Automated Pavement Distress Detection Using Advanced Image Processing Techniques

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***Abstract*----In this paper, a novel, fast and self-adaptive image processing method is proposed for the extraction and connection of break points of cracks in pavement images. The algorithm first finds the initial point of a crack and then determines the crack's classification into transverse, longitudinal and alligator types. Different search algorithms are used for different types of cracks. Then the algorithm traces along the crack pixels to find the break point and then connect the identified crack point to the nearest break point in the particular search area. The nearest point then becomes the new initial point and the algorithm continues the process until reaching the end of the crack. The experimental results show that this connection algorithm is very effective in maximizing the accuracy of crack identification.**

I. INTRODUCTION

The demand for automated inspection, monitoring, and pattern recognition for transportation applications are ever increasing. This increasing demand is partly driven by the decreasing costs of imaging technologies. A typical inspection process, including pavement distress inspection can be divided into three stages: preprocessing, segmentation, classification and measurements. Preprocessing is used to improve the quality of the input image in order to facilitate the analysis and interpretation at subsequent stages. Important tasks in preprocessing can include filtering for noise removal, deblurring the image, and the highlighting of specific features, e.g., cracks on the pavement. Image segmentation is the process of dividing an image into meaningful regions, such as objects of interest and background. The main parameters of interest for pavement management is the pattern classification and measurement of various parameters from crack features.

Recent advances include the use of wavelet transform methods as a tool for crack detection in various applications. The advantage of the wavelet transform is its multi-resolution property, which allows the efficient identification of local features of a signal [1]. The wavelet transform has been successfully applied to crack localization in beam structures [2-4]. Douka proposed a method for estimating both the location and size of the crack by defining an intensity factor which relates the size of the crack to the coefficients of the wavelet transform [5]. Q. Q. Li [6] proposed a robust and high-efficiency model for segmentation and the calculation of distress statistics of massive pavement images which is based on multi-scale space. S. K. Sinha [7] proposed a method for detection of crack falls within the scope of the Bayesian framework.

H.D.Cheng [8] proposed a method which can check connectivity of cracks using the fuzzy set theory. The objective is to eliminate pixels lacking in connectivity and to remove isolated darker pixels, which are considered to be noise. Y. Huang and B. Xu [9] proposed the crack cluster connection method. First, it finds verified seeds of a crack, and then connects the individual seeds into seed clusters. Starting from one seed, a crack cluster grows by accepting adjacent seeds one at a time until no nearby seeds can be found.

The proposed algorithm in this paper operates on binary images obtained after some pre-processing steps. First, it finds the initial pixel of a crack and decides on its direction, for example, transverse or longitudinal. Then, the algorithm searches in each direction for break points of cracks using different methods. After finding a break point, the algorithm will find the nearest crack pixel in a particular searching area to fill the gap. The algorithm continues to search the break points until the end of the crack is located.

The rest of this paper is organized as follows: Section II describes the details of the proposed method, Section III presents several computer simulation results, and finally, conclusions are given in Section IV.

II. ALGORITHM DESIGN

A. Step 1. Preprocessing: Filtering and Noise Removal Techniques

The aim of preprocessing in pavement image inspection is to suppress the unwanted information from the image data and enhance the desired image features important for further processing. Preprocessing is an important step in the sense that with an effective process much of the subsequent

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analysis will be simplified. Due to non-uniform lighting or weather conditions, the contrast between distresses and background is often very low. In addition, the image is often corrupted with noise and undesired features. Therefore, an image enhancement method capable of removing non-uniform background illumination effects and noises is required.

A promising technique would be to use a nonlinear filter which takes the mean and variance of local gray values into account. Other techniques, such as median filtering can be used to reduce the noise while preserving much of the details in the image. To remove the non-uniform background intensity effect we used the following nonlinear filter, as show in (1),

$$f^{*}= Z(i,j)^{*} [f_{org}(i,j)-f_{blur}(i,j)]+m \quad (1)$$

where f^{*} , $f_{org}(i,j)$,and $f_{blur}(i,j)$ are respectively the filtered, original and blurred images of the pavement, m is the mean value of the original image, and Z(i,j) is a local gain factor sensitive to local variations which is 1 for here. The blurred image is obtained by convoluting a low-pass Gaussian spatial filter [8] with the original image. Here we chose Gaussian low-pass spatial filter because it avoids a bright ringing effect.

