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A Crack Detection Method in Road Surface Images Using Morphology

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Abstract

In this paper , a new crack detection method in road surface image based on morphological technique is proposed. Cracks are difficult to detect directly at the pixel level because of the noise and the vagueness. Some kind of structural information is needed. A crack is thought to be a succession of dark saddle points with the linear feature. In the proposed method , the detection of cracks is realized through black pixel extraction , saddle point detection , linear feature extraction and connecting processing . Although the method requires the setting of some parameters , it is robust for detecting vague cracks in the noisy road surface image.

1 Introduction

The detection of cracks in the infrastructures which are made of concrete or asphalt , e.g. roads and bridges , is one of the major problems for their maintenance . Cracks in a image are easily recognized by the human visual systems, but are difficult to segnent . This difficulty arises from the fact that cracks cannot be detected directly at the pixel level because of the noise and the vagueness . Some kind of structural information is also needed .

The classical methods to detect lines [1] asumme a sufficient width to the linear features . However ,in the case of the cracks , one cannot make such assumption to the cracks [2].

In this paper, we describe a new system that dectcts cracks in the road surface image. The main techniques are based on mathematical morphology [3], [4] , which includes four basical operations and top-hat trasform operation [5]. A crack is thought to be a succetion of dark saddle points with the linear feature. Following that property, the proposed method is composed of the four stages : black pixel extraction, saddle point detection, linear feature extraction and connectiong processing. Experimental results are also shown.

2 The Definition of Cracks

We assumed that cracks have the properties as follows :

Property 1 : Cracks are dark objects against a background.

Cracks are darker object than the background such that the pixels belonging to cracks are locall minima .

Property 2 : A crack is a succession of (reversed) saddle points.

A cracks is a thin groove such that the cross section of a crack has a saddle shape.

Property 3 : A crack has linear feature or directionality.

A crack is a connected subset of the image such that there exists a privileged direction .

3 Notation

3.1 Morphological operation

Mathematical morphology includes four basic operations: dilation, erosion, opening and closing . We make use of these four operations and conditional dilation and top-hat operation throughout this work . The four basic operations are also distincted into binary operations and gray scale operations, they are denoted as follows:

Dilation($\oplus, \oplus_g$), Erosion($\ominus, \ominus_g$), Opening($\circ, \circ_g$) and Closing($\bullet, \bullet_g$).

The top-hat operation and conditional dilation are denoted as follows:

Top-hat($G_o(x) \bullet_g K_{disk} - G_o(x)$) , Conditional dailation($G_o(x) |_{\oplus I}$).

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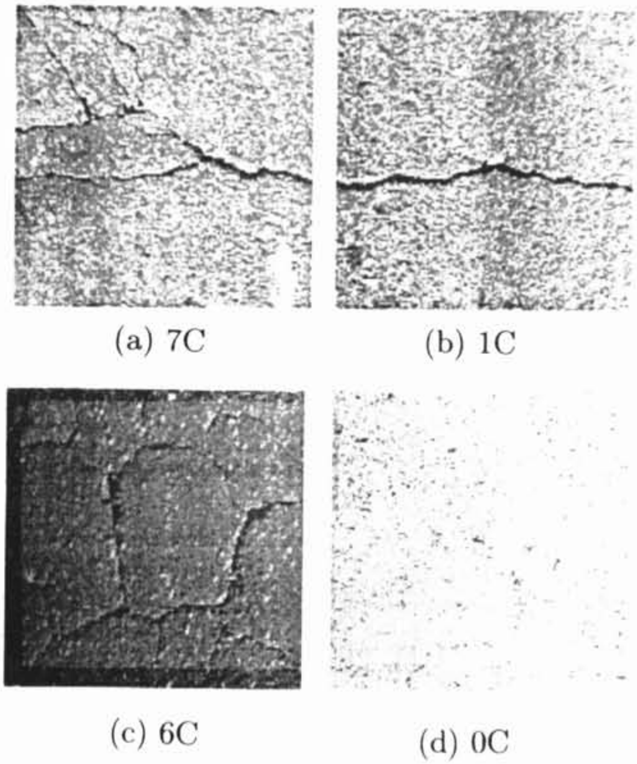

(a) 7C (b) 1C

(c) 6C (d) 0C

Figure 1: Original images $G_o(x)$.

