

A MODEL FOR SEGMENTATION AND DISTRESS STATISTIC OF MASSIVE PAVEMENT IMAGES BASED ON MULTI-SCALE STRATEGIES

LI Qingquan^a, LIU Xianglong^{b,*}

^a State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, 129 Luoyu Road, Wuhan, 430079, PR China - qqli@whu.edu.cn

^b School of Remote Sensing and Information Engineering, Wuhan University, 129 Luoyu Road, Wuhan, 430079, PR China - liuxianglong@live.cn

Commission V, WG V/1

KEY WORDS: Image Processing, Recognition, Image Understanding, Feature Detection, Location Based Services, Industrial Measurement

ABSTRACT:

Conventional distress detection method which dealing with each image through single algorithm and under single scale with lower efficiency. A robust and high-efficiency model for segmentation and distress statistic of massive pavement images which based on multi-scale space is proposed in this paper. It based on the facts that: (1) the crack pixels in pavement images are darker than their surroundings and continuous; (2) images associated with the same road section with the consistence of pavement texture structure. The proposed model contains three stages mainly: Image segmentation is implemented based on neighboring difference histogram method, then the weighted multi-scale based distress statistical is executed to get the crack index of the pavement images, in the end it separates the cracked images from massive images through the distribution of the crack index and achieved the objective of improving detection efficiency. Experiments results demonstrated that the proposed method can pick up the cracked images from massive pavement images correctly and effectively, and the time consuming is less than one third of the classical flow while the missing detection rate not exceed five percent.

1. INTRODUCTION

The traditional human-visual and manual pavement crack detection method and approaches are very costly, time-consuming, dangerous, labor-intensive and subjective (Cheng, 1998), which can not meet the demands of the booming development of the public transportation and logistics. Pavement condition data collection style has transformed from manually to automatically because of the development of computer technologies, digital image acquisition and multi-sensors technologies (Toshihiko, 1990), but the complexity of the digital image processing always made the data processing come to the bottle-neck of the application system. Many researchers have paid a great deal of attention to automated pavement cracking detection through image processing.

Over the past several decades, a number of approaches for automatic pavement cracking detection have been proposed which can be divided into two kinds of method classes: the image edge detection based class and the image area segmentation based ones. At the early stage of the image-based pavement cracking detection, several kinds of edge detection methods were proposed such as Sobel-based algorithm (Li, 2003), Wavelet-based Canny algorithm (Bahram, 2003), snake-based algorithm (Chen, 2001), and Dijkstra-based algorithm (Yu, 2007), they have been shown successful under limited condition according to their experimental results. However, due to the highly textured nature of road surface, which resulted in highly noisy pavement images, the edge detection based approaches can not get reliable results. In recent years, researchers pay more attention to image regional segmentation

based automatic pavement cracking detection such as image gray histogram based algorithms (Kirschke, 1992; Chua, 1994), image-tile and BP Neuro Network based image segmentation method (Chu, 2003), artificial population algorithm was proposed according to the fact that distressed pixels are darker than the mean value of the whole image (Zhang, 2005) and image tile based PCA method (Abdel-Qader, 2006). These methods are concentrated on dealing with each pavement image under single scale which resulted in lower efficiency pavement defects detection, and with lower precision because they neglected the noisy and uneven nature of the pavement source images. The multi-scale method was widely used on various applications such as object detection, data compression, viewing expression, massive data retrieval and so on. In this paper, an model based on multi-scale strategies for segmentation and distress totalization for massive pavement images was proposed to eliminate uneven illuminance and to separate the cracked pavement images from massive source images. It contains two multi-scale process stages, the first stage is the multi-scale based image segmentation and the second one is the multi-scale based pavement distress statistical.

This paper is organized as follows. Section 2 describes the architecture and flowchart of the proposed method. The methodology of the proposed method is detailed described in Section 3, experimental results and analysis are widely and deeply executed in Section 4, conclusions and discussion followed as in Section 5.

* LIU Xianglong, PhD Candidate, Tel.: +86-27-68778222, Fax: +86-27-68778043, E-mail: liuxianglong@live.cn

2. ARCHITECTURE

The objective of the proposed method is mainly about how to improve the efficiency and precision of pavement image distresses detection. It consists of the following steps: (1) Multi-scale based image segmentation to remove the uneven illumination influence; (2) Multi-scale based distresses statistical to get the pavement cracking index of each image; (3) Distress index based pavement distressed images sieving to separate the distressed ones from the massive pavement source images. Figure 1 expressed the architecture of the proposed method.

