Crack Detection Based on Support Vector Data Description

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Abstract: It is difficult to detect concrete cracks because of the existence of background interference. To solve this problem, some methods for crack detection on concrete surfaces are analyzed. According to shape features, a new concrete crack detection method is proposed. First of all, iteration method is applied to get the optimal threshold for image segmentation after grayscale transformation. Secondly, binary images are processed by morphological closing operation and deburring. Features including eccentricity, circularity and packing density are selected as input training vectors for Support Vector Data Description ($SVDD$). The experimental results show that crack detection method based on $SVDD$ can accurately distinguish cracks from other kinds of defects (non-crack) and reduce the false negative detections.

Key Words: Concrete crack detection, Optimal threshold, Shape feature, Support Vector Data Description

INTRODUCTION

Cracks can be frequently observed on the surface of concrete structures such as pavement and bridge when in construction and service. The cracks endanger the safety of concrete structure seriously. Therefore, it is important to detect and measure the concrete cracks in structures regularly. Human inspection, which means operators use conventional measurement systems to inspect the structures and identify the cracks, is a traditional method. Not only it is a waste of time and energy, but also dangerous for operators when they need to measure the cracks on the surface of viaduct bridges.

With the fast development of digital image processing technique, automatic crack detection and measurement based on image processing has become a research hotspot. It has advantages such as non-contact, convenience and accuracy. In the past few years, many researchers have made great efforts on crack detection and achieved abundant research results, based on edge detection [1], pattern recognition [2-3], fractal theory [4-6], etc. Cracks on concrete surfaces have irregular shapes. Moreover, there is much noise included in the crack image because concrete structures are exposed to the environment. Therefore, as a key issue in crack detection, it's significant to find a method to distinguish cracks from the background.

As the important basis of image segmentation, edges in images are defined as sharp intensity transitions. Edges that represent the end of a region and the beginning of another region mainly exist between the object and background. There are traditional edge detection algorithms include first-order differential operators such as Roberts, Prewitt, Sobel and second-order differential operators such as Laplacian, Logarithm of Gaussian, etc. [7] In recent years, some new edge detection methods have been proposed, for example, multi-scale morphological edge detection, which can detect the edge information more accurately than above mentioned methods. It can restrain noise effectively but does not eliminate the problem [8].

The edge grayscale of concrete cracks does not have much difference with that of background in an image. What's more, the grayscale of concrete cracks shows an uneven distribution, holes and impurities on concrete surfaces have negative effects on crack detection as well. In [9], Mandelbrot first put forward the concept of fractal and some studies indicate that the ceramic, rock and concrete cracks are fractal structures. There are obvious differences between the self-similarity characteristics of cracks and other defects. So cracks can be distinguished easily from other defects according to fractal characteristics [10]. However, the demand of high definition and integrity for cracks are required in the method.

The crack detection methods based on artificial neural network or fuzzy recognition have been developed rapidly, and received popular attention in recent years. A complete methodology to detect and characterize pavement cracks is proposed in [11], which using clustering techniques and one-class classification strategy to train system. Because the interference might be considered as short cracks mistakenly in the same image, a few false positives could be detected. In [12], a feature is presented to distinguish cracks from other kinds of objects, but details on experimental results are not provided.

In [13], Tax and Duin proposed a data description methodology, the Support Vector Data Description. It has several obvious advantages such as simple structure, fast learning rate, good generalization and fewer training samples are needed to characterize the background in high-dimensional spaces. In addition, a variety of classification surfaces are obtained by correcting kernel function.

This work is supported by the Fundamental Research Funds for the Central Universities (YS0104);

Foundation of State Key Laboratory of NBC Protection for Civilian (SKLNBC2014-10)

978-1-5090-4657-7/17/$31.00 ©2017 IEEE

$SVDD$ can precisely classify the objective class data apart from the other data. It is a machine learning method based on small sample statistics study theory and has been successfully applied to some kinds of classification of agricultural products, surface defect detection. However, to the best of the authors' knowledge, the application on concrete crack detection after interference elimination is still an open problem. Hence, this gives us the motivation of the study, it will enrich the crack detection method based on $SVDD$ and perfectly solve the problem of concrete crack detection.

This paper proposes a method to identify concrete cracks based on $SVDD$. First at all, using the optimal threshold based on grayscale distribution to segment the image and binary images are then obtained. Binary images are processed with dilation and deburring. Secondly, according to obviously different shapes of cracks and other defects (such as holes, impurities), the features including eccentricity, circularity and packing density are extracted from images. All the features compose a feature vector X. Finally, crack detection model based on $SVDD$ can be built, and it provides a basis for measuring the feature values of cracks (such as area, length, orientation, etc.).