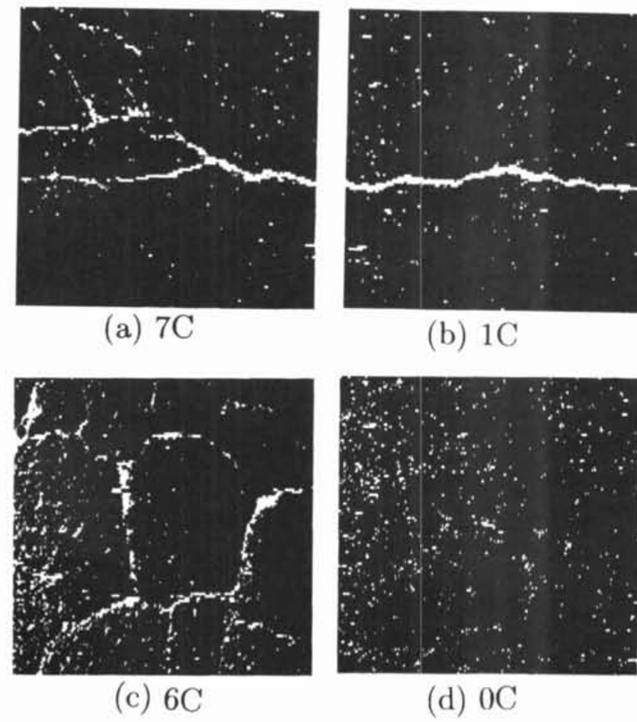

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Figure 2: Black points images $B(x)$.

3.2 Structure Element

Three standard shaped structure element DISK , LINE and SQUARE are selected in our studying. They are descripted as following:

- A DISK structure element with its origin at the center and radius i is denoted by $K_{disk}(i)$.
- A LINE structure element with length l and derection θ is denoted by $K_{line\theta}(l)$.
- A SQUARE structure element with length of e is denoted by $K_{square}(e)$.

4 Crack Detection System

The crack detection system is composed of four main stages, black pixel extraction , saddle point detection , linear feature extraction and connecting processing.

4.1 Black pixel extraction

Following Property 1 , pixels belonging to cracks should be locall mimima. Because cracks have thin shape , we can assume that the area of cracks is not so large against a background. The algorithm for black pixels extraction is as follows .

Let the input image of the road surface be $G_O(x)(512 \times 512$, shown in Fig.1) and I_{min} is set to 20 and θ_2 is set to 0.03×512^2 .

I. Set $\theta_1 = I_{min}$

II. Get the minimum grey level L in $G_O(x)$.

III. $B(x) = \begin{cases} 1 & (G_O(x) \leq \theta_1 + L) \\ 0 & (G_O(x) > \theta_1 + L) \end{cases}$

IV. If $\sharp B(x) > \theta_2$ then STOP

else $\theta_1 = \theta_1 + 1$

where the symbol "$\sharp B(x)$" means the number of non zero pixels of $B(x)$.

V. GO TO step III

Examples of $B(x)$ are shown in Fig.2.

4.2 Saddle point detection

Saddle point detection by top-hat transformation for the input $G_O(x)$ is defined as follows:

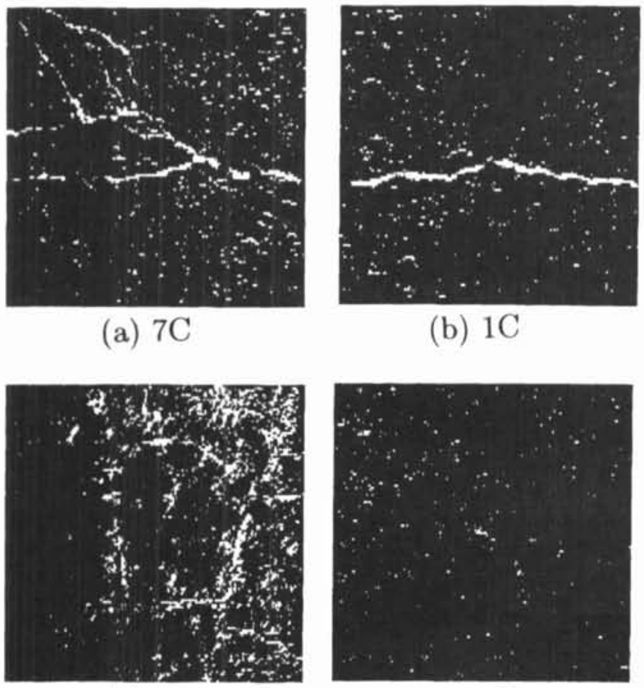
$$T(x) = |HT(G_O(x) \bullet_g K_{disk}(20) - G_O(x))|_{\theta_3}$$

where $HT()$ and $|\ |_\theta$ mean a histogram equalization and binarization with threshold θ respectively. And θ_3 is set to 150.

