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Grid-based Pavement Crack Analysis Using Deep Learning

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***Abstract*—Pavement crack detected plays an important role in pavement maintenance. Image recognition is a traditional way for pavement crack detected. Recently, deep learning is a state-of-the-art method for target detection. CNN (convolutional neural network), a significant method in deep learning, is widely used in image target detection and brings about breakthroughs. However, CNN has not been applied to pavement crack detection. In this paper, we apply CNN to detect pavement crack and PCA (Principal Component Analysis) to classify the detected pavement cracks. Firstly, two databases are obtained by using two different scales of grid (32×32, 64×64) to segment pavement images. Each database has 30000 images for training set. We obtain two kinds of trained CNN. Each CNN is trained by one training set, which is part of each scale databases. We use trained CNN to detect the existence of pavement crack in corresponding scale grids. We confirm the scale of segment grid by comparing the results of pavement crack detected. Secondly, we only keep the grids containing crack and achieve the skeleton of crack in a pavement image. Lastly, we use PCA to analyse the skeleton of crack. The classification of crack can be obtained. The F-measure for crack detection is 94.7%. Meanwhile, the proposed method achieves 97.2%, 97.6% and 90.1% correct rate of classification for longitudinal crack, transverse crack and alligator crack, respectively. The results show proposed method can detect the pavement crack and evaluate the type of crack precisely.**

Keywords*—crack classification ; crack detection ; CNN ; Deep learning Stuctures

I. INTRODUCTION

Pavement crack detected is a challenge test. Manual visual surge is the most frequently method being used in pavement crack detected. However, this method is costly with low rate of effectiveness. What's more, the operator needs a lot of related knowledge and subjectivity. The automatic pavement crack detection and classification has been developed for over two decades.

With the development of equipment and data collection, many researches began to design the pavement crack detection algorithm based on the image. Most of research detects pavement crack by its characteristic. Generally, the pixel for the pavement crack is darker than the pixel for the background. The researchers design a lot of automatic pavement detection algorithms. While it still hard to fulfill this target without human interference cause by the different texture of pavement. Base on this, automatic pavement crack detection and classification is a hot research area. The method to pavement crack detection subdivided into three major classes: space-domain, frequency-domain, machine learning [1].

The space-domain can be divided into three classes: 1) threshold segment algorithm. 2) edge detection algorithm. 3) seed-growth algorithm. For the threshold segment algorithm, the Otsu[2] method is widely used in pavement crack detection. Li and Liu improve the classical method[3]. For the edge detection algorithm, Wang et al. extract the crack information combine fast LoG operator with non-negative feature[4]. For the seed-growth algorithm, Zhou et al. proposed an approach combining crack seed and Euclidean Minimum Spanning Tree [5].The frequency-domain is widely used to detect pavement crack. The main tool of frequency-domain to detect pavement crack are wavelet and Gabor filter[6], proposed a pavement crack detection method combining slope of mode shape with angle coefficience of complex continuous wavelet transform [6]. Zalamz et al. utilize Gabor to detect the longitudinal crack and transverse crack[7]. The machine learning, especially supervised learning, is used to detect pavement crack. The supervised learning training the network by the label set data. Then it used the trained network to realize pavement crack detection. Chou et al proposed a method computed a set of moment invariants as training feature to train back propagation (BP) neural network, then it uses BP model to distinguish the type of pavement crack[8]. The BP neural network also utilized in[9], which adopt an anisotropy measure as the feature.

Oliveira et al proposed a method on ICIP08, which calculated mean and deviation as feature for crack detection[11]. They added the content which using Bayesian classifier to crack detection[12]. It is proposed on EUSIPCO08 (European Signal Processing Conference 2008). Mathaven et al use self-organizing map (SOM) to detect road cracks[13]. The deep learning method increases the detection accuracy to pavement crack. As a three major frame of deep learning, convolutional neural network (CNN) is widely used to text classification. Krizhevsky et al use CNN to image classification[14]. Cimpoi et al. propose a new descriptor for CNN filter bank and utilize it for texture classification[15].