1. ANOMALIES DETECTION

After image acquisition, image preprocessing methods must be adopted to remove noise, highlight cracks and provide a basis for image analysis. Image processing technique in this paper mainly includes grayscale transformation, contrast adjustment, threshold segmentation, morphology processing (corrosion and expansion), etc.

2.1 Gray Processing

Color images need too much memory for information storage, and sometimes the gray information of images is enough. With the purpose of reducing calculation time and increasing operation speed, the color images should be convert to gray images, as expressed in Equation (1):

$$Gray = 0.3B + 0.59G + 0.11R \tag{1}$$

2.2 Gray-scale Transformation

Grayscale transformation is an effective method to enhance the image contrast. Piecewise linear grayscale transformation is used in this paper. In practical applications, a range of gray value is often locally stretched or different ranges of gray value are stretched differently in order to highlight specific objects in the image.

As shown in Fig. 1, the grayscale range is relatively narrow, and the grayscale focuses on a certain part of the gray histogram. Partial crack regions are not obviously different from the background. After grayscale transformation, Cracks are highlighted in the image.

2.3 Threshold Segmentation and Subsequent Processing

The image binaryzation is an essential process, which converts a gray image into a white and black image. Some common methods that determine the optimal threshold are proposed, such as Otsu's method, Niblack's method, Bernsen's method. Image segmentation based on gray threshold is the process that identifies specific objects from the captured image. The geometric characteristics of specific objects can be calculated after image segmentation, such as size and location. 128×128 pixels blocks are considered in this paper. On the one hand, it can decrease the number of false positive detections when those blocks are too small. On the other hand, it can prevent the impact of small cracks from tending to vanish in the computation of features when those blocks are too large.

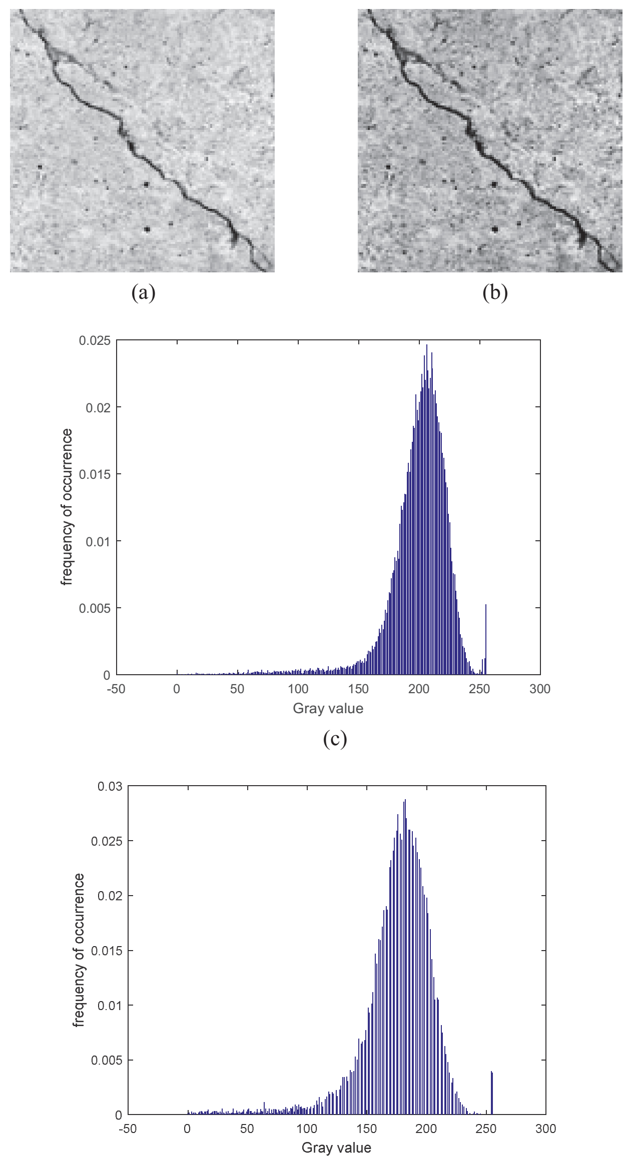


Fig. 1: (a) Original color image (b) Gray-enhanced image (c) Gray histogram of original image (d) Gray histogram of gray-enhanced image

This paper uses iterative method to obtain the optimal threshold. The steps of iterative threshold method are given as follow

1) Choose a threshold $T(j)$ and $j=0$ at the beginning.

$$T(0)=\frac{\mu_{\max}(0)+\mu_{\min}(0)}{2} \tag{2}$$

Where $\mu_{\max}(0)$ and $\mu_{\min}(0)$ denote the maximal gray value and the minimal gray value, respectively.

