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IMAGE ANALYSIS FOR AUTOMATED PAVEMENT CRACKING EVALUATION

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ABSTRACT

Image processing technology plays an important part in the analysis and evaluation of pavement surface cracking. The pattern recognition method for crack geometry proposed in this paper makes it possible to extract data necessary for evaluating the extent and severity of cracking quantitatively. In this newly developed method, low-resolution images are used first to extract crack regions, and then high-resolution images are used to identify the type of crack. The method proved to be effective when used for areas containing two or more types of crack.

1. INTRODUCTION

Images of pavement surface are one of the most important data required for a proper maintenance of the ever-expanding road networks. This is because evaluation of road surface distress is based on the MCI (Maintenance Control Index) obtained from three information elements: cracking, rutting, and longitudinal roughness.[1] The processes of data collection, recording, and analysis for rutting and longitudinal roughness have already been almost fully automated, and systems that require little human intervention and interpretation have been developed and in use.[2] With regard to cracking, survey methods based on human interpretation of photographic images of pavement surface cracking taken with slit cameras have been employed not only in Japan but also in the United States, as exemplified by the SHRP (Strategic Highway Research Program). However, in order to give more objectivity to the process of human interpretation and evaluation, automation of the process is being called for both in Japan and abroad. Automation of film imagery interpretation is expected to improve both the quality and the productivity of data. It is difficult, however, to replace human-dependent interpretation and evaluation with computer-based image analysis and develop a system that is faster and more reliable than the human-dependent approach. This is because of variations of pavement surface condition and demanding shooting environments which make images to be processed vary widely. The efforts to realize such a system have not yet born fruit.

To realize automatic inspection of pavement surface, the authors conducted a study on the methodology of image analysis with two specific goals in mind. One of the goals was to develop a method for accurate extraction of cracks from pavement surface image data. The other goal was to develop a method for pattern recognition of the geometric properties of cracks. These two methods provide basic information necessary for quantitative evaluation of the extent and severity of cracking.

In the field of crack extraction, a marked progress has been made by the development of a technique for enhancing line features corresponding to cracks while generating hierarchical images.[3] No practicable method has been developed, however, for pattern recognition of crack geometry.

A considerable number of studies have been made on the pattern recognition of pavement surface cracking. H. N. Koutspoulos et al. performed a classification by the decision tree method in which regional density, the angle of inclination of the axis of minimum inertia, the ratio of the principal moments of inertia, and the aspect ratio were used as characteristic quantities.[4] The present authors used the same approach and carried out a classification using Oira number (4 connections, 8 connections) as a topological characteristic quantity in addition to the above quantities.[5] S. G. Ritchie et al. used characteristic quantities of pixel-related statistics in the directions of lines and columns in the image (mean, dispersedness, mean of runs, mean run length) as input vectors for a neural network.[6] M. H. Mohajeri et al. classified cracks in a region under consideration by applying a directional filter with thresholds and then using the numbers of pixels in the columns and lines where the number of pixels corresponding to cracks exceeds 50%.[7]

Thus, in the study of pattern recognition of crack geometry, cracks can be classified by use of the quantities mentioned above in cases where only one type of crack exists within a region under consideration. However, classification has not been successful in cases where two or more types of crack exist in the same region. In other words, if two or more types of crack exist in a region under consideration, the region needs to be segmented before classification.

This paper discusses a method for classifying the geometric patterns of cracks which uses segmentation of the regions.

2. METHODOLOGY

A crack in pavement is a set of short vectors, and the type of crack is dependent on how those short vectors are connected. Human beings do not recognize a crack as a set of connected short vectors. Instead, they recognize a crack as a fuzzy vector. For example, a slightly meandering crack is described as a crack "like a straight line." In designing a method for recognition of the geometric patterns of cracks, therefore, the authors determined an approximate region of cracking and examined the cracks in the region in detail instead of dividing cracks into short vectors and treating them as elements. In other words, possible regions of one-dimensional (1-D) and two-dimensional (2-D) cracking distress were extracted from low-resolution images, and then types of crack were identified by use of high-resolution images. This process is illustrated in Fig. 1 and will be explained below.

