Wall Crack Detection based on Adaptive Double Threshold Greyscale Transform

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Abstract

The construction industry is an important industry supporting social-economic development. Detecting cracks in walls could help to maintain the conditions of buildings. A wall crack detection algorithm based on adaptive double threshold greyscale transform is proposed. The MATLAB built-in '*graythresh*' function is modified in order to have a flag bit to preliminarily selection of the greyscale transformation threshold where the grey transform threshold and the binarization threshold can be automatically adjusted based on the image processing effect using a preliminary-selected threshold. The algorithm enhances the crack information and weakens the background information by multiple morphological operations of removing isolated small area pixels. The MATLAB simulation results show that the proposed algorithm has an accuracy of 96.16%, time from inputting the image to the completion of the labelling is 3-15 seconds, which depends on the complexity of the crack.

Keywords: wall crack detection; image processing; double threshold; adaptive greyscale transform; MATLAB

1. Introduction

In recent years, with the rapid development of the economy, the speed of urban construction is accelerating and the scale of old city renovation is also expanding. The construction industry has become an important industry to support social and economic development. Therefore, regular detection of wall cracks is an important task for building health inspection.

In the past, the inspection and maintenance of buildings mainly relied on manual inspection. Some wall cracks were located in an unpredictable dangerous areas, so it was very difficult to carry out inspection work. With the development of digital image processing and computer vision, morphological image processing based on computer vision technology is widely used in target detection and has been successfully applied to bridge and building crack detection. Compared with the manual inspection method, crack detection based on morphological image processing provides a lower cost and better real-time performance [1][2][3]. In this work, an adaptive double threshold greyscale transform and binarization algorithm for wall crack detection is proposed.

2. Related Works

At present, crack image detection methods mainly include spatial domain image processing and transform domain analysis such as frequency domain and wavelet domain processing.

S. Ogawa *et. al.* [4] proposed a wall crack image recognition based on crack feature extraction combining Gaussian mixture model and image filtering, and classification by support vector machine. This method is able to achieve an accuracy of up to 80%.

H. B. Yun *et. al.* [5] proposed crack recognition and segmentation using morphological image-processing techniques for flexible pavements. The algorithm consists of two subprocesses: (a) the grouping of fragments by using a morphological dilation transform and (b) the connection of fragments by using a morphological thinning transform. This method could improve crack detection accuracy.

L. Zhang *et. al.* [6] proposed an automatic detection method based on deep convolutional neural networks for road crack detection. Results show that the learned deep features with the proposed deep learning framework provide superior crack detection performance when compared with features extracted with existing hand-craft methods.

Q. Zou *et. al.* [7] proposed a DeepCrack-an end-to-end trainable deep convolutional neural network for automatic crack detection by learning high-level features for crack representation. In their work, multi-scale deep convolutional features learned at hierarchical convolutional stages are fused together to capture the line structures. Results show that DeepCrack achieves over 0.87 ODS *F* -measure value.

X. Yang *et. al.* [8] proposed a novel deep learning technique named fully convolutional network to detect cracks. Results show that the fully convolutional network is feasible and sufficient for crack identification and measurement.

3. The Proposed Method

In this paper, a wall crack detection algorithm based on adaptive double threshold greyscale transform is proposed. The MATLAB built-in function, '*graythresh*', is modified in order to select the greyscale transformation threshold which is the grey transform threshold and the binarization threshold. The algorithm enhances the crack information and weakens the background information through multiple morphological operations. Since the fixed threshold is not suitable for small-size image detection, the image size is transformed before image preprocessing to convert images of different sizes into standard sizes and resize them back to the original size after completing them to match the threshold value. The traditional edge detection is discarded, and the closed operation is used to increase image connectivity. A judgment method of an overlapping anchor is proposed to solve the problem of repeated marking that usually occurs in the traditional marking algorithm. Fig. 1 shows the flow chart of the algorithm.

