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Automated Concrete Crack Detection and using Deep leaning and Image Processing Method

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ABSTRACT

The damage investigation and inspection methods for infrastructures performed in small-scale (type III) facilities are usually visually examined by the inspector using the surveying tools (e.g., cracking, crack microscope, etc.) in the field. These methods can interfere with the subjectivity of the inspector, which may reduce the objectivity and reliability of the record. Therefore, a new image analysis technique is needed to automatically detect cracks and analyze the characteristics of the cracks objectively. In this study, an image analysis technique using deep leaning is developed to detect cracks and analyze characteristics (e.g., length, width) in images for small-scale facilities (type III). Two stages of image processing pipeline are proposed to obtain crack segmentation and its characteristics. In the first stage, two-dimensional convolutional neural network is used for crack image segmentation. Based on modern deep learning architecture for image segmentation, residual network and dilated convolution technique are applied into our deep learning network. After deep learning-based segmentation, in the second stage, thinning and profiling algorithm were applied to analyze length and width of crack in the image. Using the image processing pipeline, the performance of the method is tested using various crack images with label which are collected from various facilities and the results showed good performance of crack segmentation.

Keywords : deep leaning, crack detection, image processing, type III facility

1. INTRODUCTION

In general, inspectors use measuring tools (crack rulers, crack microscopes, etc.) in the field to visually investigate and inspect concrete cracks in small-scale ground concrete structures and manually prepare appearance examination documents. This method relies on the subjectivity of the inspector, which reduces the objectivity and reliability of the records, and it is also difficult to determine the progress of damage if the responsible inspector is changed. Therefore, in order to overcome these issues and to improve the objectivity and accuracy of inspecting facility damage and the convenience of recording and storing data, research on an image processing method that automatically extracts the appearance examination results by acquiring images through imaging equipment was performed.

Image processing methods refer to the entire process of processing and analyzing images acquired from a facility, and consists of functions such as image input/output, preprocessing for digitization, segmentation, defect management, and defect detection. For effective crack detection, studies were conducted on a morphology technique based on morphological computation (Byun et al., 2005; Lee et al., 2005; Lee et al., 2008) and a method of detecting cracks by applying RGB channel values to fuzzy techniques (Kim et al., 2010), in addition to research on shooting and imaging equipment (Park, 2013; Kim, 2016).

The rule-based method, which is a conventional image processing method, is a method in which users derive the results by modeling filters that remove noise from images to effectively detect cracks. However, the weakness of the rule-based method is that new filter modeling is required depending on the focal length of the image, the influence of the shooting environment (illuminance, intensity, etc.), shooting quality, and the resolution. In order to compensate for this, high-resolution imaging equipment that can shoot at speeds up to 80 km/h was developed, but the economic feasibility was low due to high costs.

Recently, the need for image analysis technologies using machine learning and deep learning is emerging and related research is being actively performed to overcome the limitations of the rule-based method. In particular, studies have been performed on methods to inspect and analyze the appearance of aging large-scale infrastructure with image processing techniques based on deep learning using Unmanned Aerial Vehicles (UAV) such as drones equipped with imaging equipment (Kim et al., 2017; Lee et al., 2018; Cho et al., 2018). However, damage inspection technologies using drones are still in the early stage of development, and require drone experts and expensive equipment. In addition, practical application is still a long way off as regulatory and institutional issues need to be addressed.

The purpose of this study is to investigate cracks in concrete structures (type III facilities) with relatively low-cost portable imaging equipment such as mobile phones and tablet PCs, to develop a deep learning method and image processing technique that can detect cracks effectively and quickly from the obtained images and analyze the characteristics (length, width) of the cracks, and to verify the performance of the developed method and algorithm for practical application.

2. STUDY METHOD

2.1 Deep learning algorithm

In general, the risk assessment of buildings is performed by accurately determining, quantifying, and recording the characteristics (length, width) of the cracks in concrete structures, which in turn help plan maintenance for the structures. The purpose of this study is to detect concrete cracks using deep learning and quickly determine the characteristics (crack, length) through image processing. The most common method to achieve this is to build a database of concrete crack images and to use it to segment the cracks. Segmentation refers to the conversion of low-level information (original image) into high-level information (partitioned image), which means removing unwanted information such as noise from the images. Various algorithms for segmentation have been developed, and typical algorithms include convolution-based segmentation deep learning methods and autoencoder-based segmentation deep learning methods.