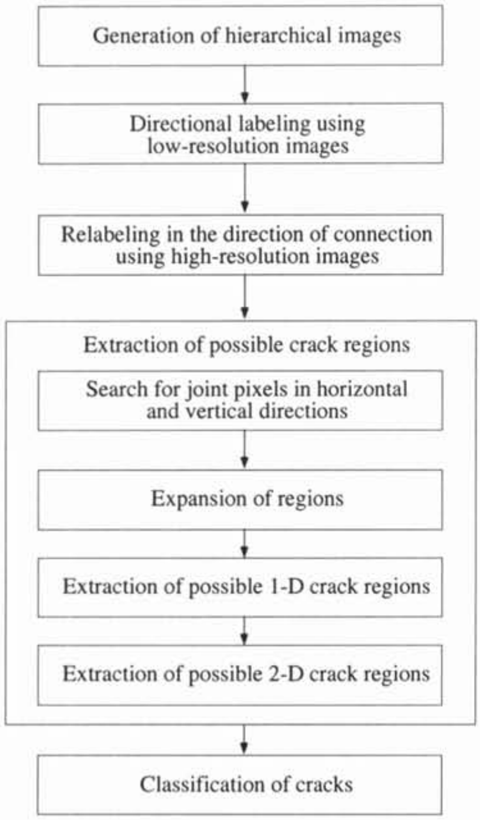

Figure 1. Procedure for Identification and Classification of Cracks

1) Generation of Hierarchical Images

The purpose of hierarchical image generation is to generate images of multilevel resolutions. Hierarchical images are generated by converting n x n pixels for extracted cracks into single pixels, where n is a multiple of 2. Images from which cracks are extracted are binary. In this conversion, if one or more pixels corresponding to cracking exist in n x n pixels, the value "1" is assigned to the converted pixel.

2) Labeling by Direction of Connection

Pixels are labeled by the direction of connection, using 3 x 3-pixel directional operators for images of the lowest-level resolution. To distinguish between four types of directional operators, namely, horizontal, vertical, isolated point, and joint, directional operators were defined as follows:

① Horizontal-direction operator (H)

x	0	x
1	1	1
x	0	x

0	0	x
1	1	0
0	0	x

x	0	0
0	1	1
x	0	0

② Vertical-direction operator (V)

x	1	x
0	1	0
x	1	x

0	1	0
0	1	0
x	0	x

x	0	x
0	1	0
0	1	0

③ Isolated-point operator (I)

x	0	x
0	1	0
x	0	x

④ Joint operator (J)
Patterns that do not belong to ① to ③ above.

("x" in the above operators is either 0 or 1.)

3) Relabeling by Direction of Connection

This process involves conversion of joint pixels labeled for the lowest-resolution image into those for a higher-resolution image. The objective of this processing is to determine the direction of connection of joint pixels. An outline of this process is shown in Fig. 2. The first step in the process is directional labeling, as mentioned above, of a high-resolution image of hierarchical level (m), as shown in Fig. 2. The next step is to search pixels labeled as joint for a lower-resolution image of hierarchical level (m+1). Then, pixels of hierarchical level (m) corresponding to the pixels thus identified are examined. If the pixels of hierarchical level (m) are labeled as H or V, the pixels of hierarchical level (m+1) are changed from J into H or V. These steps are repeated for higher-resolution images. For example, if pixels labeled as joint at hierarchical level (m) are not replaced with H or V pixels, the above steps are performed for a higher-resolution image of hierarchical level (m–1). If both H and V exist among four pixels of hierarchical level (m) corresponding to one pixel of hierarchical level (m+1), the iterative process is terminated after determining the "joint" identity.

4) Extraction of Regions

Images containing different types of cracks include a large number of pixels labeled as joint. This makes division into crack regions difficult to perform. As a first step, therefore, crack regions are divided into those of one-dimensional cracks and those of

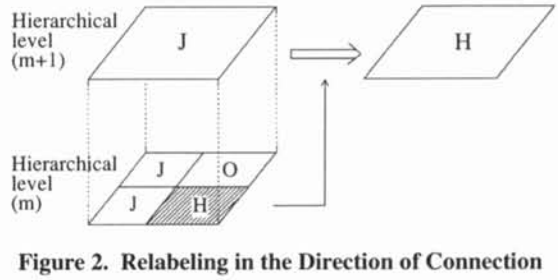

Figure 2. Relabeling in the Direction of Connection

two-dimensional cracks. For the purpose of extracting possible one-dimensional crack regions, mainly pixels labeled as H or V are searched. For example, search conditions in the case where possible horizontal crack regions are to be extracted are as follows:

① Pixels labeled as H are searched, and then pixels labeled as H in the horizontal and diagonal directions around those pixels are searched.

