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Report No: MIOH UTC TS18p1 2009-Final

A Novel Image Database Analysis System for Maintenance of Transportation Facility



FINAL REPORT

PROJECT TEAM

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SPONSORS

This is a Michigan Ohio University Transportation Center project supported by the U.S. Department of Transportation and the University of Toledo.

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A Novel Image Database Analysis System for

Maintenance of Transportation Facility

TS18 Project 1 - the first of a three project series

ABSTRACT

The current project was funded by MIOH-UTC in the Spring of 2008 to investigate efficient maintenance methods for transportation facilities. To achieve the objectives of the project, the PIs undertook the research of various technologies of image analysis and storage. Therefore, initially a database was developed to store various information and images obtained from the regional roads. In this direction, a number of methods for storage of images were investigated and compared such as storage of images into database directly versus the storage of images into database after compression; or storage of the location of the images only in database.

In another direction, the PIs investigated various imaging technologies for the identification of the state of various roads, since 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 software and hardware technologies which allow faster access to the required information for these applications. The structured storage provided by the use of modern database technologies provides proper mechanism to store a variety of information artifacts which can be merged from different perspectives for investigation. For example, combined image and textual information regarding different attributes of a typical inspection would identify accurately the region and the proper maintenance path. 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.

This report looks at the imaging technologies to enhance the management of pavements. The main parameters of interest for pavement management are the pattern classification and measurement of various parameters of crack features. The first section explains the imaging technologies used for processing images. In section 2 the algorithm is explained and section 3 shows the simulation result and our progress in achieving the goals set in this project.

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<u>1. Imaging Technologies</u>

Recent technological advances in automated road maintenance inspection 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 that falls within the scope of the Bayesian framework.

H.D.Cheng [8] proposed a method which can check the 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 search area to fill the gap. The algorithm continues to search the break points until the end of the crack is located.

2. Methodologies

We used several steps to detect cracks in the pavement image including enhancement, threshold, dilation, erosion, and connection method. All the steps are shown in Figure 1.



Figure 1. Processing Steps

2.1. Step 1: Enhancement

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 is 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 detail in the image. To remove the non-uniform background intensity effect, we used the following nonlinear filter, as show in (1),

$$f^* = Z(i,j)^* [f_{org}(i,j)-f_{blur}(i,j)]+m$$
 (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 a Gaussian low-pass spatial filter because it avoids a bright ringing effect.

2.2. Step 2: Thresholding

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.

Here, we use a segmentation method based on fractal theory. A fractal is generally a rough or fragmented geometric shape that can be split into parts, each of which is (at least approximately) a reduced-size copy of the whole, a property called self-similarity. The term was coined by Benoît Mandelbrot in 1975 and was derived from the Latin fractus meaning "broken" or "fractured." a mathematical fractal based on an equation that undergoes iteration, a form of feedback based on recursion. Following Ref. [11], first, we introduce the concept upper surface $u(i, j, \epsilon)$ and lower surface $b(i, j, \epsilon)$. Initially, given the gray level function f(i, j) = u(i, j, 0) = b(i, j, 0). For $\epsilon = 1, 2, 3$ The upper surface and lower surface are defined as follows:

$$u(i, j, \epsilon + 1) = \max\{u(i, j, \epsilon) + 1, \max[u(m, n, \epsilon)]\}$$
(2)

$$|(m,n) - (i,j)| \le 1$$

$$b(i,j,\epsilon+1) = \min\{b(i,j,\epsilon) + 1, \min[b(m,n,\epsilon)]\}$$

$$|(m,n) - (i,j)| \le 1$$
(3)

The image points (m,n) with distance less than one from (i,j) were taken to be the four immediate neighbors of (i,j). The covering blanket is defined by its upper surface and its lower surface. A point (x, y, f) will be included in the blanket for $b(x, y, \epsilon) < f < u(x, y, \epsilon)$. The volume of the blanket is computed from u and b by

$$V(\epsilon) = \sum_{i,j} (u(i,j,\epsilon) - b(i,j,\epsilon))$$
(4)