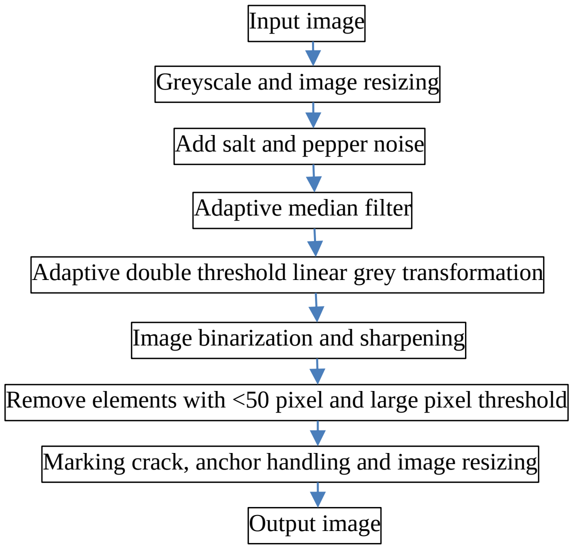
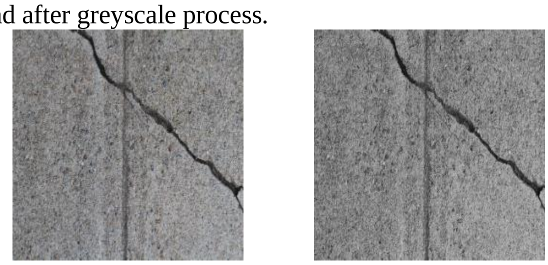


Fig. 1. The flow chart of the algorithm

4. Results and Discussion

To increase the accuracy, the greyscale process is performed on the collected colour using a MATLAB built-in function *rgb2gray*. Fig. 2 shows the image before and after greyscale process.



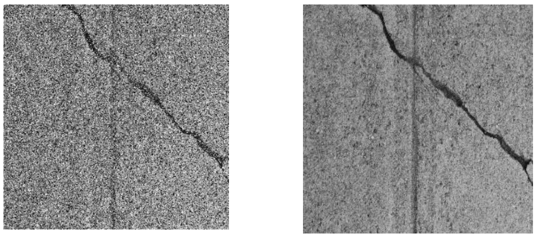
(a) (b)

Fig. 2. Greyscale process (a) before and (b) after.

Since the fixed threshold is not suitable for small-size image detection, image size transformation is introduced to convert images of different sizes into standard sizes of 2500×2500 . In this work, the nearest neighbour interpolation is used for reducing image size. Cubic spline interpolation and bilinear interpolation are used to enlarge images.

Due to the interference of noise, the quality of the image will be reduced and the crack information in the image will become fuzzy. In this work, an adaptive median filtering technique is applied to smooth and reduce the noise of images [9][10].

Through simulation experiments, the results show that the adaptive median filtering algorithm is significantly better than the traditional filtering algorithm in preserving the edge details of the image. Fig. 3 shows the difference between added salt and pepper noise to the image and the image after adaptive median filtering is applied.



(a) (b)

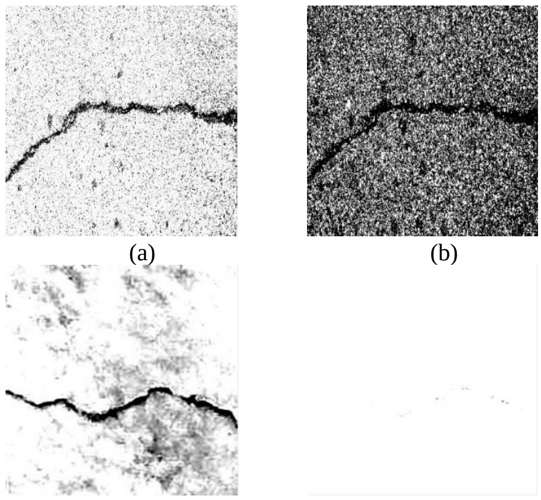
Fig. 3. Comparison between (a) adds salt and pepper noise to the image with 0.3 of noise density (b) image after adaptive median filtering

Due to the complexity and variety of crack images, the fixed single grey transform threshold cannot well adapt to the complex image. A MATLAB built-in function *gradthresh* is modified by adding a flag bit to achieve the purpose of initial selection of the grey transform threshold. The grey transform threshold and the binarization threshold can be automatically adjusted based on the image processing effect using a preliminary-selected threshold.

The experimental results show that images with little difference between the crack information and background information need to be enhanced. Based on the value of each colour component count matrix from the histogram, the maximum value is larger and the variance is smaller for images with an obvious difference between the crack information and background information which required a smaller grey threshold. On the other hand, the maximum value of each colour component count matrix of the histogram counts has a smaller maximum value and a larger variance. Therefore, *graythresh* function is modified. If the maximum value of counts is larger than 10^5, the flag is set to 1, otherwise flag is set to 0.