In this paper, we segment the pavement crack images into different scales of grids. We choose suitable scale of grids to segment image. We design the structure of CNN to detect pavement crack. To classify the type of crack, we utilize principal component analysis (PCA) to calculate the distribution of grids. After analysis the distribution of grids, we achieve the pavement crack classification.

II. THE PROPOSE METHOD

The flowchart of proposed method for pavement crack detection is illustrated in Figure 1.

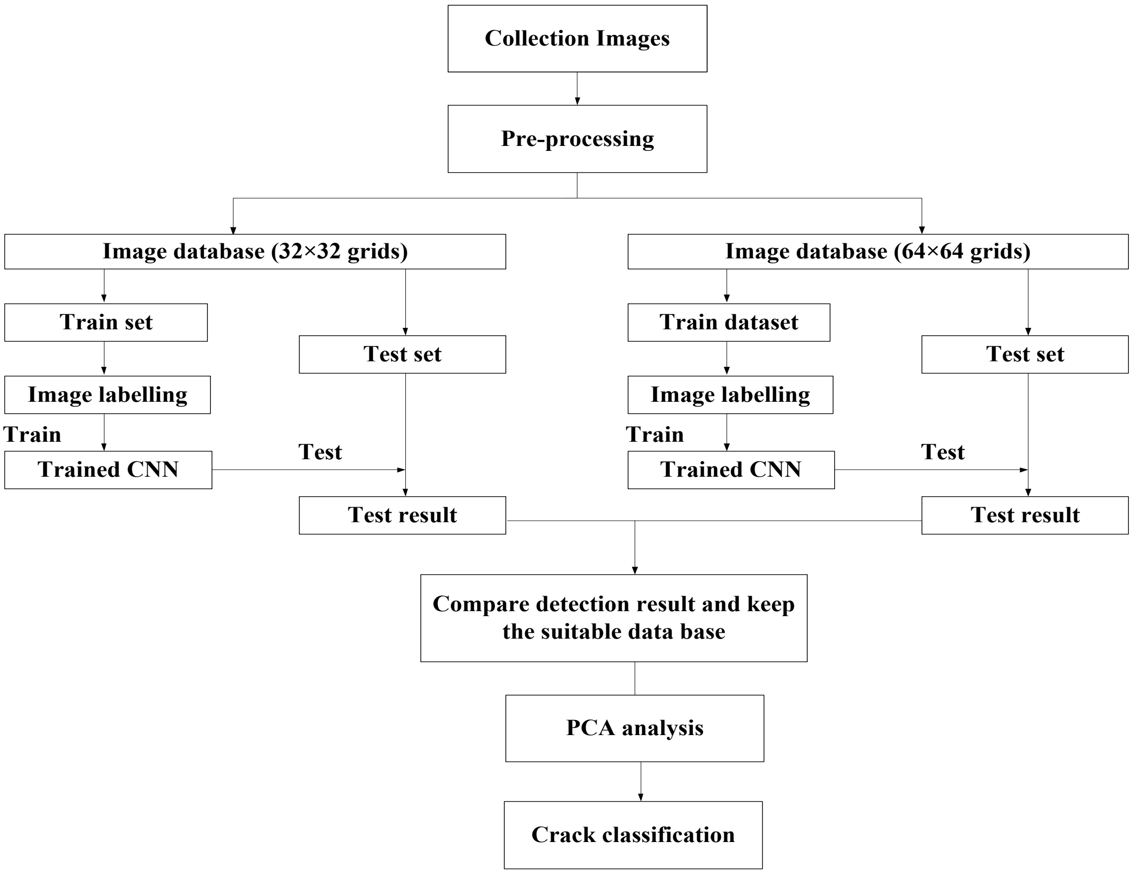


FIGURE 1 Flowchart of the proposed method

The collected images need to be pre-processed which includes the RGB to gray conversion and resizing pictures (3264×2448 pixels transform into 960×704). There are two kinds of scale grids (32×32, 64×64) to segment the pavement images. For each scale grid, we segment the images into grids and grids make up the image database. After that we achieve two scales of image database. For each image database being divided into two classes, class one is training set and the other class is testing set. Each class includes the grids containing crack and non-crack grids. Then we train the CNN with training set. We achieve two different structure of trained CNN corresponding to the two kinds of scale grids. It uses trained CNN to detect existence of crack for the grids from testing set. Then, we choose the segment grid's scale by comparing the result of pavement crack detection. It just keeps the image database corresponding the chose grid's scale. After that, we only keep the grids containing crack. Then, we use PCA to classify the type of crack.

III. PRE-PROCESSING

Smart phone is very popular and it is convenient to achieve one. We use iphone6 to take the pictures. The pixel of camera is 3264×2448. The camera takes a picture towards the ground and archives the RGB image. The distance between ground and camera approximate 1.3m. In order to simplify and accelerate image process, the image should be converted to be a gray image of 960×704 pixels. The gray images should be normalized which is divided by 255. Then the image is segmented into 15×11 non-overlapping grids, each of grid is 64×64 (pixel), and segmented into 30×22 non-overlapping grids, each of grid is 32×32 (pixel) as shown in Figure 2.