As the surface area measured with radius ϵ we take the volume divided by 2ϵ

$$A(\epsilon) = V(\epsilon)/2\epsilon \tag{5}$$

The area of a fractal surface behaves according to the expression:

$$A(\epsilon) = k\epsilon^D \tag{6}$$

After taking logarithm of expression (6), we get the equation:

$$logA(\epsilon) = Dlog\epsilon + logk \tag{7}$$

According to the expression (7), the slope D and the values of k can be calculated by least-square fitting.

When a pure fractal image is analyzed, the value of k is a constant. However, for the image of different texture, the value of k changes on scale, so the parameter k reflects the change of the surface area on different scales. Obviously, when the surface is even, the value of k is smaller. Contrarily, when the surface is rough, the value of k is larger. Thus, we can set the parameter k as a local threshold to segment the image. [12].

The algorithm can be presented as the following:

Step 1: Set a window of size $s \times s$ and move it in the image of $M \times N$ from the beginning of the image step by step. Then calculate every *k* of each window.

Step 2: Get the minimum of the k and assume fix values for $\alpha 0 < \alpha < 1$ and β . Set the threshold $T = \alpha \times k_{min} + \beta$ to segment the image.

After many tests, we selected = 3 , $\epsilon = 9$, $\alpha = 0.22$ and $\beta = 45$.

2.3. Step 3: Dilation and Erosion

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. After thresholding, some crack pixels are removed and as a result, there are lots of gaps on the crack. Therefore, closing operations can be used to join the break points of the cracks and improve the accuracy of cracks.

Here, after many tests, we chose a morphological structuring element "disk" for dilation and erosion. It creates a flat, disk-shaped structuring element and the radius is 5. The structuring element is described in Figure 2.



Figure 2. Structuring Element "Disk"

2.4. Step 4: Eliminate Noise

There are several methods that can be used to eliminate the noise, for example, median filtering. The median filter is a non-linear digital filtering technique, often used to remove noise from images or other signals. The idea is to examine a sample of the input and decide if it is representative of the signal. This is performed using a window consisting of an odd number of samples. The values in the window are sorted into numerical order; the median value is then selected as the output. A new sample is acquired, and the calculation repeats[13]. However, a median filter is usually used to remove "salt and pepper" noise. Some crack pixels are also removed after using this filtering. This will lead to the creation of many gaps on the crack. Therefore, 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 and removed. Although this algorithm cannot remove isolated noise more than median filtering, it can maintain crack information as much as possible.

2.5. Step 5: Connect Break Points

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 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 immediately checks the pixel in the first direction. 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. Figure 3 shows the break point in Case 1.



Figure 3. 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. Figure 4 shows the break points in Case 2.



Figure 4. 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. Figure 5 shows part of the search 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 6 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 6. 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 for 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.

3. Simulation and Result

The proposed algorithm has been implemented in MATLAB R2008, and its performance and simulation results are presented in this section. Figure 7 shows an original pavement image with cracks. Figure 8 shows an enhanced image. Figure 9 shows the image after thresholding. Figure 10 shows the image after dilation. Figure 11 shows the image after erosion. After morphological filtering, Figure 12 shows the image after eliminating isolate noise. And, the final connected crack feature is shown in Figure 13. 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. Figure 14 shows the image after median filtering based on the erosion image. When compared to the Figure 12, we can see that the noise still cannot be removed completely, but a significant amount of crack pixels are removed. Large gaps are generated which cannot be connected.



Figure 7. Original Image

Figure 8. Difference Image



Figure 9. Binary Image



Figure 10. Dilation Image



Figure 11. Erosion Image



Figure 13. Connecting Image



Figure 12. Filtering Image



Figure 14. Median Filter Image

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