Thresholding is a widely used technique for image segmentation and feature extraction. For a given image, most of these techniques involve creating a histogram of the gray level values to be used to find the peaks that exist in the image. A threshold is then chosen according to the valley between these peaks or modes (usually two prominent peaks are assumed). Adaptive thresholding applies a different threshold to different regions of the image and results in better segmentation. Pavement cracks usually involve abrupt changes in gray level of two adjacent regions of variant gray levels. With an appropriate threshold that is extracted from the block and lies somewhere between the means of the two regions, the block can be binarized.

Mathematical morphology is an important tool for low-level image processing [10]. Most morphological transforms are constructed from elementary morphological operations such as dilation and erosion. This operation is guided by structural elements. Applying dilation before eroding is called a closing operation, and it can fill the holes in an image. In the crack image, closing operations can be used to join the break points of the cracks. To remove the isolated noise, the algorithm checks all eight neighbors including the neighbor in the same direction of the bright pixel. If all these neighbors are dark pixels (i.e. non crack pixels), then this pixel is considered an isolated noise. The pre-processing steps are shown in Fig 1.

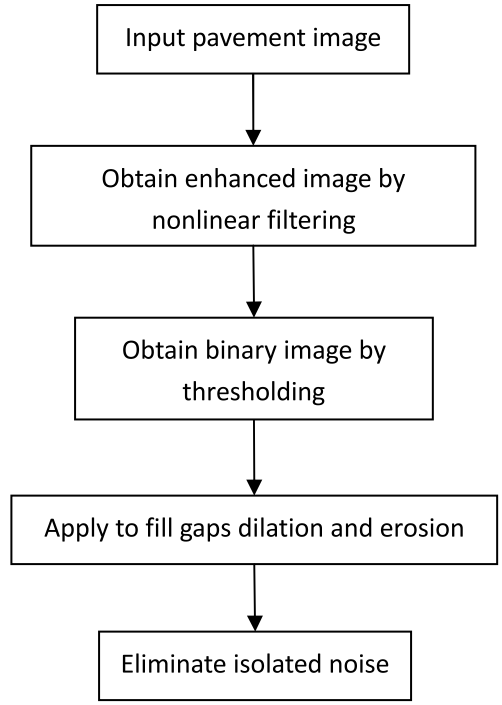


Figure 1 Pre-processing steps

B. Step 2. Connectivity Analysis of the Crack Pixels

The connectivity analysis of the crack pixels is based on a depth-first searching method. The process consists of two steps: break point determination and gap connection. The method does not require checking every crack pixel but only finding the break points. First, the algorithm finds the initial pixel of a crack. A crack pixel is denoted by a bright pixel. This pixel can be verified as the initial point of a transversal crack if we find a bright pixel within a distance of 5 or 10 pixels in the transverse direction and 2 or 4 pixels in the longitudinal direction, otherwise, it will be considered as noise. Similarly, if we find a bright pixel, whose distance is 5 or 10 pixels in the longitudinal direction and 2 or 4 pixels in transverse directions, this pixel could be the initial pixel of a longitudinal crack. In the following we describe a procedure for finding the transversal cracks; the procedure for longitudinal cracks would be similar.

After finding the coordinates of the initial pixel of a transverse crack, we define a search area and three prioritized directions, namely, the right, up, and down directions to denote the first, second, and third directions of the search, respectively. The basic rule of the searching method is to follow the bright pixels in the first direction from the initial pixel until there is no bright pixel in this direction. It will then continue along the second direction and if no bright pixel is found in this direction, it then checks the pixel in the first direction immediately. If there is a bright pixel the algorithm will continue in the first direction again, otherwise, it will go along the third direction. In searching for transverse cracks, the high priority level of searching is followed by the second direction and then finally in the third direction with the lowest priority.