The convolution-based deep learning method can convert an input image into an image that highlights the sought after characteristics by using a convolution filter, which is an image processing method. Just like applying the sobel filter, which is a filter to detect edges to create an image emphasizing edges, the method learns the appropriate filter for the problem to be solved and uses this to properly partition the segmentation target area in the input image.

Autoencoder refers to a deep learning method consisting of convolutional neural networks and de-convolutional neural networks. In general, a convolution-based neural network can be viewed as an encoder that reduces the amount of information and extracts only desired information from the corresponding input data, while de-convolution, which is the inverse operation of convolution, is a kind of decoder that expands the amount of information and reverts to the dimension of the original input data from the reduced information. Deep learning techniques based on autoencoder produce various functions that remove noise, change the texture of images, and perform segmentation through reducing and expanding information, and the corresponding functions depend on the learning data. In a bottleneck where information is finally reduced, the information is compressed to form an output image from the corresponding image, which is restored using de-convolution.

2.2 Configuration and training the deep learning method

In terms of configuring the two deep learning methods to obtain concrete crack information, at least 1,000 images of various concrete structures and concrete crack training data (data with cracks labeled) are needed for the learning process; it is very difficult to actually obtain them and manually perform crack segmentation. In addition, as the size of the architecture increases excessively in the images obtained from high-resolution cameras (2960 * 1440 based on QHD), proper training becomes impossible. Since the pixels of crack images may account for less than 1% of the pixels of the entire images, the learning performance can decline significantly due to imbalanced datasets.

Therefore, as shown in Fig. 1, this study proposes a deep learning method which divides images into patch units and consists of a crack classification neural network that determines whether cracks exist in the corresponding image patches and a crack segmentation neural network that performs crack segmentation on image patches classified to have cracks thereafter. The deep learning method proposed in this study can overcome the lack of training data by obtaining multiple image patches from a single image, prevent the decline of architecture performance for high-resolution images, and overcome the imbalanced dataset problems by using only image patches with cracks as the training data for segmentation. In addition, by separating the classification and segmentation neural networks, this method can process not only fixed-sized images but also data obtained in various environments.

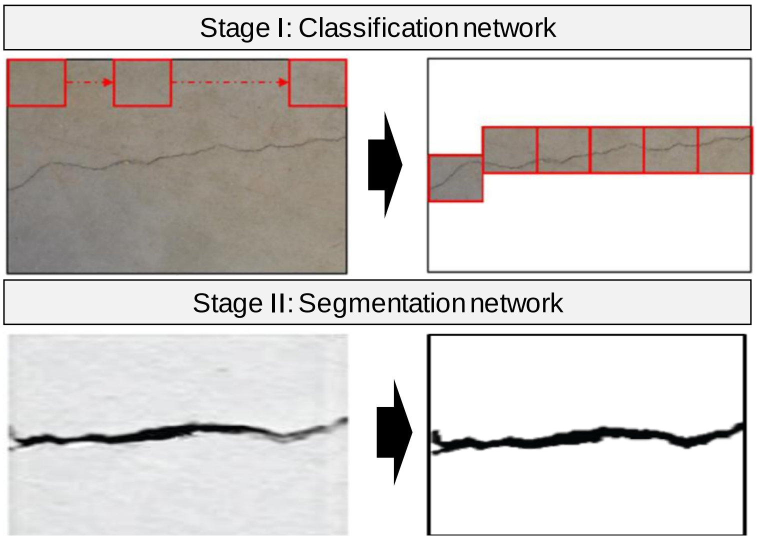


Fig. 1 Image segmentation for crack detection

In order to detect cracks through deep learning, various training data are required for the training process to teach the neural network the different characteristics of crack and non-crack data. Therefore, this study performed the initial training process of the classification network by using 40,000 concrete images (20,000 crack images, 20,000 non-crack images) shared by Özgenel (2018). The images contain information on the status of cracks, but since the cracks are not segmented, this study prepared crack segmentation data separately based on the data. Fig. 2 shows a concrete image without cracks (left), a concrete image with cracks (middle), and a partitioned image (right) from the concrete images shared by Çağlar Fırat Özgenel.