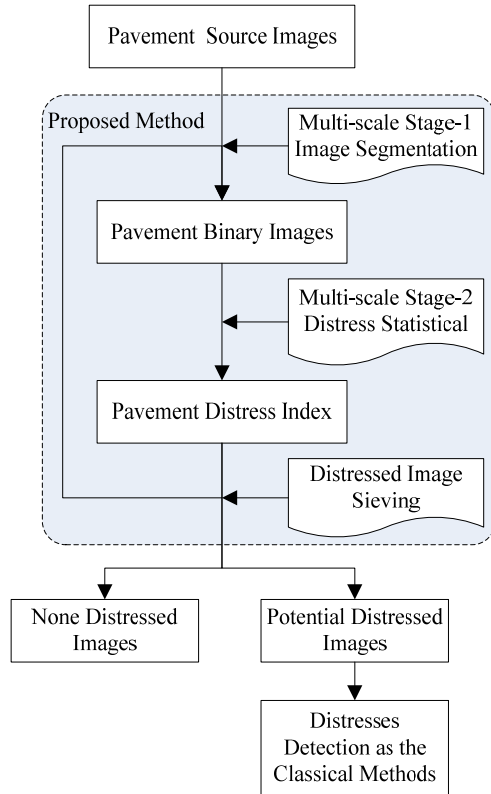


Figure 1. Architecture of the proposed method

3. METHODOLOGY

3.1 Multi-scale Image Segmentation

The pixel intensity in an image is the product of illumination and reflectance. Due to the highly textured nature of road surface, there are plenty of white noises presented in the captured pavement images, the noises are based on pixel level scale, while the cracked areas are based on pixels unit level scale, the pixel scale based detection method is time consuming and noneffective, so the pixels unit based scale is proposed in this paper. Another common sense is that the uniformity of the pavement image is uneven because of the influence of the sunshine shadow and the different usage frequency between the local area of the pavement, the higher usage frequency of an area, the reflectivity of the area is stronger, and then resulted in higher gray level in corresponding district pavement source images, inversely much darker in images, so just one threshold value to the whole image will resulted in an invalid segmentation. According to the above

description, it is reasonable to split the whole image into several blocks, and tranform the pixel based scale image block into the pixels unit based scale image block, and compute the threshold value to each pixels unit based scale image block separately. The proportion of the cracking area in a pavement image is quite low which resulted in some classical gray-level-based image segmentation algorithm such as Otsu and Kapur can not getting a effective thresholding value. Based on the fact that the cracking pixels in pavement images are darker than their surroundings and continuous, the weighted difference statistical value of each potential cracking pixel with their surrounding pixels is executed. If the number of the surrounding pixels which bigger than the object pixel in grey-level larger, then the proportion of this pixel to be a cracking one should much more bigger. If the absolute differential value between the surrounding pixel and the object pixel is larger, the weight which provided by the surrounding pixel should be much more, inversely much less, but if the grey-level of the surrounding pixel is smaller than the object pixel, the weight might be a minus value.

Let $I_w(x, y)$ stand for the whole image, and $I_{b,r,c}(x, y)$ stand for one block image separated from the whole image, the relationship between the whole image and the block images can expressed as follows:

$$I_w(x, y) = \{I_{b,r,c}(x, y) \mid r \in [0..R], c \in [0..C]\} \quad (1)$$

where R and C are the rows and columns of the block level image. According to each blkok image $I_{b,r,c}(x, y)$, let $p_{r,c}(x, y)$ stands for the object pixel of the block image $I_{b,r,c}(x, y)$, i ($[1, 2, \dots, L]$) is the grey-level of $p_{r,c}(x, y)$, and let W be the number of the adjacent pixels, then the neighboring difference statistical value $a_{i,p(x,y)}$ of $p_{r,c}(x, y)$ is as follows:

$$a_{i,p_{r,c}(x,y)} = \sum_{j=1}^W [p_{r,c,j} - p_{r,c}(x, y)] \delta \quad (2)$$

where

$$\delta = \frac{(p_{r,c,j} - p_{r,c}(x, y))}{\sum_{j=1}^W |p_{r,c,j} - p_{r,c}(x, y)|} \quad j \in [1, 2, \dots, W] \quad (3)$$

Now, if the pixel number of the block image in row and column are denoted as $M_{r,c}, N_{r,c}$ separately, then collect the total neighboring difference statistical value $A_{r,c,i}$ to each grey-level i of the block image $I_{b,r,c}(x, y)$ and the discrete mathematical format of $A_{r,c,i}$ can express as follows:

$$A_{r,c,i} = \sum_{x=1}^{x=M_{r,c}} \sum_{y=1}^{y=N_{r,c}} a_{i,p_{r,c}(x,y)} \quad (4)$$

where $x \in [1, 2, \dots, M_{r,c}]$, $y \in [1, 2, \dots, N_{r,c}]$.