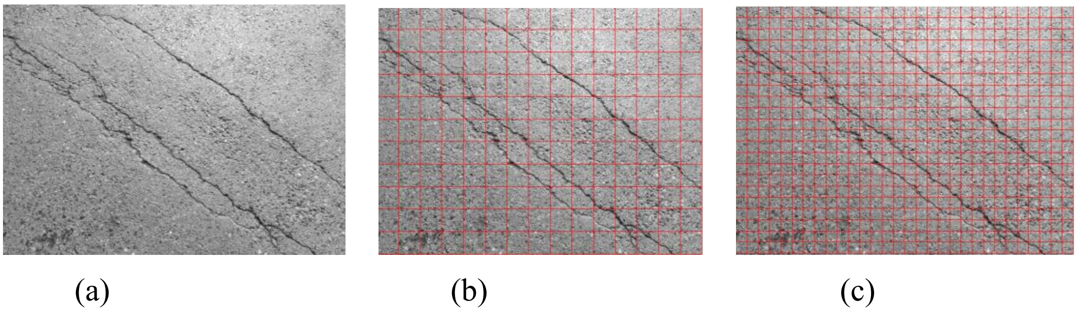


FIGURE 2 (a) The original image (b) The gray image segment into 15×11 non-overlapping grids (c) The gray image segment into 30×22 non-overlapping grids

We confirm the segment grid's scale by comparing the result of pavement crack detection. The detail will be introduced in the experiment results. Then we utilize CNN to detect crack in the grids. Extracting the grids containing crack, we get the skeleton of crack. This procedure will be introduced in the section of crack classification.

IV. PAVEMENT CRACK DETECTION USING CNN

Deep learning also called deep structured learning. It is a part of machine learning and it derives from artificial neural network. It composed by a set of simple and Non-linear feature model which are transformed into high-level feature model. All the feature models are extracted from input data rather than manual design. Supervised learning and unsupervised learning both part of machine learning. Supervised learning needs building manual labels to extract feature while unsupervised need not. CNN (convolutional neural network) is a part of supervised learning. It is a type of feed-forward artificial neural network. It brings a rapid development to image recognition in the past few years. There are some researches utilize artificial neural network to detect pavement crack. At present, CNN has not been used for the pavement crack detection. This section describes the pavement crack detection by using CNN.

A. The CNN Construction

CNN is composed by convolutional layer, pooling layer and fully-connected layer. The convolutional layer is made up of a various changeable filters, also known as kernels. Each kernel is a feature. The convolutional lay can be seen as a respond to a feature. The pooling is a statistic for region. The pooling layer statistic the non-overlapping regions so that it can reduce feature parameter and prevent over-fitting. The last layer of CNN is fully connected layer which is extracted the final feature of image.