2) Images can be divided into two regions, $C_1^{(j)}$ and $C_2^{(j)}$, then the average gray value of two regions can be expressed as follows

$$\mu_1^{(j)}=\frac{1}{N_1^{(j)}}\sum_{f(x,y)\in C_1^{(j)}} f(x,y) \tag{3}$$

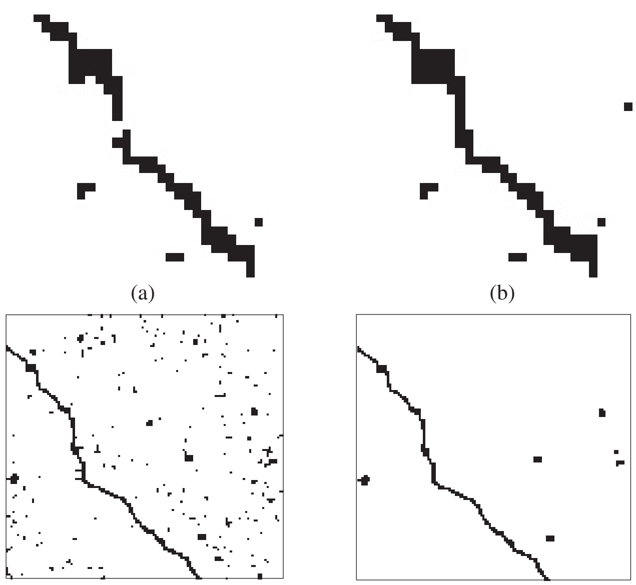
$$\mu_2^{(j)}=\frac{1}{N_2^{(j)}}\sum_{f(x,y)\in C_2^{(j)}} f(x,y) \tag{4}$$

Where $N_1^{(j)}$, $N_2^{(j)}$ are the numbers of pixels located in each region, and $f(x,y)$ denotes the gray value at position (x,y).

3) The new threshold can be given by

$$T(j+1)=\frac{\mu_1^{(j)}+\mu_2^{(j)}}{2} \tag{5}$$

4) $j=j+1$, repeat the above steps until j reaches the maximum iterative times or the mismatch of $T(j+1)$ and $T(j)$ is less than the specified value.



(a) (b) (c) (d)

Fig. 2: (a) Local binary image (b) Local image after morphological closing operation (c) Image after morphological closing operation (d) Result image

After image segmentation, sometimes the cracks in binary images are discontinuous, as shown in Fig. 2 (a). The image can be processed with morphological closing operation in order to keep the connectivity of thinning cracks. The closing operation is a method that can close holes and slots by erosion after dilation. The gaps of cracks can be filled after morphology processing, but noise points may form some burr attached to the cracks. An additional step can be used to deburr the edge and remove the isolated noise points with less than 10 pixels.

2. CRACK DETECTION

According to geometrical form， cracks can usually be classified as horizontal, vertical, diagonal or complex [14]. The proportion of complex geometry is only 6% of all cases.

3.1 Support Vector Data Description

This paper proposes a crack detection method based on $SVDD$. $SVDD$ is a method that attempts to find a hypersphere that best describes the region of the feature space in which a set of date points lie [13][15]. The hypersphere should be as small as possible and contain the training set T. In fact, minimizing the volume of the hypersphere is equivalent to solving a quadratic programming problem stated as follows

$$\min_{R,a,\zeta_i}(R^2+C\sum_{i=1}^{n}\zeta_i) \tag{6}$$

The constraints can be expressed as

$$\|x_i-a\|^2\le R^2+\zeta_i$$
$$\zeta_i\ge 0, i=1,2,3,\ldots,\mathrm{n} \tag{7}$$

Here, a is the center of the minimum enclosing hypersphere and R is the radius. The size of the hypersphere may be too large due to the existence of a few abnormal training samples. Using slack variable ζ_i, those abnormal samples are allowed to be outside of the hypersphere. ζ_i can make the hypersphere describe object samples more accurately, and enhances the robustness of classification. The constant C represents the trade-off between the volume of the hypersphere and abnormal samples. a , R can be obtained by optimizing the following Lagrangian

$$L(R,a,\zeta_i,\alpha_i,\lambda_i)=R^2+C\sum_{i=1}^{n}\zeta_i$$
$$-\sum_{i=1}^{n}\alpha_i(R^2+\lambda_i-\|x_i-a\|_2)-\sum_{i=1}^{n}\lambda_i\zeta_i \tag{8}$$

Where $\lambda_i\ge 0$ and $\alpha_i\ge 0$ represent the Lagrange multipliers.