The search algorithm for connectivity analysis is summarized below:

1) *Start from an initial crack pixel.*
2) *Follow the crack pixels in three directions right, up and down until no crack pixel is found.*
3) *Check 8-neighbors of the pixel visited last*
4) *Determine the presence of either a break point or a column of break points.*
5) *Look for the nearest crack pixel in a specific search area.*
6) *Connect them and repeat the process for the entire image.*

Case 1: Note that, when there is no bright pixel in any of the three directions, the method will then check the upper right and bottom right pixels, i.e., diagonal pixel elements. If neither pixel is bright, the final bright pixel is a break point. Otherwise, the search algorithm will continue in the first direction from one of the right pixels. Fig 2 shows the break point in Case 1.

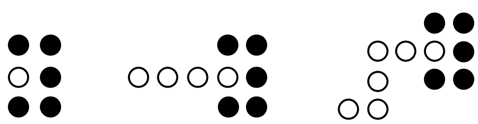


Figure 2 The break point in Case 1

Case 2: On the other hand, after continuing along the third direction, if there is no bright pixel in the next column, we obtain a series of break points. Fig 3 shows the break points in Case 2.

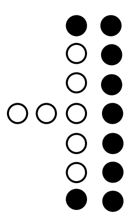


Figure 3 The break points in Case 2

To obtain a connected set of crack points, we define a search area for a possible bright pixel. The search areas for finding the nearest crack pixel would be different for these two cases. Fig 4 shows part of the searching area corresponding to Case 1. The method will check pixels in the up and down 4 rows and the right 20 columns. If there is a bright pixel found in the search areas, it will change the previous pixels in the same row to a bright pixel.

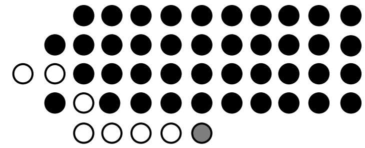


Figure 4 Searching area 1

Fig 5 shows the searching area for Case 2. In a similar way, the algorithm finds a crack pixel in the search area and connects it to the previous break point by backtracking.

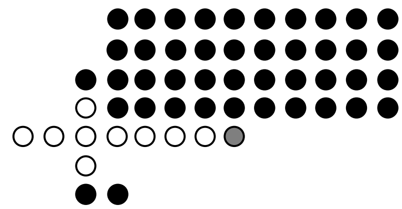
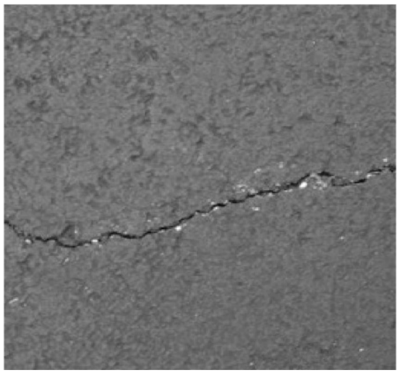


Figure 5 Searching area 2

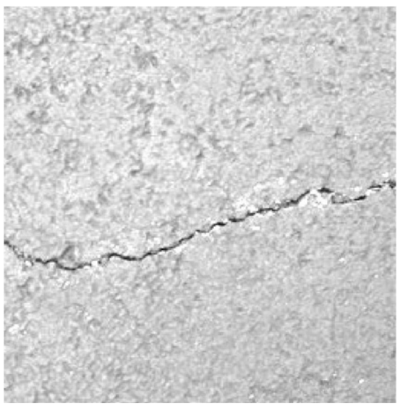
The process for obtaining a longitudinal crack is similar to the transverse; however, the three prioritized search directions will change in the following way. The downward direction is crucial for this case; therefore, it will be the first direction with high priority to search for continuity. The second and the third directions are the right and left directions, respectively. The priority level is the same as the transversal cracks. Note that, the order of priority is very important and should be observed during the search process. We cannot use the same search method for both transversal and longitudinal cracks, because the tendency for transversal cracks is in the right direction, and the tendency of longitudinal crack is in the downward direction.