By taking an intersection of $B(x)$ and $T(x)$, $S_{mix}(x)$ which contains black saddle points can derived.

$$S_{mix}(x) = B(x) \cap T(x)$$

Examples of $T(x)$ and $S_{mix}(x)$ are shown in Fig.3 and Fig.4 respectively.



(a) 7C (b) 1C

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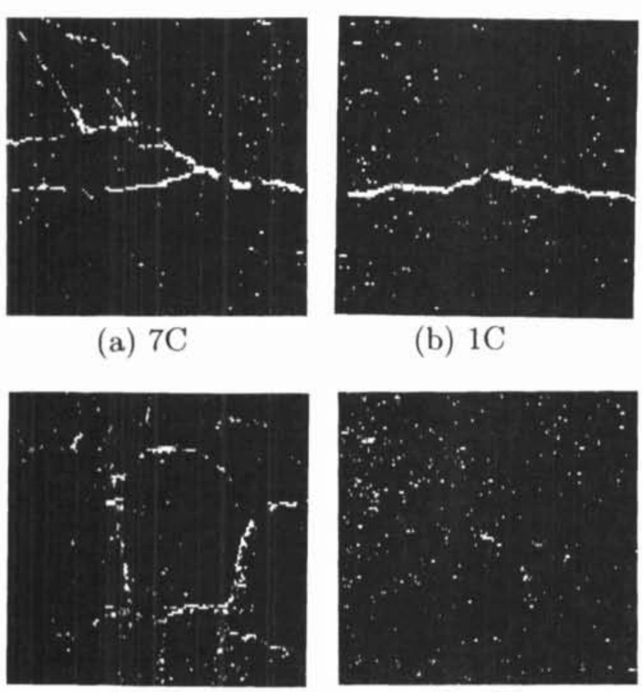
Figure 3: Saddle points images $T(x)$.



(a) 7C (b) 1C

(c) 6C (d) 0C

Figure 4: Examples of $S_{mix}(x)$.

4.3 Linear feature extraction

We defined the linear feature of a cark as follows. The linear feature can be detected on a point such that there exists a privilaged direction along which the grey level are on average significantly higher than opposite direction.

This processing is starting with the image $S_{mix}(x)$.

The extraction of the linear feature is performed as follows.

$$S_2(x) = S_{mix}(x) \oplus K_{disk}(25)$$

(i) Around each point q , get the $(2m+1) \times (2m+1)$ neighborhood.

(ii)Get mean grey level $M_q(d)$ and grey-level variance $V_q(d)$ along four direction(d) within above mask.

The linear feature points have to satisfy all of the following rules:

(i)The maximum value of the mean grey level $M_q(d)$ is greater than θ_5.

(ii)For some d, $V_q(d) > V_q(d+2)$ and $V_q(d) < V_{qave}$.

Now we can get the directional image $Sd_2(x)$.

And then, in order to fill small gaps in $Sd_2(x)$, a dilation and a closing is performed.

$$Sc_2(x) = (Sd_2(x) \oplus K_{square}(3)) \bullet K_{square}(5)$$

Examples of $S_{c2}(x)$ are shown in Fig.5.

4.4 Connecting processing

Connencting processing is also starting with the image $S_{mix}(x)$. In order to fill gaps in $S_{mix}(x)$, a dilation and four times of closing operartion are performed.

