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Road Surface Crack Identification by Using Different Classifiers on Digital Images

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Abstract: In this paper different classifier are used to identifying different type of cracks on road surface. As our experience shows Region Growing Classifier (RGC) method can be used to divide all surface road images in two main groups. First group covers alligator and block cracks. Longitudinal, transverse cracks and other kind of distress are put in second group. In first group, wavelet Statistic Feature Classifier (WSFC), vertical and horizontal histogram and proximity are used for classification. They help to judge about the kind of crack based on digital image from road surface. Histogram, RGC and proximity are classifiers which are used in second group. Multi layer Perceptron neural network is used to judge about the cracks.

Keywords: Road Crack, Region Growing Classifier (RGC), Statistic Feature Classifier (WSFC), Multi Layer Perceptron, Pattern recognition

1 Introduction

Highways and roads are a major public asset in all countries. To efficiently manage these assets road authorities need accurate, up-to-date information on the condition of their highway and road networks. For example the maintenance and rehabilitation of highway pavements in the united state requires over 17 billion dollars a year. Conventional visual and manual pavement cracking analysis methods are very costly, time consuming, dangerous, labor intensive and subjective. Automatic monitoring of some aspects of road condition, for example roughness and skid resistance, has been carried out for a number of years. However, one of the most important road quality indicators, the extent and type of cracking, has up until now been measured only by visual inspection. The result is that only very sparse sampling has been carried out, at a very high cost per kilometer, and very little information has therefore been available in this important aspect of road condition. The main idea of digital image processing methods is based on the fact that the crack pixels in pavement images are darker than the surroundings and continuous [1], [2].

Based on researchers work the distress on pavement can be categorized as follow [3-5]:

- A longitudinal crack which is appears along the highway.
- Transverses crack is a crack perpendicular to the pavement centerline.
- Alligator crack which is a series of interconnected cracks with many sides and sharp angled pieces.
- Block crack as a pattern of rectangular pieces of road surface from transverse cracks.

- Other distress, such as man-holes, construction plates, etc.

This work itself can be categorized as digital image pattern recognition. There is a wide range of pattern recognition approaches. They are categorized in two main groups as statistical and structural methods. In statistical methods, the image is processed as a whole and classified based on the distributed of the black pixels. In structural method, the image is expressed as compositions of structural units. The pattern is recognized by matching its structural representation with that of a references pattern [6]. In the first step the crack is classified as whole and in the second step judge is based on structural method.

In the following sections and subsections the theory of our method and experimental results are discussed.

2 Method flowcharts

Fig. 1 shows the flowchart of proposed method. Each block is explained briefly.

2.1 Image Acquisition

A digital handy cam is used to take road image. The degree of handy cam with horizontal axes is 30 degree and it is 1.5 meter above the surface. The film is fed to the lap-top via i-link. A computer program divided the film in separate images.

Four kind cracks images are shown in fig 2. The original image has 640 by 480 pixels. Each pixel in horizontal direction represented 0.3 cm and in vertical 0.65 cm long. In other word each original image covers an area with 416 by 144 cm of the road.

Our experience shows the best images are taken in sunny weather two or three hours after rain. As the gray level of the cracks is much different from the background of surface, such images are much better than usual images.