There four popular toolbox for deep learning: Caffe, Theano, Torch and TensorFlow. Among them, we choose TensorFlow (TF) as deep learning toolbox to detect pavement crack. The reason that we choice TF is its flexible architecture and modularization programming. The Frame of CNN consists of two convolutional layers (C1, C2), two max pooling layers (S1,S2) and two fully-connected layers (F1,F2). The next layer connecting convolutional layer is max pooling layer and the full-connected layer is the last layer of CNN. The detail construct of CNN is C1, P1, C2, P2, F1, F2.

B. The Structure of CNN Detecting Pavement Crack

The existence of pavement in a grid can be seen as a mode. Pavement crack detection is matched the training set. There are two modes for the pavement crack detection. One is the existence of crack and the other is non-existence of crack. The procedure for the pavement crack detection is similar to LeNet-5 used to identify the alphabet from hand writing letter. However, the image containing crack is different from hand writing image. In the first place, the background of pavement is more complex than letter. In addition, the pavement image obtained outdoor which has larger illumination variations. The aim of pavement crack detection as well as alphabet identification for hand writing letter, both of them distinguish the target of specific structure from the background. We can construct the CNN for pavement crack detection according to the characteristics of crack.

It uses two sets of convolutional layers and pooling layers to detect pavement crack. In order to eliminate the damage of rotation and deformation, it increases the feature map for two convolutional networks to improve success rate of crack detection. The down sampling for the pooling layers extracts the maximum value of sampling region.

The pavement crack detection can be realized by fully-connected layer. It is a regular neural network which has full connection to the second pooling layer. In this research, In order to detect the existence of crack in the grid, the number of perceptron at output layer is 1. The output value 1 represents the existence of crack and output value 0 presents non-existence of crack.

The tanh function has great performance in non-linear reflection ability.

$$\tanh(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}} \qquad (1)$$

We utilize it as activation function. The learning rate for training CNN is 0.1. The number of training batch is 32. The termination condition for training CNN is the value of cost function is less than 0.02. The output of network is a number which is 0 or 1. Number 1 means the existence of crack in grid while number 0 means non-existence of crack.

In order to find the most suitable CNN, we tested CNN with different structures and found the most appropriate structure through the recognition accurate rate. According to the testing results, the number of feature maps for two convolutional layers is 16 and 32 respectively. The region of max down-sampling for two pooling layers is 5×5 and 4×4 respectively. The structure of CNN is shown in Figure 3.

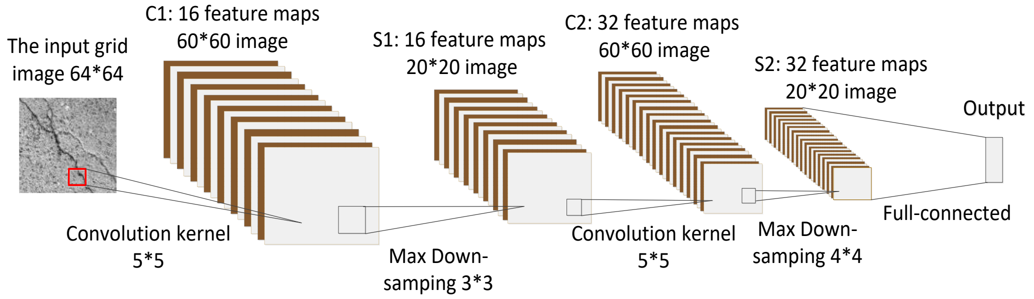


FIGURE 3 The structure of CNN

C1,S2,C3,S4 is the first convolutional lay, first max pooling layer, second convolutional lay, second max pooling layer respectively. The input to the next layer is the output from upper layer. The number of feature map and the size of down-sampling are the parameters to determine CNN's structure. To describe network's structure conveniently, it combines the figure and alphabet to describe the parameter of network. The structure can be described as 16c-3s-32c-4s-2o.

