Crack Detection on Asphalt Surface Image Using Local Minimum Analysis

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Summary. In this paper a new method of cracks detection is introduced. The proposed algorithm is applied to detect the cracks in the pavement image. Local minimum and linear relation between them was proposed. The proposed method is classify into two stages: linear local minimum and verification of detecting of pavement cracking. This method is fast although is complex. Additionally, the proposed method eliminates slight and strong variations like irregularly illuminated conditions, shading and road signs painted on pavement surface.

1 Introduction

The inspection of the concrete structures is a major part of roads management. For many years manual observation of the road surfaces has been the most common method for evaluating road surface distress around the world [1, 2, 4, 5, 8].

The general approach to the defect detection in pavement surface distress is to find a "homogeneous" feature of "no defect" textures and to detect the differences caused by presence of a defect. Major supposes are the cracked regions darker than other regions of inspected images and a crack is a continuous region. Usually the first step is to improve the contrast of inspected image, being less dependent on the illumination condition and the type of textures in road surface. The second step is camera calibration.

Over the past several decades, a number of approaches for automatic pavement cracking detection have been proposed. One of them is a ACP system [3, 12] to detect horizontal and vertical cracks, crack lengths, and severity. This is a block-based method. For all block (48×48) it was calculated vertical and horizontal projection histogram. In [9, 10] wavelet transform to crash detection surface was presented. There was proposed method consisted of three stages: pre-processing, wavelet processing, post-processing. Different approach to detect pavement destroy is proposed in [13]. There are three

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steps: subtraction pre-processings, line emphasis pre-processing and thresholding processing. Modification of this method is shown in [7]. Morphology to the pavement crack detection and the median-filter algorithm with four structural elements we found in [6]. Authors proposed method to avoid noises more ideally and introduced the structural element to median-filter of four shapes. The similar algorithm was shown in [11]. Dilatation and erosion operators were also adapted. The difference between both algorithms is pre-processing phase. Here the pre-processing is based on a histogram equalization (to be less dependent on the illumination condition and the type of textures in road surface) and two thresholds during binarization process.

2 Proposed Algorithm

In digital image cracks are characterized as basic features:

- the pavement distress is dark. Its means than the region of asphalt where are cracks is darker than the other regions;
- pounding pavement surface segment is linear;
- not all dark points build a distress.

From this assumption arises the fact that we can not use simple algorithm like thresholding to separate cracks. The key point is to study over methods which count all foregoing assumption.

In this paper was proposed a new method of cracks detection which does not use pre-procesing stage. The algorithm is applied to detect cracks on the pavement image. I propose to find local minimums and to describe the linear relations between them. This method consists of two stages: local minimums finding and verification.

2.1 Local Minimum Searching

In the first stage proposed Linear Local Minimum algorithm searches for local minimums L_x, L_y, which are described by formula (1) and (2) respectively:

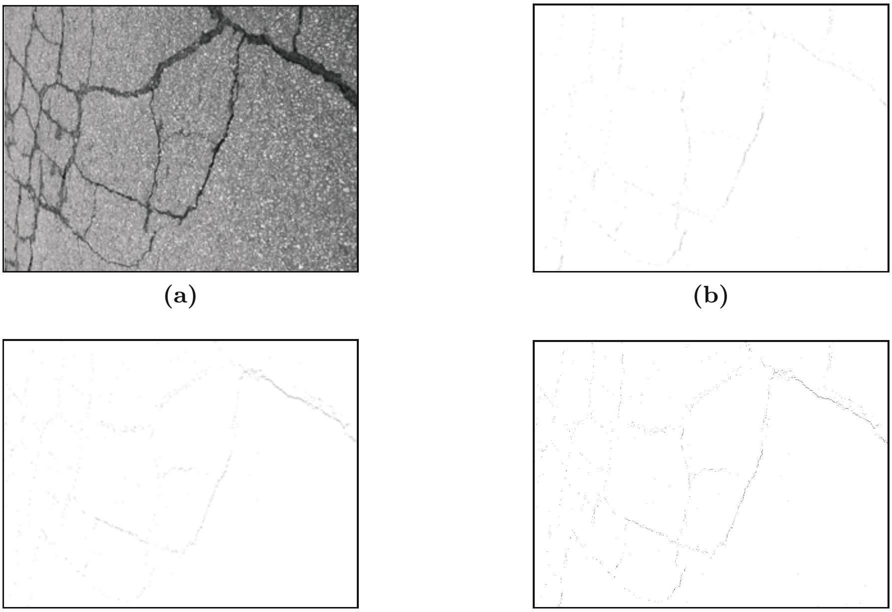
$$L_x[x,y] = \begin{cases} 1 \; \forall_{j \in \{1,2,\ldots,N\}} : I[x,y] = \min\{I[x,j] | x \in \{1,2,\ldots,M\}\} \\ 0 \text{ otherwise} \end{cases} \quad (1)$$