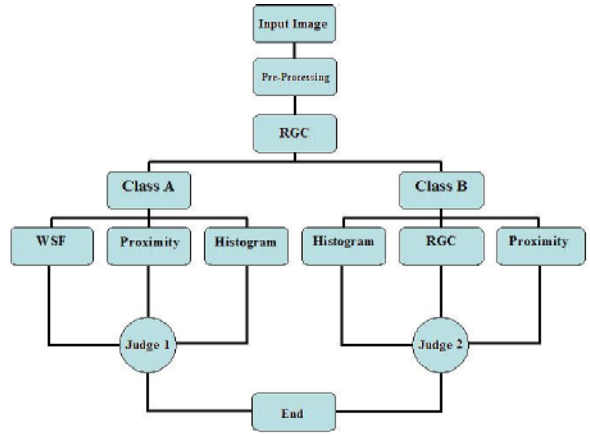

Fig. 1 Flowchart of proposed method

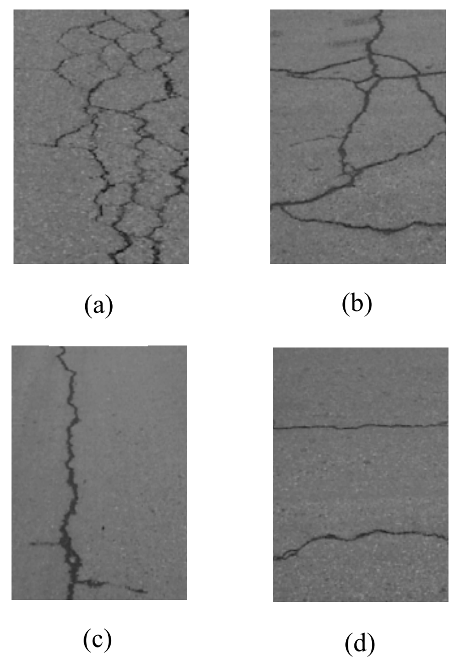

Fig.2 Scaled crack images (a) Alligator, (b) Blocks, (c) Longitudinal, (d) Transverse

2.2 Preprocessing

We are interested to put all pixels in the images in two groups, background and cracks pixels. It means the background and noisy pixels have to be shown in one group. To achieve this goal, a computer program first changed each image to gray scale then by using proper threshold all images changed to two level as zero and 255 gray scale (binary image). The produced binary image is fed to next block.

2.3 Region Growing Classifier (RGC)

In our approach, RGC plays an important and critical role. The pre-processed image is classified as class A and class B. The advantage of such a procedure is breaking the problem into a number of simpler ones.

The basic idea behind the RGC method is to segment underlying image into some disjoint regions and count the number of regions which are produced as the desirable output.

The process of forming a region-based image description (or approximation) is referred to as segmentation. Image segmentation can be described as the partitioning of an image into a number of disjoint segments or regions based on pixel grey level characteristics. These regions may be small neighborhoods or even single pixels.

There are three main classes of image segmentation techniques: statistical classification, edge detection and region growing. The segmentation to be used here is of region growing type. A region is defined as an area in the image whose pixels share common properties such as similar grey level values which enclosed in a closed contour. In other word Region growing is the process of joining neighboring pixels into larger regions based on these properties [7].

2.4 Wavelet Statistic Feature (WSF) Classifier

Wavelet transform is a powerful and famous multi-resolution analysis which has received a lot of attention at recent years.

It offers an extra advantage, which in some cases can be beneficially exploited. Its multi-resolution properties conform to the way perception is achieved by humans, through their hearing and visual systems. By using this transform at discrete case we can analysis and interpret the input image at multi scales and directions and exploit the advantages of its multi-resolution properties [8].

In our proposed method, wavelet transform plays the key role in class A. It is responsible for putting the input image into one of the longitudinal or transverse crack type. For attempting to this goal, we are used one of the most popular statistical features of the wavelet transform namely, energy of each decomposed image which is described latter.

Let $I(x,y)$ indicate the gray level of input image. One level of wavelet decomposition on $I(x,y)$ results in four sub images: first smooth sub images $I_{LL}(x,y)$ which represents the coarse approximation of the input image, and three detail sub images $I_{LH}(x,y)$, $I_{HL}(x,y)$ and $I_{HH}(x,y)$ which represent the horizontal, vertical, and diagonal directions of the image, respectively. Further, let $I_{LL}^{J}(x,y)$ represents the smooth sub image at resolution level J and $I_{LL}^{0}(x,y) = I(x,y)$ which is the original image. Then the decomposition of $I_{LL}^{J}(x,y)$ results in four sub images $I_{LL}^{J+1}(x,y)$, $I_{LH}^{J+1}(x,y)$, $I_{HL}^{J+1}(x,y)$ and $I_{HH}^{J+1}(x,y)$ at resolution level $J+1$ each of size $n/2^{J+1} \times m/2^{J+1}$. Fig. 3 shows a three level decomposition of a sample longitudinal crack.