III. EXPERIMENTAL RESULTS

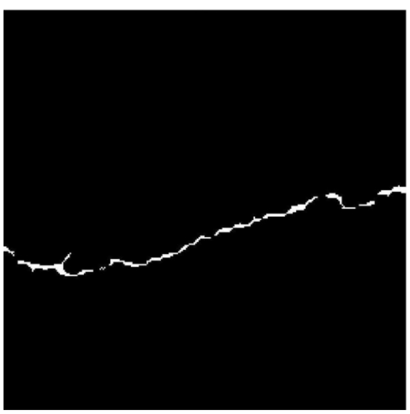
The proposed algorithm has been implemented in MATLAB, and its performance and simulation results are presented in this section. We have considered different kinds of pavement images in our implementation, for example, transverse, longitudinal or multiple cracks in a pavement image. Fig 6(a, b, c, d) shows an original pavement image with cracks, an enhanced image, a morphological filtered image, and the final connected crack feature. The image after enhancement appears to have a reduced amount of noise and definitely with much more contrast. It is obvious that almost all break points are connected except the last one because the size of the gap is too large relative to the searching area.



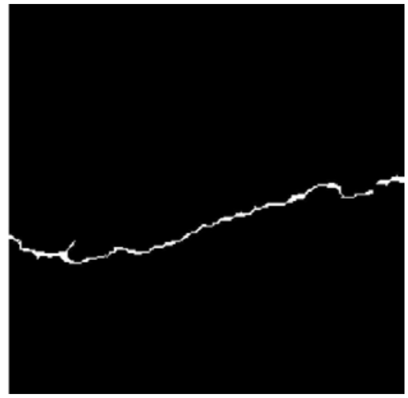
(a) Original image



(b) Difference image



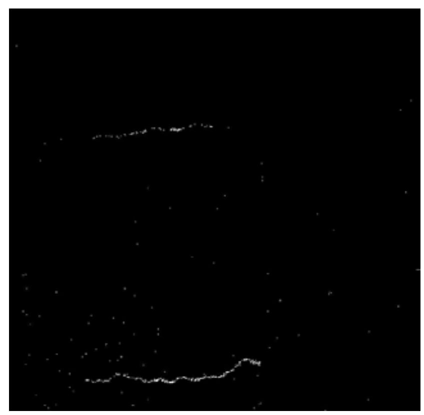
(c) Filtering image



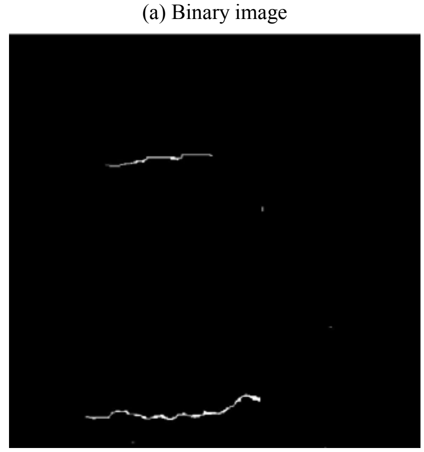
(d) Connecting image

Figure 6 Transverse crack

Similarly, Fig 7 (a, b) shows a pavement image (after converting to a binary form) with two cracks and the final results of extracted crack features. We can see that the result is very satisfactory with two cracks well extracted from the image.



(a) Binary image



(c) Connecting image

Figure 7 Multiple cracks

IV. CONCLUSIONS

A novel algorithm for the extraction of both transversal and horizontal cracks from pavement images is presented. The first step of the proposed method involves pre-processing which consists of enhancement, thresholding, morphological operations using dilation and erosion to eliminate the remaining noise. One of the major components of the algorithm is the determination of the break points and their connection for extraction of the crack features. Experimental results clearly demonstrate that the method can effectively and efficiently extract the crack features from the pavement images. Future work includes the calculation of the length and width of the cracks.

ACKNOWLEDGMENT

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