V. CRACK CLASSIFICATION

An image is cut into many non-overlapping grids, and then we use CNN to detect the existence of crack. We only keep the grids that containing crack so that the skeleton of crack can be preserved. After building the coordinate system for skeleton of crack, we achieve the coordinate of grid. Then we use PCA to estimate crack's classification.

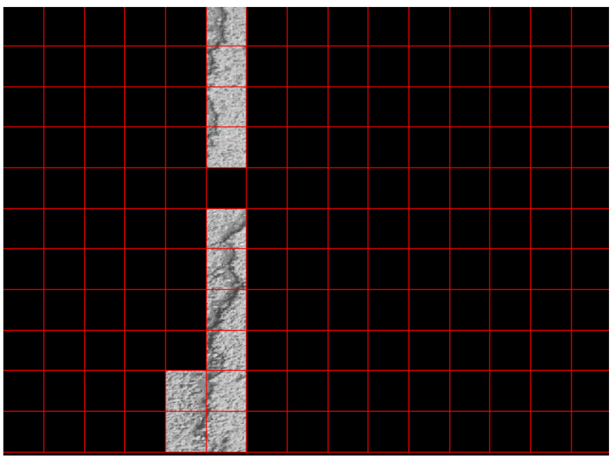


FIGURE 4 The skeleton of crack

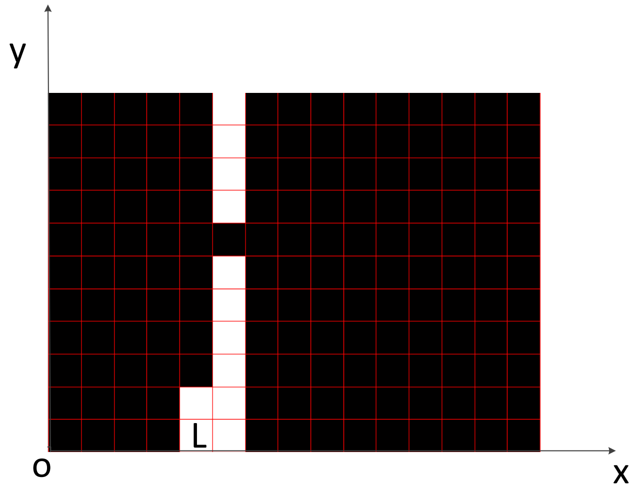


FIGURE 5 Crack regions

We take the scale of 64×64 as an example for building crack region. Building crack region scale of 32×32 as same as Building crack region scale of 64×64. In order to find the skeleton of crack, as shown in Figure 4, we simplify the 64×64 (pixel) grid into a region which the size is 1×1. The value of region is 0 or 1. Value 1 (white block) means the grid containing crack while value 0 (black block) means none. Then it transforms an image (960×704) into a binary matrix which the size is 15×11. As shown in Figure 5 the white region containing crack, meanwhile, the crack region is consist of 12 white regions. We build the Cartesian coordinate system for crack regions. The region's center represents the coordinate of region. For example, as shown Fig.5, the region named L is labelled as crack which ranges from 4 to 5 on the X axis and the range from 0 to 1 on the Y axis. The center of region L is (4.5, 0.5). According this method, we calculate the coordinate value of crack regions for an image.

A. PCA Analysis

The PCA (Principal Component Analysis) is a dimension reduction method which reveals the principle component of data. It uses SVD (Singular value Decomposition) to transform input data into a set of eigenvalues and corresponding eigenvectors which are linearly independent.

