets contained images with similar color information. CNN learning is conducted using the generated sub-datasets.

To select a proper sub-dataset for test images using the proposed selection method, a distance calculation is conducted between the attributes of the sub-datasets used for CNN learning and those of the test images. In the case of concrete walls, the brightness values of the images are used as image attributes for a distance calculation. The distance between the brightness values of the input images and the sub-datasets is calculated, and a sub-dataset with the minimum distance is selected. In the case of brick walls, the color information of the images is used as the image attribute for the distance calculation, and a sub-dataset is selected based on the minimum distance.

The key novelty of the proposed methods lies in the sub-dataset generation from a large dataset and the selection of a proper sub-dataset for each test image by calculating the distance between the attributes of the test image and sub-datasets during crack detection.

Sub-dataset Generation and Selection Methods are validated by numerical experiments. In the numerical experiments for crack detection of concrete walls, an open dataset containing 40,000 (20,000 cracks and 20,000 no-cracks) non-shadowed images of concrete walls were used. A total of 2,000 images (1,000 cracks and 1,000 no-cracks) were generated by adding shadows using Adobe Photoshop. Shadows were generated from different angles in the images (10–360°) with different distances (10–250 pixels), as well as different sizes and opacities.

On the other hand, in the numerical experiments for crack detection of brick walls, 400 images (200 crack and 200 no-crack images) of brick walls were generated by manually cropping 100 raw images, which were obtained from the Internet. A total of 30 (15 crack and 15 no-crack) images were used to evaluate the performance of the proposed method for crack detection of brick walls.

Based on the results of experiments on concrete and brick walls, the effectiveness of the proposed sub-dataset generation and selection methods was validated with four metrics, i.e., precision, recall, F-measure, and accuracy. Namely, it was observed that CNN-based crack detection using the sub-datasets by the proposed methods performed better than that of the conventional CNN-based crack detection using one large dataset.

In Chapter 4, an image augmentation method, which generates large datasets of no-crack images and crack images for each maintenance target is proposed.

In the First Step of the proposed image augmentation method, sequential cropping is conducted to generate multiple images from a single large input image. For no-crack images, the datasets are generated through sequential cropping. On the other hand, for the crack input images, many crack and no-crack images are generated through sequential cropping. The generation of no-crack images for the crack dataset results in a failed crack detection. To discard the no-crack images from the crack dataset, the crack and no-crack images must be correctly differentiated. Hence, in the proposed method, crack cropping is conducted after sequential cropping to discard the no-crack images from the crack dataset. In addition, all images in the training dataset are labeled as either a crack or no-crack image during dataset generation.

In the proposed image augmentation method, adaptive threshold value calculations and thresholding are conducted before crack cropping. The brightness values varied for the different concrete walls. Therefore, the threshold value is determined adaptively for each input image after sets of crack-brightness values are obtained. Namely, in Step 2 of the proposed method, the sets of crack brightness values are considered to determine the threshold value. The image of a large wall is divided into small regions, and the brightness values of the cracks are collected from small regions containing cracks to cover all regions of the large wall. Then, in Steps 3 and 4, the threshold values are determined from these sets of crack brightness values. In this method, two thresholding methods, i.e., Method 1 and Method 2, are developed. In Method 1, the threshold value is calculated by considering the brightness mode value of the input image. In Method 2, two threshold values, i.e., the upper and lower thresholds, are calculated from sets of values using the percentile calculation (e.g., the 95th percentile). Finally, in Step 5 of the proposed method, crack cropping is conducted after thresholding through edge detection using the Sobel edge-detection template. If no edges are detected for an image, it is then assumed that the image contains no cracks and will be discarded from the crack dataset. To determine whether the detected edges are cracks, the edge connectivity is evaluated. Namely, the crack images are selected by evaluating the edge connectivity, and the no-crack images are discarded.

To evaluate the performance of the proposed image augmentation method, input images (crack and no-crack) with an image size of 5312 pixels × 3000 pixels were captured from several buildings of Kanagawa University. The images were captured with different properties, such as different surfaces (rough and smooth), crack shapes, and widths. Namely, four datasets were successfully generated from input images with different properties using the proposed method, as well as two different thresholding methods, i.e., Method 1 and Method 2. However, Method 2 outperformed Method 1 in terms of the number of images in the crack datasets because in the former method two threshold values were applied using the 95th percentile for thresholding. Therefore, a wide range of brightness values for the crack region were considered. Hence, more images were included in the crack dataset using Method 2.

In addition, cross-validation was conducted to evaluate the effectiveness of crack detection using the CNN and the proposed image-augmentation method. Cross-validation was applied for the crack detection of three different concrete buildings (e.g., Buildings 5, 16, and 23) at Kanagawa University, Japan. Five different datasets were generated for cross-validation from five different large input images of each building. The crack datasets were generated using Method 2 using the 95th percentile. Two experiments were designed for each building to compare the crack detection performance. One experiment was conducted using the generated datasets to train the CNN model with the proposed method, and the other was applied using the open dataset to train the CNN.

For the cross-validation of each building, one dataset was selected as the test dataset, and the remaining four datasets were used for training. Based on the result, it can be observed that when CNN learning was conducted using the datasets that were generated using the proposed image-augmentation method, the performance was higher than that using the large open dataset. This was because when the training and testing datasets were used from the same concrete walls, the attributes of the images (e.g., crack width) of the training and test datasets were similar. Therefore, higher performance was obtained for crack detection.

Finally, in Chapter 5, a summary of this dissertation, limitations, and future research directions are provided.