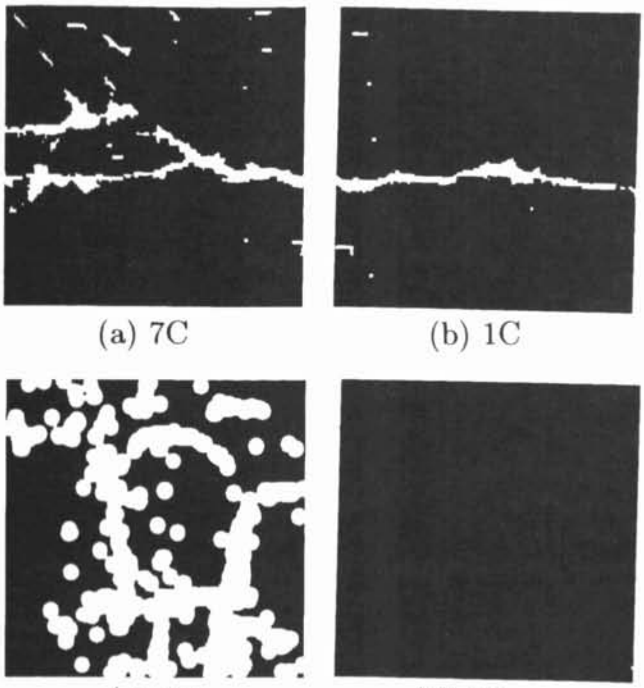
$$S_3(x) = S_{mix}(x) \oplus K_{square}(3)$$

$$S_4(x) = (S_3(x) \bullet K_{line90}(5)) \cup (S_3(x) \bullet K_{line0}(5)) \cup (S_3(x) \bullet K_{line45}(5)) \cup (S_3(x) \bullet K_{line135}(5))$$

Finally the resulting image $S_{con}(x)$ can earned by taking intersection of $Sc_2(x)$ and $S_4(x)$.

$$S_{con}(x) = \| Sc_2(x) \cap S_4(x) \|_{\theta 4} |_{B(x)'} \oplus K_{square}(3)$$

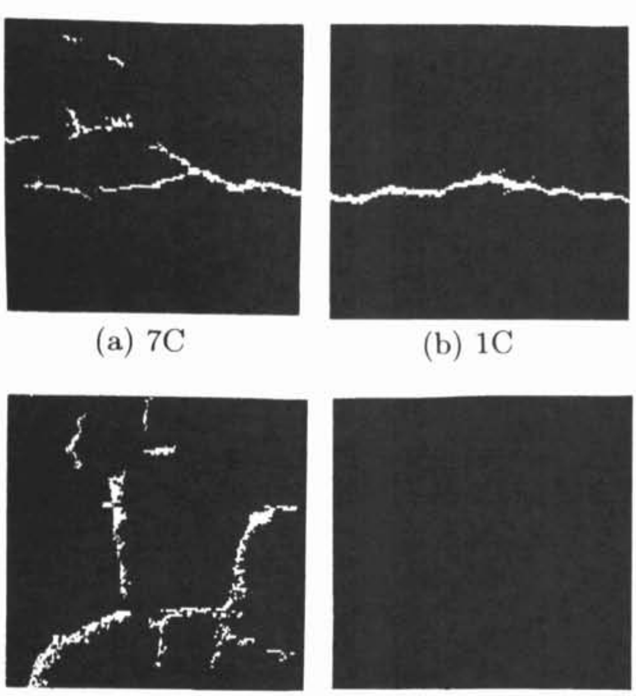
where the operation $\| \|_\theta$ means elimination of small regions which have smaller areas than θ. Examples of $S_{con}(x)$ are shown in Fig.6.



(a) 7C (b) 1C

(c) 6C (d) 0C

Figure 5: Directional images $S_{c2}(x)$.



(a) 7C (b) 1C

(c) 6C (d) 0C

Figure 6: Results images $S_{con}(x)$.

Table 1: The experimental results of the clack detection.

original	correct	correct ratio
With clack(44)	43	97.7 %
Without clack(22)	20	90.9 %
Total(66)	63	95.5 %

5 Experiment and Result

Gray scale images of the road surface , which have the size of 512×512 with 256 gray level , are used in our experiment. The experimental results are shown table 1.

In the experiments , the 66 images are used totaly, which composed of the 44 with clack images and the 22 without clack images. For only one image , no clack is detected , although there exist some clack in the image (type I error). To the contrary , for two image clacks are wrongly detected in the without clack images(type II error). The reason for the type I error is that the clacks have not enough length to be detected , and the existence of the small gaps nearly like clacks caused the type II error.

6 Conclusion

A morphological method to detect caraks in road serface image was proposed in this paper. Although the proposed method requires the setting of some parameters , it is robust for detecting vague crack in the noisy road surface image.

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