The eigenvectors represent the characteristics of input data. The eigenvalues represent the degree to the character. By comparing the eigenvalues, it can find the main eigenvector which is the principle component. PCA calculates the eigenvectors and corresponding eigenvalues by the covariance from input data. The detail of PCA is introduced as follows. Assume input data is n×m, which is composed by a set of vector X_1, X_2, X_3… X_m, each of them is n×1. The covariance matrix is

$$C = \begin{bmatrix} \mathrm{cov}(x_1,x_1) & \mathrm{cov}(x_1,x_2) & \dots & \mathrm{cov}(x_1,x_m) \\ \mathrm{cov}(x_2,x_1) & \mathrm{cov}(x_2,x_2) & \dots & \mathrm{cov}(x_2,x_m) \\ \dots & \dots & \dots & \dots \\ \mathrm{cov}(x_m,x_1) & \mathrm{cov}(x_m,x_2) & \dots & \mathrm{cov}(x_m,x_m) \end{bmatrix} \quad (2)$$

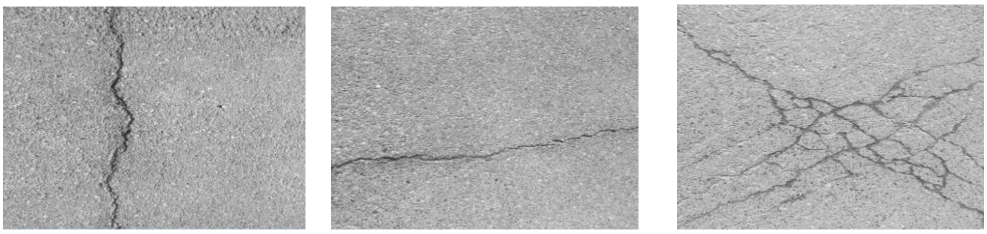
The size of C is m×m. The covariance of X_i and X_j as follows:

$$\mathrm{cov}(X_i,Y_j) = \frac{\sum_{k=1}^{n}(X_k-\overline{X_i})(X_k-\overline{X_j})}{(n-1)} \quad (3)$$

After transforming covariance matrix C by SVD, it achieves a set of eigenvector and corresponding eigenvalue. The crack classification based on the eigenvector and eigenvalue. It is introduced in next.

B. Crack Classification using PCA

Generally, the main type of crack classification is as follows: longitudinal crack, transverse crack and alligator crack, as shown in Figure 6. The longitudinal crack and transverse crack are linear crack while alligator crack is non-linear crack. The linear property of crack can be detected by linear correlation coefficient (LCC) which is introduced next.



(a) (b) (c)

FIGURE 6 Three crack classification: (a) longitudinal crack (b) transverse crack(c) alligator crack

The size of crack regions matrix is n×2 which is composed by vector X and vector Y, each of vector is n×1. The vector X is a set of crack region coordinates on the X-axis and the vector Y is a set of crack region coordinate on the Y-axis. After being calculated by PCA, We achieve a 2×2 eigenvector A and corresponding eigenvalue B which size is 2×1. The LCC (linear correlation coefficient) is the ratio of the maximum value to the minimum value of B.

$$\mathrm{LLC} = \frac{\max\ \text{value of}\ B}{\min\ \text{value of}\ B} \quad (4)$$

Here, after testing sample images, it achieves the experiential value for LLC. The range of LLC of linear crack is bigger than 80, while the LLC of non-linear crack is less than 50.

The longitudinal crack and transverse crack can be detected by the eigenvector A. The eigenvector A is consisted of vector a_1 and vector a_2, each of vector is 2×1. Both vector a_1 and vector a_2 can indicate the direction of crack region. There is a primary direction for the crack region and the primary direction is the vector corresponding to max value of B. We extract the primary direction vector as A which is [x_1, y_1]. We can calculate Θ by the vector A as follows:

$$\theta = \arctan\frac{|y_1|}{|x_1|} \quad (5)$$

θ for longitudinal crack is varying from 45° to 90°. While for transverse crack is varying from 0° to 45°. We obtain the direction of crack by θ , then the crack classification can be classified.

VI. EXPERIMENTAL RESULTS

The pavement images are collected by author along the Youyi Avenue in Wuhan city. There were 510 pavement images which including three kinds of crack pictures and non-crack pictures. We took 30000 grid images as training set images. The rest of images were testing set images.