The distance to the center of the hypersphere can be calculated to test a new sample point

$$\|x-a\|^2=K(\mathrm{x}\bullet x)-2\sum_i\alpha_i(\mathrm{x}\bullet x_i)$$
$$+\sum_{i,j}\alpha_i\alpha_j(x_i\bullet x_J)\le R^2 \tag{9}$$

The $SVDD$ decision function then can be expressed as

$$f(x) = 1 - 2\sum_{i} \alpha_i K(x_i, x) + \sum_{i,j} \alpha_i \alpha_j K(x_i, x_j) - \mathrm{R}^2 \tag{10}$$

Where x_i, x_j are called support vectors, lying on the boundary of the hypersphere, and K is a kernel function.

3.2 Feature Extraction

Holes and impurities are frequently observed on the surface of concrete structures besides cracks. As shown in Fig. 2(c), cracks are identified completely but plenty of other defects can also be preserved because there are many low grayscale pixels in the image background. The interference could be erroneously identified as the crack due to the segmentation algorithm used in this paper. Although an additional step has been used to remove the isolated noise points, the interference is still serious to result in false positive detections. Compared with other defects, the shape and orientation of cracks are obviously different (see as Fig. 3). Shape is an important visual feature of images and it has invariance to the displacement, rotation and scale transformation. People often identify objects according to their shapes. As a result, it is necessary to study the shape features.

This paper uses three characteristic quantities based on the differences about shape features between the crack and the interference:

1) Eccentricity F_e of the ellipse that has the same second moment with the region to be identified. The value of F_e ranges from $0 \sim 1$. Actually, the ellipse with F_e=0 is the circle and F_e=1 is the line segment.

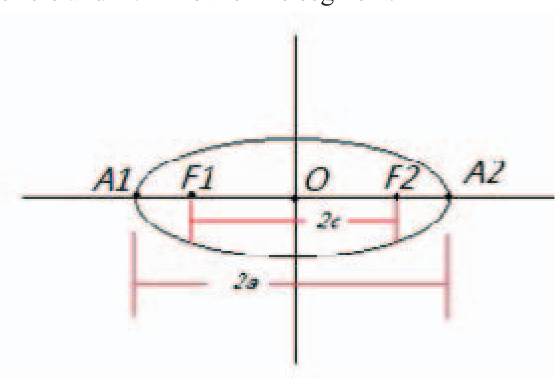


Fig. 3: Ellipse that has the same second moment with the region to be identified

The moment set calculated from a digital image generally describes the global shape features of the image, and provides a lot of information about different geometric features, such as size, location, orientation and shape, etc. For the discrete image $F(j,k)$, the $(p+q)$ moment formula is given as follows:

$$m_{pq} = \sum_{j}\sum_{k} j^p k^q F(\mathrm{j,k}) \tag{11}$$

The $(p+q)$ central moment formula is given as follows:

$$\mu_{pq} = \sum_{j}\sum_{k} (j-\bar{j})^p (k-\bar{k})^q F(j,k) \tag{12}$$

Where $\bar{j} = \frac{m_{10}}{m_{00}}$, $\bar{k} = \frac{m_{01}}{m_{00}}$.

In fact, if only the second moment set is considered, the detection region is equivalent to an ellipse with certain size, orientation and eccentricity. The long axis and short axis of the ellipse then can be calculated.

Eccentricity F_e can be expressed as follows:

$$F_e = \frac{c}{a} \tag{13}$$

Where a is the semi-major axis of the ellipse and c is the semi focal.

2) Circularity F_θ. The circularity is a parameter indicating the shape of an object, and insensitive to the size and laying angle of object contours. It is determined by the area and perimeter

$$F_\theta = \frac{4S}{\pi L^2} \tag{14}$$

Where S and L are the area and perimeter of the object, respectively. F_θ is equal to 1 for a circle and tends toward 0 for an extremely elongated object. The bigger the value, the more complex the shape.

