Patch-based crack detection in black box road images using deep learning

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Abstract -

This paper proposes a method for patch-based crack detection of black box road images, for efficient road pavement monitoring. The proposed method is based on deep learning and consists of two modules: road extraction and crack detection. The road extraction module uses the segmentation process of a Fully Convolutional Network (FCN) called FCN-8s to leave only the road area in the image. The crack detection module performs patch-based crack detection on the extracted road area using a convolutional neural network. To the best of the authors' knowledge, the proposed method is the first attempt to detect road cracks of black box images, which are not orthogonal but skewed actual road images.

Keywords – Crack detection; Deep learning; Patch-based analysis; Road surface monitoring

1 Introduction

Proactive road maintenance is an important process for repairing road defects like cracks. For proper maintenance, monitoring of road surface conditions should be performed frequently for large areas. However, it is difficult to efficiently inspect pavement conditions with conventional monitoring methods utilizing inspectors or special vehicles. Recently, mobile devices such as mobile phones and automobile black boxes have become popular. As the performance of the camera mounted on the mobile device increases, it is possible to observe the surface condition of the road by the device attached to the windshield. If a method to utilize this video data for road condition monitoring is developed, significant improvement is expected in the traditional road monitoring method.

Various computer vision algorithms and machine learning based models have been developed for automatic road crack detection. A widely used vision-based crack detection method was to detect the morphological features of cracks by detecting the intensity change of pixels [3,5,7]. Some studies were based on machine learning approaches, which derived features of crack images through a large number of images, and then classified the images into crack and non-crack, or analyzed the types of cracks [4,5,9]. Recently, crack detection methodologies using deep learning have been emerging. Deep learning trains the weights that make up the neural network model based on a large amount of images, and conducts crack detection even with complex backgrounds. The crack detection study using deep learning is divided into patch-based and pixel-based method [1,2,10]. In this study, deep learning based method for detecting cracks in the unit of patch is pursued in black box images.

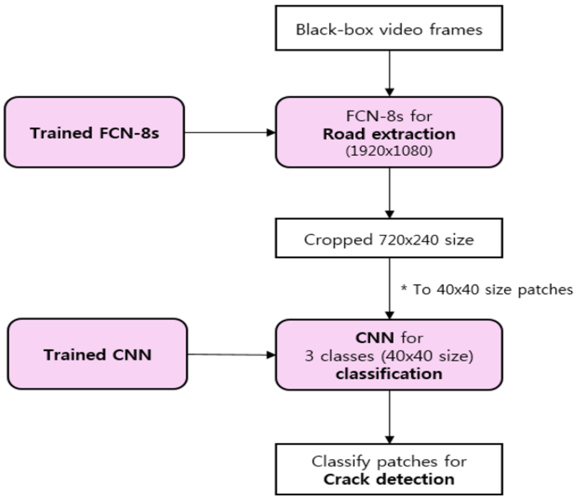

Figure 1. The patch-based crack detection of black box images.

2 System description

Figure 1 shows the patch-based crack detection method proposed in this study, and the method consists of two modules. The first module performs road extraction using a Fully Convolutional Network (FCN) architecture [6], and the second module performs crack detection in the extracted road area using the CNN model suggested in this paper. Cropping is performed between the first module and the second module, in order to limit the area to which the CNN is applied in the extracted road image.

Areas other than roads within a black box road image are not needed when performing crack detection. For the extraction of the road area only, the first module utilizes the segmentation process of FCN-8s [6] which consists of the 13 upstream convolutional layers of VGG16 [8] and an upsampling process. The second module divides the extracted road surface into several small images and then classifies each image into three classes: crack, lane, and others. In this study, a CNN architecture was designed to detect cracks in image patches with a 40 × 40 pixel resolution.

The proposed CNN model consists of five convolutional layers, three pooling layers, and two fully connected layers. The kernel sizes of the convolutional layers are determined considering the small size of the input image. The kernel sizes of the first convolutional layer (C1) and the second convolutional layer (C2) are7 x 7 and 5 x 5, respectively. The kernel size of the remaining convolutional layers (C3, C4, and C5) is 3 x 3. The pooling layers (P1, P2, and P3) are used for maxpooling to reduce the size of the feature map by half. The first fully connected layer (FC1) has 128 channels and the last fully connected layer (FC2) contains three channels for the classification into the three classes. Figure 2 shows more information about the CNN model for crack detection.