A. The result of crack region detection

The size of segment grid has an impact on pavement crack detection. Too large size will lead detection not detail enough. Too Small size will cost time-consuming and over-fitting. To find the suitable size for grid segment, it tests different size of grids which are 64×64 and 32×32. We respectively build the training set and the testing set for 32×32 scale grids and 64×64 scale grids

To evaluate the affections of different size of grid, we introduce an evaluation method. It evaluates the pavement crack by the Precision (pr), the Recall (re), and the F-measure, which are shown in Eq. (6) ~ (8)

$$pr = \frac{\text{the number of region correctly classified for crack}}{\text{the total number of crack region detected}} \quad (6)$$

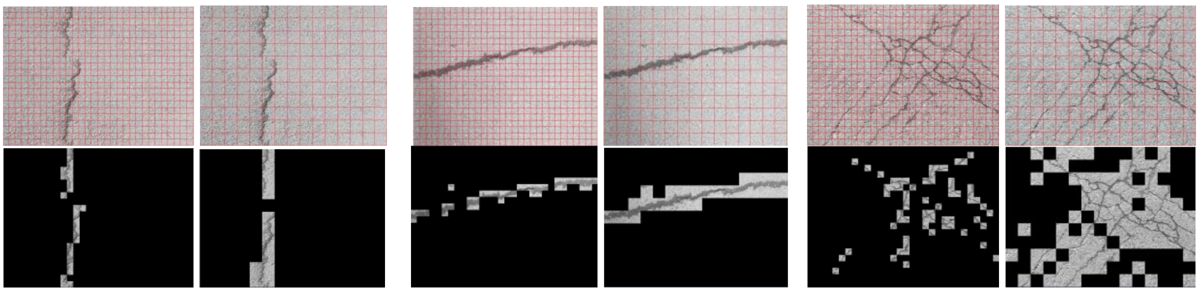
$$re = \frac{\text{the number of region correctly classified for crack}}{\text{the total number of crack region(ground truth)}} \quad (7)$$

$$F-measure = \frac{2\times pr\times re}{pr+re} \quad (8)$$

We used different size of grid (16×16, 32×32) to test the crack detection. Then we evaluated crack detection. We chose three representative images about three kinds of crack, as shown in Figure 7. The detection result for crack region as shown in Table 1.

TABLE I. THE DETECTION RESULT FOR CRACK REGION

Size of grid	*pr*	*re*	*f-measure*
32×32	97.3	88.3%	92.5%
64×64	95.9%	93.5%	94.7%



(a) (b) (c)

FIGURE 7: the detection result for crack region: (a) longitudinal crack (b) transverse crack (c) alligator crack. The top is an image of two scale of grids segment. The bottom is the detection result for crack region using CNN.

According to the detection result for crack region, the degree of precision for 32×32 grids and 64 ×64 grids is 97.3%, 95.9%, respectively. The recall for 32×32 grids and 64×64 grids is 88.3%, 93.5% respectively. The F-measure for 32×32 grids and 64×64 grids is 92.5%, 94.7% respectively. As we can see, the 32×32 grids have better performance than the 64×64 segment grids in precision. However, the segment grids of 64×64 have better comprehensive performance than the segment grids of 32×32. So we choose 64×64 scale grids to segment.

B. Crack classification using PCA

It only keeps the grids containing crack, then, the skeleton of crack can be obtained. We use PCA to calculate the eigenvectors and corresponding eigenvalue of crack's skeleton. The crack classification can be realized by analysis the eigenvectors and the eigenvalues.

Here, we take the examples for crack classification. These cracks are shown in Figure 7.

It calculates the eigenvectors and corresponding eigenvalue for a longitudinal crack which is shown in Figure 8.