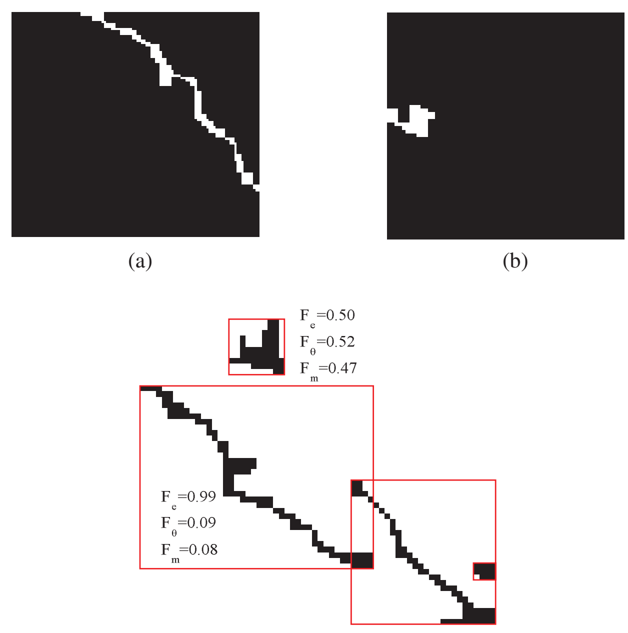


Fig. 4: (a) A crack-shaped object (b) A non-crack shaped object (c) Shape factors for various objects

3) The packing density F_m can be given by Eq. (15):

$$F_m = \frac{A_o}{A_{cc}} \tag{15}$$

Where A_o represents the object area and A_{cc} is the area of the circumscribed rectangle that circumscribes the object. As the structure becomes compact, the F_m value becomes large.

As shown in Fig. 4, cracks and other defects have different shape factors (F_e , F_θ and F_m). Then three shape factors are selected to compose the feature vector $X = \{F_e, F_\theta, F_m\}$.

3.3 Experimental Results

In this paper, features extracted from 30 different sizes and shapes of other defects (non-crack) are taken as input training vectors to establish concrete cracks detection model based on $SVDD$. The Gaussian function is chosen for the kernel (kernel parameter σ=1.0). The radius of the hypersphere is 0.4084 and the number of support vectors is 9.

Extract the features of 76 regions from 30 image blocks as test data. The experimental results are shown in Fig. 5.

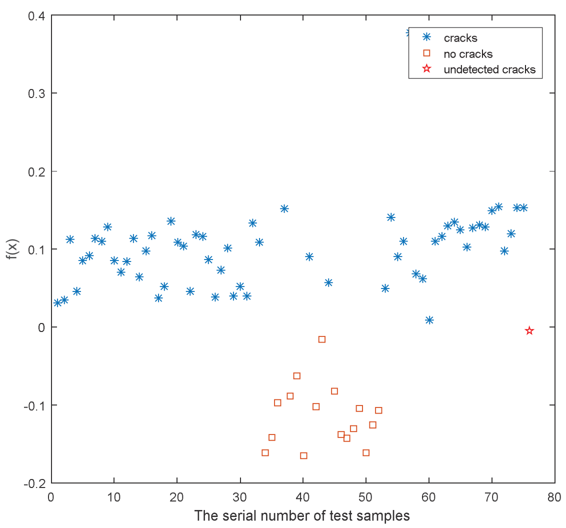


Fig. 5 Experimental results

Those image blocks consist of 60 crack regions and 16 non-crack regions. The detection rate of this method (see as Table1) is not 100% because some cracks are so incomplete that tend to be mistakenly considered as other defects (non-crack) with inconspicuous shapes. In practical applications, ε can be used to reduce false positive detections and improve detection rate by considering $f(x)$-ε as decision function.

Table1. Crack Detection Results

Test Set	False-positive Rate	False-negative Rate
Image block	0	1.67%

3. CONCLUTION

This paper proposes a method based on $SVDD$ to identify concrete cracks, and has been verified by experiments. An iteration method is applied to get the optimal threshold for image segmentation according to its grayscale distribution, then "crack" pixels are obtained after image processing. The features (including eccentricity, circularity and packing density) extracted from different shapes are selected as input training vectors for Support Vector Data Description to recognize the concrete cracks. Finally, the experimental results show that crack detection method based on SVDD can accurately distinguish cracks from other defects, and solve the problem of crack detection effectively.

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