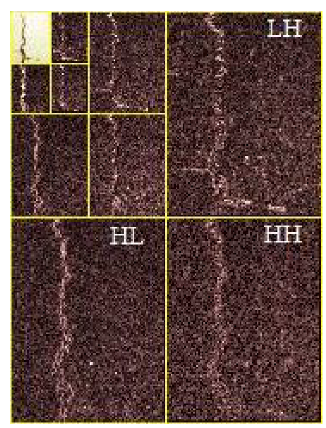

Fig. 3 Three decomposition levels with discrete wavelet transform

Now, we introduce the Energy Statistic Feature (ESF) of wavelet transform and use it in our WSF method. The energy of each decomposed sub image is calculated as follows:

The energy of the smooth sub image which is in fact a coarse approximation to its original image at level J is given by:

$$E_s^J = \sum_x \sum_y [I_{LL}{}^{(J)}(x,y)]^2 \tag{1}$$

The energy of the horizontal detail sub image at level J is:

$$E_h^J = \sum_x \sum_y [I_{LH}{}^{(J)}(x,y)]^2 \quad ,J = 1,2,3 \tag{2}$$

The energy of the vertical detail sub image at level J is:

$$E_V^J = \sum_x \sum_y [I_{HL}{}^{(J)}(x,y)]^2 \quad ,J = 1,2,3 \tag{3}$$

The energy of the diagonal detail sub image at level J is:

$$E_d^J = \sum_x \sum_y [I_{HH}{}^{(J)}(x,y)]^2 \quad ,J = 1,2,3 \tag{4}$$

And the normalized energy of each decomposed sub image is defined as:

$$E^J = E_s{}^J + E_h{}^J + E_v{}^J + E_d{}^J \tag{5}$$

$$E_V{}^J = \frac{E_v{}^J}{E^J} \tag{6}$$

$$E_H{}^J = \frac{E_h{}^J}{E^J} \tag{7}$$

Now we define Φ^J as the ratio of normalized vertical energy E_V^J to the normalized horizontal energy E_H^J at sub band J as follows:

$$\Phi^J = \frac{E_V^J}{E_H^J} \tag{8}$$

It is obvious that for a longitudinal crack, $E_V{}^J$ is bigger than $E_H{}^J$ and for a transverse crack $E_H{}^J$ is bigger than E_V^J. So if Φ^J is bigger than 1, then WSF suggests that the input image is a longitudinal crack and if it is less than 1, the WSF suggests that the input image is a transverse crack.

2.5 Histogram

From the pre-processed input image two kinds of histograms are calculated, a vertical histogram and a horizontal histogram. The vertical histogram of a binary image is defined as the number of non-zero values in each column and the horizontal histogram of a binary image is defined as the number of non-zero values in each row. Based on these definitions for a given $n \times m$ image formula (9) and (10) are introduced as vertical histogram and horizontal histogram, respectively.

$$V_H(j) = \sum_{i=1}^{n} I(i,j) \quad j = 1,\ldots,m \tag{9}$$

$$H_H(i) = \sum_{j=1}^{m} I(i,j) \quad i = 1,\ldots,n \tag{10}$$

Histograms show a clear pattern of a crack. If a crack is developed in a longitudinal direction, there is a clear peak in the vertical histogram and has a smooth or constant variation in the horizontal histogram. Instead, if a crack is developed in a transverse direction, there is a clear peak in the horizontal histogram and has a constant variation in the vertical histogram. If a crack is an alligator crack, the peaks can be found in both vertical and horizontal directions. For a block crack, peaks can be also found in both histograms but with a magnitude lower than those of an alligator crack.