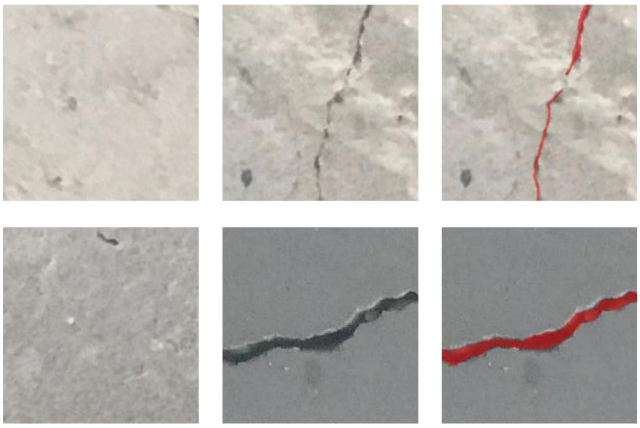


Fig. 2 Database of concrete cracks (Özgenel, 2018)

2.2.1 Concrete crack classification network

The concrete crack classification neural network detects whether concrete cracks exist in the input image. For this purpose, Cha and Choi (2017) extracted the characteristics of crack detection using convolutional neural network techniques, and proposed a crack detection method using dense networks while gradually reducing the dimensions of the images using stride and pooling.
The concrete crack classification neural network (Fig. 3) used in this study used 128 convolution filters, and in order to prevent information loss due to pooling, stride convolution only once after convolution filter group operation are performed, instead of pooling for every convolution filter. This study also applied a residual network to prevent the gradient vanishing problem during backpropagation. Finally, the network is configured to improve performance by adjusting the order of convolution, batch normalization, and activation to maximize batch normalization and performance.

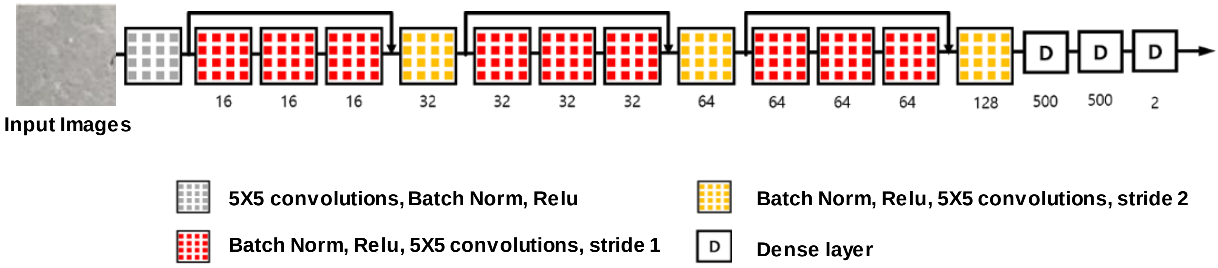


Fig. 3 Classification network for determination of crack presence

2.2.2 Concrete crack segmentation network

The crack segmentation neural network developed in this study is based on HiRes3DNet (Li et al., 2017), which is mainly used for medical image segmentation among various neural networks for segmentation. The architecture features a neural network with all the latest neural network technologies (batch normalization array, stride/pooling, residual neural network, and convolution-based segmentation). This study modified and used this network to perform segmentation on 2D images (Fig. 4).

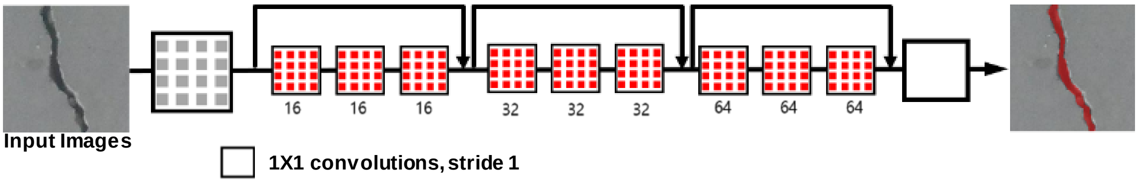


Fig. 4 Segmentation network for concrete cracks

3. PERFORMANCE VERIFICATION

3.1 Deep learning performance verification

3.1.1 Concrete crack classification network

As mentioned above, this study used 40,000 concrete images for the training and evaluation process of the artificial neural network, of which 36,000 images were used as training data and 4,000 as test data. A neural network with a batch size of 50 in order to go through 12,140,400 iterations (337 epochs) was used for training and the softmax cross entropy was used as the loss function. As a result of evaluating the accuracy, a final verification accuracy of 99.98% was obtained.