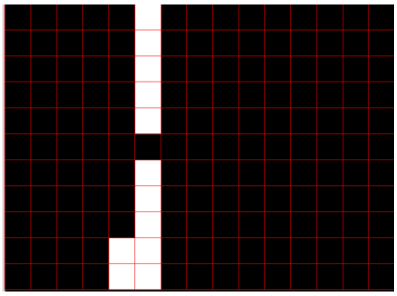


FIGURE 8 The skeleton of longitudinal crack

The eigenvectors are:

$$\begin{bmatrix}0.0522 & 0.9986\end{bmatrix}^T$$
$$\begin{bmatrix}0.9986 & -0.0522\end{bmatrix}^T$$

Corresponding eigenvalues are 12.9136, 0.1167, respectively. The LLC is 110.65, which means the crack is a linear-crack. The eigenvector correspond the max eigenvalue is $[0.0522,\ 0.9986]^T$ and angle θ =87.77. The crack is longitude crack.

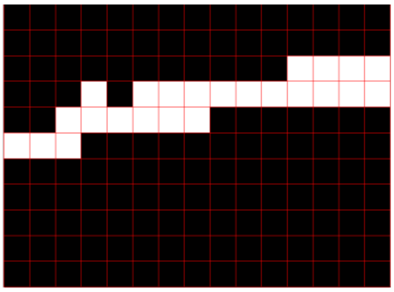


FIGURE 9 The skeleton of transverse crack

It calculates the eigenvectors and corresponding eigenvalue for a transverse crack which is shown in Figure 9.

The eigenvectors are:

$$[-0.0086 \quad 1.0000]^{T}$$

$$[1.0000 \quad 0.0086]^{T}$$

Corresponding eigenvalue is 0.3219, 20.0081. The LLC is 621.31, which means the crack is a linear-crack. The eigenvector correspond the max eigenvalue 20.0081 is $[1.0000 \quad 0.0086]^{T}$, and angle θ=0.4927. So the crack is transverse crack.

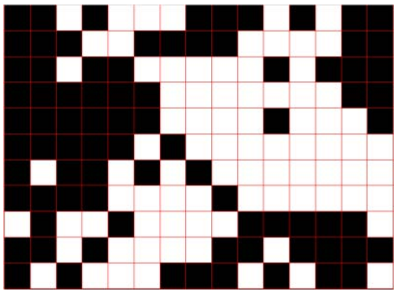


FIGURE 10 The skeleton of alligator crack

It calculates the eigenvectors and corresponding eigenvalue for an alligator crack which is shown in Figure 10.

The eigenvectors are:

$$[0.9747 \quad 0.2227]^{T}$$

$$[-0.2227 \quad 0.9749]^{T}$$

Corresponding eigenvalue is 8.9283, 13.5893. The LLC is 1.522, which means the crack is an alligator crack.

There are 310 pavement images, which have 96 longitudinal crack images, 87 transverse crack images and 127 alligator crack images. We compare the performance of proposed method with the method used neural network to classify the type of crack[16].

The result for crack classification is shown in Table 2.

TABLE II. THE RESULT FOR CRACK CLASSIFICATION

	Correct classified rate (proposed method)	Correct classified rete (neural network)
Longitudinal crack	97.2%	96%
Transverse crack	97.6%	96.6%
Alligator crack	90.1%	84%

As we can see from Table 2, the correct classified rate for alligator crack has a great improvement, which from 85% to 90.1%. The main reason for the improvement owe to the crack detected by CNN. With more grids containing cracked pavement detected, it can demonstrate more detailed distributions of pavement crack. The detail about distribution of pavement crack raises correct classified rate.

VII. CONCLUSIONS

Automatic pavement crack classification is a crucial step for pavement crack detection which offers information for pavement maintenance. This paper has proposed a novel method for automatic crack classification which uses deep learning to detect crack and PCA to classify the detected crack. The proposed method is validated with pavement crack images collected by author. The proposed method achieves 97.2%, 97.6% and 90.1% correction rate of classification for longitudinal crack, transverse crack and alligator crack respectively. The correct rate of classification is increased compared with pavement crack classification using neural network.

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