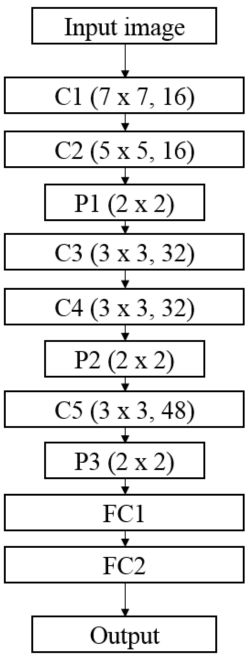

Figure 2. The CNN architecture for crack detection

3 Experiments and Results

The road extraction model was trained with 352 images of 1920 × 1080 pixel resolution, while the CNN model for crack detection was trained with 30,000 images of 40 × 40 pixel resolution. For testing, a total of 50 black box images were used. The black box images were cropped to 720 x 240 pixel size after the road extraction process. In the cropped image, patches that contain non-road areas were excluded from the analysis for crack detection. Consequently, 7259 patches of 40 x 40 pixel size were classified into the three categories. The results of the road extraction were a precision of 98.78% and a recall of 96.13%. In equations (1) and (2), True Positive is the number of patches classified as crack among the real crack patches. False Positive is the number of patches classified as crack among the patches truly belonging to either lane or others. False Negative is the number of patches classified as lane or others when the patches are in fact cracks.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (1)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (2)$$

The classification accuracy of the three classes was 91.13%, and the precision and the recall were 88.14% and 72.01%, respectively. The factors that reduce the performance of crack detection are as follows. A patch containing a lane or shadow was, in some cases, misclassified as crack; this is a factor of affecting the precision. On the other hand, patches with blurry cracks or with both cracks and lanes caused the recall to drop.

The results of the road surface extraction and crack detection are given in Figure 3. The middle images in Figure 3 is the result of road extraction and the background pixels are marked with white. The patches classified as crack are indicated with yellow borders in the images on the right side in Figure 3.