From the test results, for images with a large distinction between crack information and background information, stretching the original greyscale interval from [0.25 0.35] to [0, 1] provides a good processing effect. However, for images with a small distinction between crack information and background information, stretching the original greyscale interval from [0.5 0.6] to [0, 1] gives a good processing effect.

However, a single threshold cannot satisfy the needs of all different images, the adaptive double threshold transformation method is needed to solve this problem. The selection of the greyscale transform interval is depended on the initial greyscale transform interval which was selected by the flag bit. Fig. 4 shows the difference between various transformation intervals.



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

Fig. 4. (a) images with large distinction ([0.25 0.35] to [0, 1]), (b) images with large distinction ([0.5 0.6] to [0, 1]), (c) images with small distinction ([0.5 0.6] to [0, 1]) and (d) images with small distinction ([0.25 0.35] to [0, 1])

For the greyscale transformation interval of [0.25, 0.35], if the black pixel ratio of the processed image after binarization is less than 1%, the initial interval can be considered inappropriate and should be replaced with the greyscale transform interval of [0.5,0.6]. Whereas, for the greyscale transform interval of [0.5 0.6], if the black pixel ratio of the processed image, after binarization, is greater than 35%, the initial interval can be considered inappropriate and should be replaced with the greyscale transform interval of [0.2 0.35].

Combined with the selection of parameters in the previous steps, it was found that an acceptable result is achieved on the image with an obvious crack with a 0.2 threshold value. Whereas, for images without obvious crack information, a 0.7 threshold value is selected to achieve a better effect.

Considering the diversity of the image between the crack and background, in order to enhance the robustness of the algorithm, a threshold of 0.48 was selected. Fig. 5 shows the difference between images with and without obvious cracks.

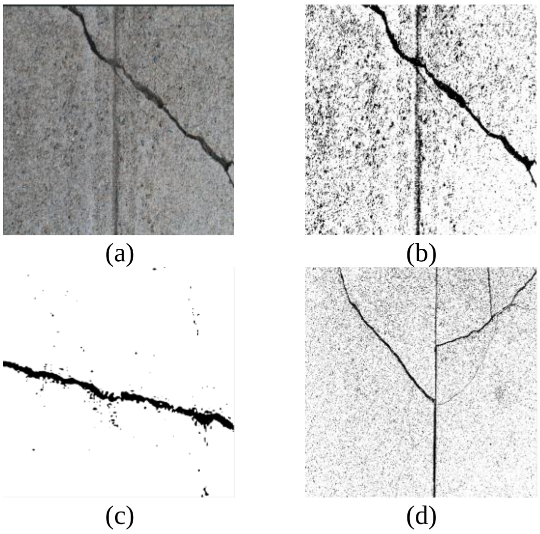


Fig. 5. Illustration of the proposed approach:(a) original image (b) image after binarization with threshold 0.48 (c) not obvious crack image with threshold 0.7 (d) complex background image with threshold 0.2

Image noise can be observed even after binarization and Gaussian filtering enhancement. In this work, two small area removing operations were performed followed by a close operation between the two removing operations. Choosing only one large threshold-removing operation, not only the small area cracks will be removed but all the crack information will also be filtered. Therefore, two filtering processes are performed. The first filtering process which is a small threshold filtering operation is applied to remove most of the noise and protect the crack information followed by the second filtering process which is a close operation to compensate for the crack information that is filtered out in the first filtering operation. After these two filtering processes, the image only left most of the crack information, hence, a larger threshold can be chosen to completely filter out the noise. Since the depth and thickness of the cracks vary from image to image, automatic thresholding in the second filtering operation is used to fit most of the images.

Experimental results show that most of the noise areas are in the range of 0-30 pixel points, so, the threshold value of 50 was chosen for the first filtering operation. On the other hand, for most 2500×2500 images, the maximum connected domain area is between $10^3 - 10^6$, while the other areas are relatively small. Hence, 1% of the maximum connected domain area was chosen as the threshold for the second filtering operation. It was found that the selected threshold value for the second filtering operation achieves a better preprocessing effect for most images. Fig. 6 show the difference between the images before and after the double removing operation.