② In the case where there are any adjoining pixels labeled as H, the region of the original pixel is expanded. This process is repeated.

③ In the case where there is no adjoining pixel labeled as H, the region is expanded only if an adjoining pixel is labeled as J.

④ In the case where continuity of labeled pixels is interrupted, the region is expanded only if there is a region containing a pixel or pixels labeled as H in the horizontal direction.

In the above process, possible crack regions in the vertical direction are extracted after those in the horizontal direction are extracted. A pixel or region may be assigned to a crack region in both the vertical and the horizontal direction. As a next step, the crack regions other than the one-dimensional crack regions are considered to be possible two-dimensional crack regions.

5) Classification of Cracks

Before cracks are classified, the identified crack regions are superimposed on the original images, and the original images are trimmed. For each of the trimmed images, characteristic quantities, such as regional density, the angle of inclination of the axis of minimum inertia, the ratio of the principal moments of inertia, and profile projection, the types of crack in each region are identified.

① *Ratio of principal moments of inertia*: This is the ratio of the maximum moment of inertia[8] about the center of gravity of an object under consideration to the minimum moment of inertia. The ratio of the principle moments of inertia is used to determine whether cracking distribution on pavement surface is one-dimensional or two-dimensional.

$$Mpg = \sum_i \sum_j (i - ig)^p (j - jg)^q f(i, j) \qquad (1.1)$$

where Mpg is the moment of inertia about the center of (p+q) dimensional gravity, and ig and jg are the coordinates of the center of gravity.

$$Q_0 = \frac{1}{2}\tan^{-1}\frac{2M_{11}}{M_{20} - M_{02}} \qquad (1.2)$$

where the Q_0 is the angle between the axis of inertia and X axis.

In this case

$$M_{max} = MAX\,(M_{20}, M_{02}) \qquad (1.3)$$

$$M_{min} = MIN\,(M_{20}, M_{02}) \qquad (1.4)$$

$$M_R = \frac{M_{min}}{M_{max}} \qquad (1.5)$$

Eq. (1.5) gives the ratio of the principal moments of inertia, which is used as a feature element.

② *Angle of axis of inertia*: This is the angle between X axis of the image and the axis of inertia, which is expressed in Eq. (1.2). This angle is used to classify linear cracks in the longitudinal and transverse directions on pavement surface. Characteristically, longitudinal cracking is cracking along shoulders, and transverse cracking is cracking perpendicular to longitudinal cracking.

③ *Topologically characteristic quantities*: These quantities, which are based on the concepts of adjacency and connectedness, represent the topological characteristics of regions, and are 4-connection and 8-connection Oira numbers, and the number of connections. Oira number is used to classify two-dimensional cracks. For classification of potholes, Oira number is related with attributes representing the connectivity of pixels, such as the number of branching points or the number of intersecting points.

$$E^4 = V - E + R$$

$$E^8 = V - E - D + T - R$$

Oira number is given as E^4 in the case of 4 connections and as E^8 in the case of 8 connections.

In the above equations, V is the number of vertices; E, the number of sides; R, the number of partial regions; D and T, the number of alternating combinations of pixels assigned the values of "1" and "0" in a 2 x 2-pixel matrix.

$$N_c^4(P) = \sum_{k \in K}[f(P_K) - f(P_K)\, f(P_{K+1})\, f(P_{K+2})$$

$$N_c^8(P) = \sum_{k \in K}[\bar{f}(P_K) - \bar{f}(P_K)\, \bar{f}(P_{K+1})\, \bar{f}(P_{K+2})$$

$$\bar{f}(P_k) = 1 - f(P_k),\ \kappa = \{0, 2, 4, 6\}$$

The number of connections in a binary image f(P) is given as N_c^4 in the case of 4 connections and as N_c^8 in the case of 8 connections.