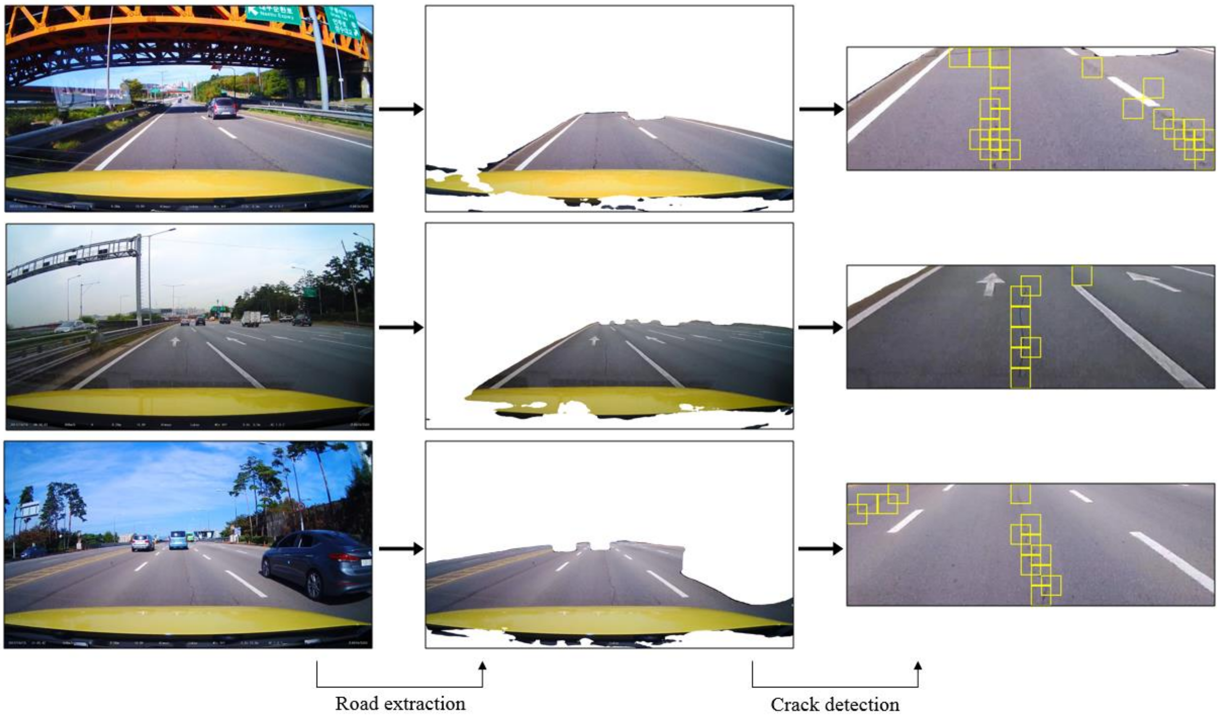

Figure 3. Three example images of road extraction and crack detection; original images (left), road extraction images (middle), and crack detection images (right).

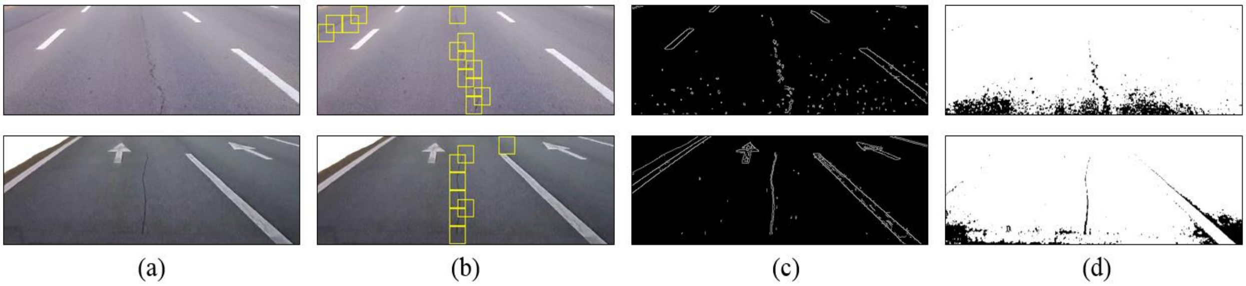

Figure 4. Comparison with other operators for crack detection; (a) original images, (b) proposed method, (c) Canny edge detector, (d) simple thresholding.

Figure 4 shows the comparison of the results of applying the proposed method and other methods to the black box images. In Figure 4(b), the yellow patches were classified as crack by the proposed CNN model. It can be seen that the patches with cracks were well distinguished from the lane and the undamaged road area. Figure 4(c) shows the results of crack detection using Canny edge detector. Because of the large difference in pixel intensity values between the cracks and the surrounding roads, cracks can be detected by the edge detector, but noisy parts of the road surface or lanes can be detected as cracks, as shown in Figure 4(c). Figure 4(d) shows the results of crack detection by simple thresholding. Because cracks are darker than road surfaces, they can be detected when images are binarized with an appropriate threshold. However, since the intensity of the road surface is not constant, areas with dark intensities other than cracks can be mistaken for crack. To detect cracks with an edge detector or thresholding, preprocessing of the input data or post-processing of the output image may be required. However, in the proposed method, no other work is required before and after the crack detection in the extracted road area.

4 Conclusion

This study suggested the use of black box images for effective road maintenance. The black box image has the merit of being easy to acquire; however, the image has a limitation that it is skewed and objects such as other vehicles or buildings are included in it. In this study, we applied the deep learning to extract the road surface from a black box image and detect the crack patches on the extracted road surface. The performance of the road extraction was more than 96% for both precision and recall; it was performed well as a preparatory work for detecting cracks in an image. In the crack detection, the accuracy, precision, and recall were 91.13%, 88.14%, and 72.01%, respecetively. For more detailed analyses, the patches can be categorized into more than three classes or more training data can be used. Using the data of many vehicles equipped with mobile devices as proposed in this study, efficient pavement management can be achieved.

Acknowledgments

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