$$L_y[x,y] = \begin{cases} 1 \; \forall_{j \in \{1,2,\ldots,M\}} : I[x,y] = \min\{I[j,y] | y \in \{1,2,\ldots,N\}\} \\ 0 \text{ otherwise} \end{cases} \quad (2)$$

This way we obtain two matrix which are added to produce matrix $L[x,y]$, described by eq. 3.

$$L[x,y] = L_x[x,y] + L_y[x,y] \quad (3)$$

where: $L : \{1,2,\ldots,M\} \times \{1,2,\ldots,N\} \rightarrow \{0,1,2\}$, N and M are width and height of image.



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

Fig. 1. Image I and computed arrays L_x (b), L_x (c) and L_T (d)

We can note that the value of $L[x, y]$ is interpreted as:

- $L[x, y] = 0$ - in $[x, y]$ point of image I is a not local minimum;
- $L[x, y] = 1$ - $[x, y]$ is a point of image I where is vertical or horizontal minimum;
- $L[x, y] = 2$ - $[x, y]$ is a point of image I where we found a local minimum in two directions;
- maximum amount of non zero elements in matrix $L[x, y]$ is equal to $N+M$, and minimum is equal to $\sqrt{N^2 + M^2}$.

The array of labels $L[x, y]$ implies only the most probable points fall into cracks. In other words, the non zero elements of $L[x, y]$ are only the candidate points, which increase the probability of place being the crack is. Additionally, the number of non zero elements of $L[x, y]$ are not impacting to the results. That's why the binarization process is calculated as:

$$L_T[x, y] = \begin{cases} 1 & \text{if} \quad\quad L[x, y] > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

2.2 Verification Process

In this stage we eliminate "false" points in L_T matrix and classify other as crack or not. We defined line segment between two points $L_T[x_1, y_1]$ and $L_T[x_2, y_2]$:

$$l_{1,2} : (y - y_1)(x_2 - x_1) - (y_2 - y_1)(x - x_1) = 0 \quad \forall_{x \in \langle x_1, x_2 \rangle, y \in \langle y_1, y_2 \rangle} \tag{5}$$

The line $l_{1,2}$ is classified as the crack when the following condition is met

$$M_e \geq \frac{1}{l_{1,2}(S)} \sum_{a,b \in S} (I[a,b] - Me) - \tau \tag{6}$$

were $M_e = \text{mean}\,(I[x_1, y_1], I[x_2, y_2])$ and S is a set of points of line segment $l_{1,2}$. This condition is checked for all pairs of nonzero point from array L_T.

To decrease the number of calculations we defined new condition: the d between two point $L_T[x_1, y_1]$ and $L_T[x_2, y_2]$

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{7}$$

must be shorter than established value r.

The proposed algorithm of verification process is show in Algorithm 3.