To find a way for using the abilities of histogram method we proposed using the mean value of each vertical histogram and horizontal histogram as follows:

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$$\mu_v = \frac{1}{m}\sum_{1}^{m} V_H(j) \qquad (11)$$

$$\mu_h = \frac{1}{n}\sum_{1}^{n} H_H(j) \qquad (12)$$

Where μ_v and μ_v are the mean or dc value of vertical histograms and horizontal histograms, respectively. One advantage of using the mean values of histogram is that it gives a position invariant measure of the input image because if the crack is shifted across the horizontal or vertical direction then μ_v and μ_v are not changed.

2.6 Proximity

The mean values of horizontal histogram for longitudinal and transverse cracks are very close to each other and so the segregation between these two cracks is poor. To remedy this problem we define a proximity measure as an alternative as Vertical Proximity and Horizontal Proximity by equation 13 and 14, respectively.

$$\Omega_v = \sum_{j=1}^{m-1} \left| V_H(j+1) - V_H(j) \right| \qquad (13)$$

$$\Omega_h = \sum_{i=1}^{n-1} \left| H_H(i+1) - H_H(i) \right| \qquad (14)$$

From the above equations it can be seen that proximity is computed by accumulating the differences between adjacent histogram values. The low value of proximity indicates that there is little difference between any of the columns or rows for the input image.

It is clear that the vertical proximity for a longitudinal is bigger than vertical proximity in a transverse crack and vice versa.

2.7 Judge

Now, we are ready to produce a suitable feature vector for each described class. A Multi Layer Perceptron (MLP) is used to classify each image. The feature vector in class A is

$$F_A = \left\{ \Phi^{(1)}, \Phi^{(2)}, \Phi^{(3)}, \mu_v, \mu_h, \Omega_v, \Omega_h \right\} \qquad (15)$$

and in Class B is

$$F_B = \left\{ \Omega_v, \Omega_h, \mu_v, \mu_h, \Gamma \right\} \qquad (16)$$

3 Experimental results

As explained in section 1 an alligator crack is a series of interconnected cracks, which has many sided and sharp-angled pieces whereas a block crack is a pattern of rectangular pieces of asphalt surface. So we expect that the complexity and the number of regions in an alligator crack are bigger than a block crack. It is clear that the output of the RGC or Γ for alligator and block cracks is more than three other kinds. To show our claim, table 1 represents the average output of RGC for about 45 kinds of alligator cracks, 45 kinds of block cracks, 35 kinds of longitudinal cracks, 30 kinds of transverse cracks and 60 kinds of crack free cases. Also figure 4 shows some examples of RGC operation.

Table 1 RGC output for alligator cracks

Crack Type	Average of RGC Outputs (Γ_{av})
Alligator Cracks	15.1
Block Cracks	9.2
Longitudinal	2
Transverse	2.3
Crack Free	1.1

In our experiments as shown in table 1, it is found that the output of RGC for class A (longitudinal, transverse and others) is almost smaller than 4 and it is bigger than 4 for class B(alligator and block crack). This criterion at the first node of hierarchical algorithm which is shown in fig.1 is used.

In our proposed method the RGC is used twice. Once at the first node to assign the input image into one of the class A or class B and once for determining that the image which has been assigned to class B is an alligator crack or a block crack.