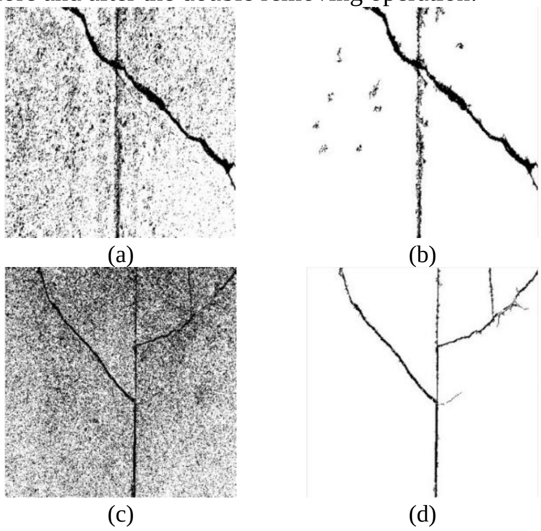


Fig. 6. Image (a)&(c) before and (b)&(d) double removing operation

The selection and setting of the structural elements are very important for the closing operation. The selection of different structural elements leads to different segmentation and different filtering effects. A disk-shaped structuring element with a radius of 3 is chosen. Fig. 7 shows the difference between images before and after the closing operation.

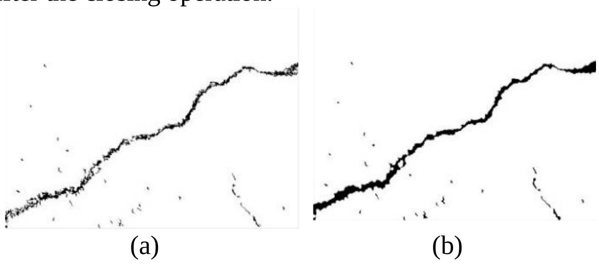


Fig. 7. Image (a) before and (b) after closing operation

The crack on the preprocessed image is marked. Due to the size of the preprocessed image is not the same as the original image, a size transformation on the image to restore it to the original size is performed. In this work, connected domain analysis is used to extract the crack information.

Due to the complexity of the crack image, especially for some block cracks, using only the connected domain approach to calibrate the cracks is not enough to achieve the expected results.

Before marking, the parameters of all the connected domains are calculated, including the coordinates of the points and the area of the anchor. If the area of the anchor box is too small, it will not be drawn. From the experimental results, the threshold to $0.08 \times Area_{max}$ gives a better annotation effect and is suitable for most images.

In order to avoid double marking of anchor boxes, it is necessary to hide the overlapping anchor boxes. If the midpoint of the smaller rectangle lies inside the larger rectangle, it is assumed that at least 50% of the area of the smaller rectangle overlaps with the larger rectangle. If there is an overlap, the larger anchor box will be kept. Fig. 8 shows the marking for different crack images.

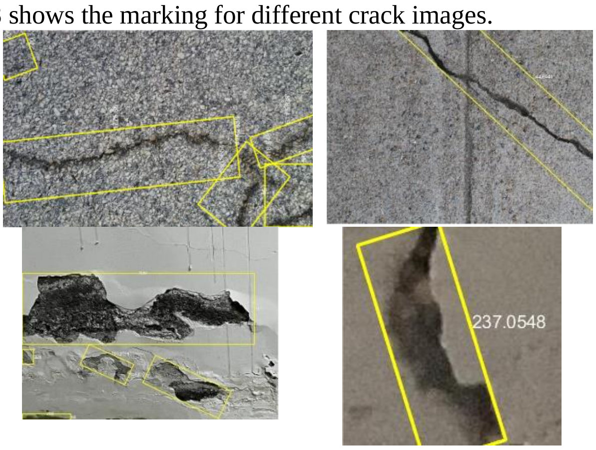


Fig. 8. Marking for different crack images

In order to verify the accuracy of the algorithm, two sets of data set were selected for testing namely the "Concrete Crack Images for Classification" dataset [11] and the "CRACK500" dataset [12][13]. The first 1000 images in the "Concrete Crack Images for Classification" dataset were selected for testing whereas the first 200 images in the "CRACK500" dataset were selected for testing, and the test results are shown in Table 1. Because the images in the "Concrete Crack Images for Classification" dataset are simple and the image background in the "CRACK500" dataset is complicated, in order to improve the scientific accuracy and the accuracy of the algorithm, the ratio of 3:1 is used between "Concrete Crack Images for Classification" and "CRACK500".

Table 1. Accuracy Results

Dataset	Total image	Fail to detect	Accuracy (%)
Concrete Crack Images for Classification	1000	6	99.40
CRACK500	200	28	86.32
Total (weighted)*	1200	104	96.16

* Concrete Crack Images for Classification:CRACK500 = 3:1

5. Conclusion

The experimental verification shows that the proposed algorithm has a detection accuracy of 96.16% for most of the images. However, the detection accuracy for some special cases or complex crack images still needs to be optimized

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