Algorithm 3. verification algorithm

Input: $I[x, y]$ - original image, $L_T[x, y]$ - binary local minimum array
Output: $B[x, y]$ - array of labels
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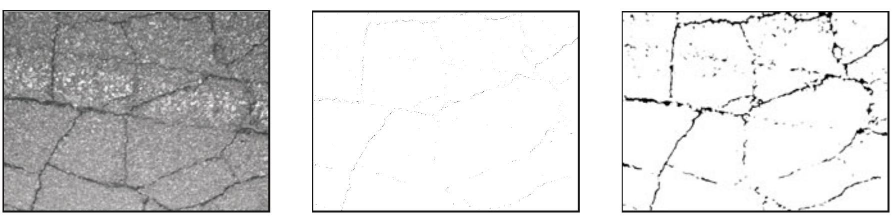
for all L[x,y] ≠ 0 do
  if |L[x1,y1]L[x2,y2]| < r where x1 ≠ x2 or y1 ≠ y2 then
    if LT[a,b] ∈ S then
      if median(I[x1,y1], I[x2,y2]) >= 1/l(S) Σ_{a,b∈S} I[a,b] − τ then
        B[a,b] = 1
      end if
    end if
  end if
end for
```

3 Experimental Results

Applying proposed method on sample images, the results were obtained (see Fig. 2-6). When we increase r we go up with probability of finding all "alligators" cracks, but too big r increaser false detection ratio.

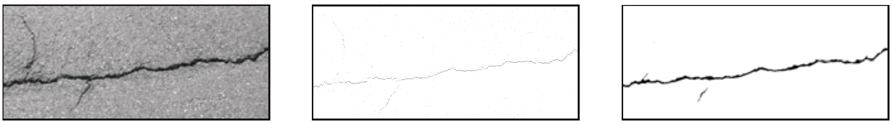


(a) (b) (c)

Fig. 2. Test Image #1, (a) array of labels L, (b) binary cracks mask B

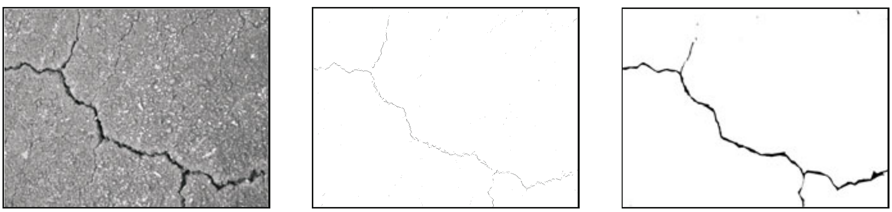
(a) (b) (c)

Fig. 3. Test Image #2, (a) array of labels L, (b) binary cracks mask B



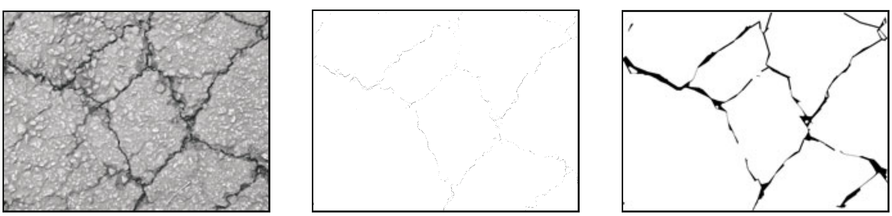
(a) (b) (c)

Fig. 4. Test Image #3, (a) array of labels L, (b) binary cracks mask B



(a) (b) (c)

Fig. 5. Test Image #4, (a) array of labels L, (b) binary cracks mask B



(a) (b) (c)

Fig. 6. Test Image #5, (a) array of labels L, (b) binary cracks mask B

Additionally, the white and yellow lines are not classified as cracks - what is the biggest advantage. The results are shown in Table1. This approach gives 10% of false positive, 19% of false negative in the summary results.

Table 1. Testing Result on Asphalt Road Images

	Method [11]		Method [6]		Proposed method	
	true	false	true	false	true	false
Non-Cracked Images	87%	13%	89%	9%	85%	10%
Cracked Images	79%	21%	78%	22%	81%	19%

4 Conclusions

The proposed method is detecting a complex linear local minimum of pavement cracking. This method is fast although is complex. Additionally proposed method eliminates slight and strong variations like irregularly illuminated conditions, shadings and road signs painted on pavement surface.

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