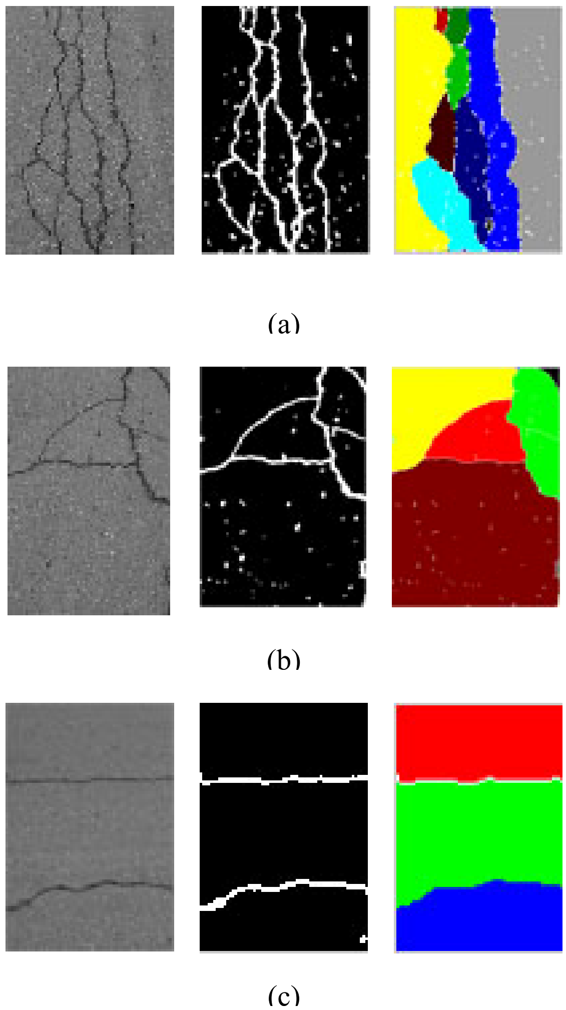

Fig. 4 RGC of three kinds of cracks a) alligator, b) block and c) longitudinal

In this paper, for WSF Daubechies mother wavelet D4 is adopted for image decomposition. Among all kinds of mother wavelets, Daubechies wavelets are proven to be good for image analysis and synthesis because of their compact support, more continuous derivatives, and zero integral of mother wavelets [8].

Therefore, Daubechies wavelets are chosen in our approach and then we are applied different orders of Daubechies family and we experimentally found that the 4^{th} order is the best choice for our classification problem which leads to high classification accuracy.

The question arises here is that how to determine the number of decomposition level. To answer this question it is important to mention that too large the number of multi resolution levels lead to loss of information and increase the processing time, whereas too small the number of multi resolution levels cannot sufficiently effective and cause to decreased the accuracy of classification. For these reasons in our proposed method the maximum decomposition level is three and sub band 3 is found to give the best results because at this level undesired small pieces, which are probably be noise, are eliminated. Naturally, we benefit by giving a higher weight to this sub band. To demonstrate the discrimination power of WSFC at sub band 3, firstly, we fed a longitudinal crack which to the WSFC which used only one decomposition level. Unfortunately it misclassified as a transverse crack. Now to remedy this problem, we are also used the 3^{rd} decomposition level and look at the result. Fortunately, the classification is successful. It is the preference of the WSFC rather than the Histogram method.

Table 1 shows the corresponding mean values μ_v and μ_v for crack free types are very small (less than 1). In class A vertical and horizontal histogram have no significant differences, but vertical and horizontal proximity can be used for recognition. For class B the table shows, all parameters for alligator cracks are bigger than corresponding parameters of block cracks. It is obvious there is a significant difference between vertical proximity for alligator and block cracks.

Table 2 Different parameters for various cracks

Crack Type (Class A)	Vertical Histogram	Horizontal Histogram	Vertical Proximity	Horizontal Proximity
Longitudinal	3.3478	2.2679	87.7680	54.0025
Transverse	2.5058	2.6974	41.5660	87.4742
Crack Free	0.2532	0.1715	15.9280	16.3576
Crack Type (Class B)	**Vertical Histogram**	**Horizontal Histogram**	**Vertical Proximity**	**Horizontal Proximity**
Alligator	10.1518	6.8771	164.6673	136.8471
Block	5.6969	3.8592	90.9989	125.6437

4 Conclusions

The proposed method classified crack free images with 100% accuracy. The crack images are classified to transverse, longitudinal, block and alligators with 98%, 90%, 89% and 88% accuracy, respectively. This method is fast, in 0.324 seconds the program classifies each image. As the algorithm is easy, Hardware implementation is easy with low cost.

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