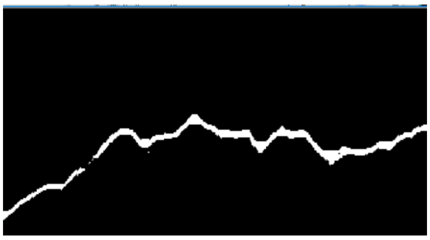
3.1.2 Concrete crack segmentation network

The segmentation network performs segmentation on the concrete cracks in the images classified as crack images. In terms of the data prepared to train this neural network, 2,000 segmentation images were used from the concrete crack database, of which 1,751 images were used for training and 249 for evaluation. As a result of going through 919,270 iterations (525 epochs) for training using sigmoid cross entropy as the loss function and IoU (Intersection over Union) as the evaluation function, the IoU value of the evaluation data was 0.87. As this is a value close to 1 which indicates 100% accuracy, a relatively high accuracy was confirmed.

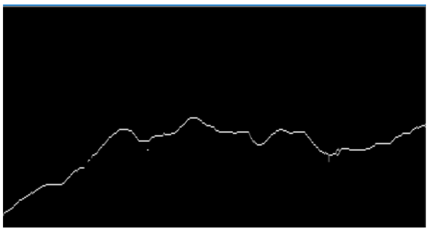
3.2 Results of crack detection and characteristic analysis

The images that go through the concrete crack classification and segmentation neural networks are returned as segmentation information on the crack points. Therefore, the total length and average thickness of cracks can be obtained, which are information about the concrete crack images, using thinning and tracking techniques. Fig. 5 shows the results of segmentation using the deep learning method on an actual concrete crack image (Fig. 5b), and the results of deriving the length and average width of the crack (Fig. 5c, 5d) based on segmented crack. The length, minimum width, and maximum width of the crack actually measured were 396.7 mm, 1.3 mm, and 5.2 mm, respectively. The crack length obtained by segmentation using deep learning and applying thinning and tracking methods in this study was 401.3 mm, showing an error of about 1%. In addition, the average crack width measured through profiling was 2.2 mm, which is similar to the crack width range actually measured.

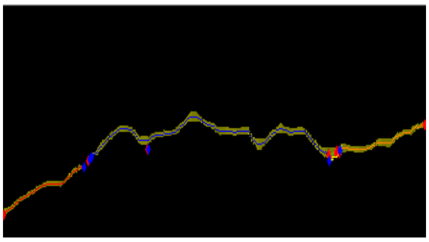
(a) Input image



(b) Segmentation



(c) Thinning and tracking



(d) Profiling

Fig. 5 Result of segmentation, thinning, tracking and profiling

4. CONCLUSIONS

The purpose of this study is to develop a deep learning method and image processing technique to detect cracks from the images obtained from portable imaging equipment and effectively analyze the characteristics (length, width) of the cracks, in order to inspect and record cracks in concrete infrastructures in an objective and efficient manner.

The deep learning method consists of a crack classification neural network that divides images into patches to determine the presence of cracks in each patch and a crack segmentation neural network which performs segmentation on the corresponding image patches in order to overcome the lack of training data, prevent the decline of architecture performance for high-resolution images, and overcome imbalanced datasets. In addition, the crack length through thinning and tracking from the concrete cracks partitioned are derived by the deep learning method, and also derived the average width of cracks through profiling. Finally, the performance of the developed method and algorithm for practical application are verified by comparing the results of the method developed in this study with the length and width measured in the field using an actual crack image.

This study is different in that it separated the classification and segmentation neural networks instead of using the conventional segmentation deep learning technique, in order to analyze images obtained from various environments as well as process fixed-sized images. However, due to the lack of objective records of crack images and their characteristics, this study only performed verification on one image. Therefore, the limitation of this study is the lack of verification regarding the accuracy and versatility of the developed method. In order to develop a more accurate deep learning method, we plan to continuously update training data and perform additional field application and verification in the future.

The concrete crack detection method developed in this study was designed to be relatively less influenced by the type and performance of the imaging equipment and the surrounding environment by using artificial neural networks. The developed method was also designed to improve accuracy through continuous learning. Therefore, the method is expected to be applicable to various types of ground concrete structures such as tunnels, water and sewer pipelines, underground roads, and utility tunnels. It will also contribute to evaluating the stability and integrity of concrete structures in the long term by efficiently inspecting and managing records of cracks in various types of structures with relatively low-cost portable equipment.

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