3. EXPERIMENT AND RESULTS

Crack images used in this study were 280 x 360 pixel images, with each pixel representing 1 cm x 1 cm area of pavement surface. These images were used to generate images of three levels of resolution (20 cm x 20 cm, 10 cm x 10 cm, and 5 cm x 5 cm) through generation of hierarchical images. Determination of the lowest resolution is dependent on recognition of linear cracks. This is because the lowest resolution represents the allowable limit of the degree of meandering of lines, and the extent of branches directly connected to cracks in the skeleton. Fig. 3 shows an original image, and Fig. 4 shows the results obtained from regional extraction. These results confirm that regions of transverse cracks, longitudinal cracks, and potholes have been identified successfully.

4. CONCLUSIONS

In this study, crack regions were identified, and then methods for classifying the geometric patterns of cracking was discussed with a view to developing a technique for pattern recognition of crack geometry. The proposed method proved to be effective even in cases where more than one type of crack existed in an image under consideration. The authors intend to further this study to develop a practicable automatic system capable of evaluating the extent and degree of cracking quantitatively.

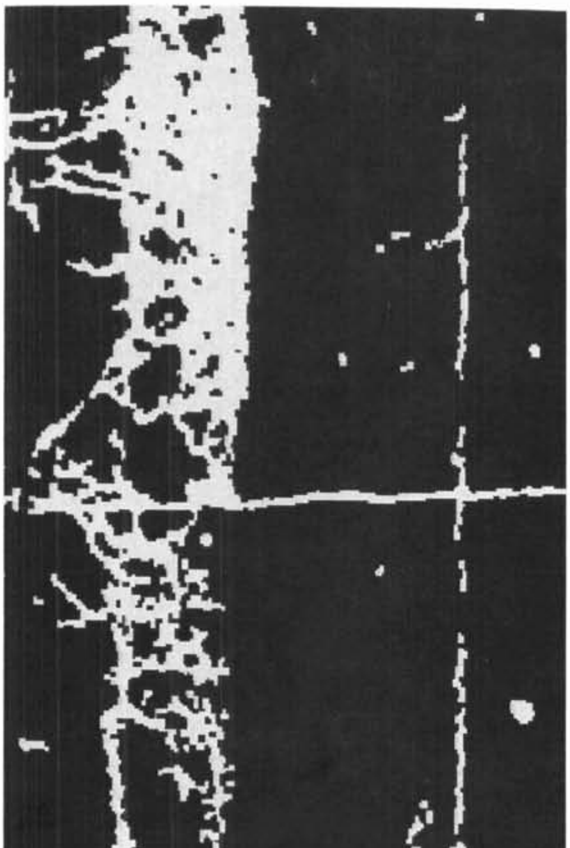

Figure 3. Original Image

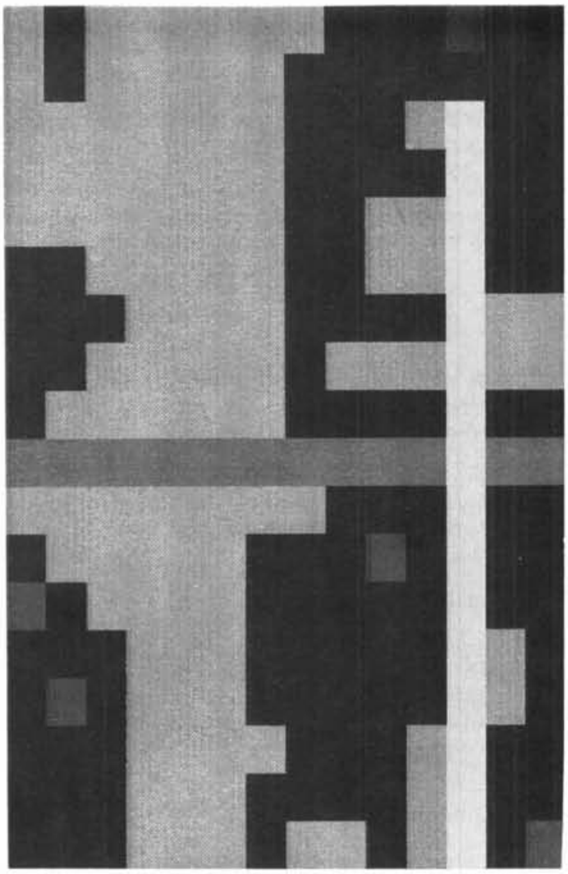

Figure 4. Possible Crack Regions Extracted

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