After the statistical processing to the differential sum of each grey-level i , the difference histogram of each block image is coming into being, through which it can get the thresholding value easily. As described above, the discrete value $t_{r,c}$ which maximizes $A_{r,c,i}$ is chosen as the threshold value.

$$t_{r,c} = \underset{i \in [0, 1, \dots, L-1]}{\text{Arg Max}} \{A_{r,c,i}\} \quad (5)$$

where variable $t_{r,c}$ represent the thresholding value of the block image $I_{b,r,c}(x, y)$ which is used to segment the cracking area from the background.

3.2 Multi-scale Distresses Statistical

The pavement distresses are segmented from the complicated background effectively after the multi-scale neighboring difference histogram segmentation, but there still exist texture noise, the classical regional growth algorithm is too time-consuming to select the cracking region from the texture noises effectively, so it is not suitable for massive pavement images sieving. According to the difference between pavement crackings and noises on spatial scale level, the multi-scale based pyramid structure can eliminate the noises high efficiency while holding the distresses. Weighted statistical based on distress density method (XIAO Wang-xin, 2004) is executed on the process of pyramid structure scale transformation. Let The higher cracking density on larger scale can provide a bigger weighted value for distresses statistical, and the lower density noises on larger scale will disappear as the scale ascending. Figure 2 describes the procedure of scale transformation.

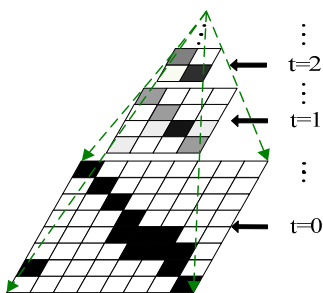


Figure 2. Scale transformation of pyramid structure

Let $f_t(i, j)$ stands for the pixel under scale level $t \in [0, 1, \dots, n]$, and $h(\bullet)$ is the core function, then the transformation function can describe as follows:

$$f_{t+1}(i, j) = f_t(U_{t,i,j}) * h(\bullet) \quad (6)$$

where $U_{t,i,j}$ is the neighboring region under scale t corresponding to the pixel (i, j) under scale $t+1$. Considering the connectivity of pavement crackings in spatial domain, the scale transformation core function $h(\bullet)$ can be

assigned as follows, and the experimental results demonstrated that it works well.

$$h(\bullet) = \frac{1}{4} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \quad (7)$$

After the scale transformation, the binary pavement image is transformed to a gray value image, and the gray level on terminal scale level depended on the distresses density under the initialization binary image. Let I to be the image, C_t corresponding to the distresses statistical value of the image, $w_t(i, j)$ to be the distresses statistical weighted value corresponding to the pixel (i, j) under scale level t , h_{Dh} and v_{Dh} are the horizontal and vertical dimension value of the scale transformation core function separately, then C_t can be expressed as follows:

$$C_t = \sum_{i=1}^{M_t} \sum_{j=1}^{N_t} w_t(i, j) * h_{Dh}^t * v_{Dh}^t \quad (8)$$

where M_t and N_t are the rows and columns number of the pixels separately under scale level t ,

$$w_t(i, j) = \begin{cases} 0 & f_t(i, j) \geq T_C \\ 1 - f_t(i, j) / L & f_t(i, j) < T_C \end{cases} \quad (9)$$

where T_C stands for the thresholding value which used to separate the potential distressed pixels from background pixels after binary image scale transformation.

3.3 Distressed Images Sieving

Based on the fact that images associated with the same road section with consistent pavement texture structure and the same noisy level, a minimum variance sieving method based on distresses statistical value ascending is proposed. Figure 3 is the illustration of this method, S , E and M are standing for the start point, end point and middle point in the C_t curve separately.

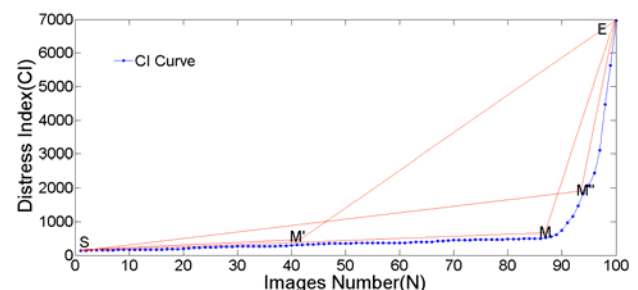


Figure 3. Distressed images sieving method after CI ascending

As described in this figure, the curve section between S and M is ascending gently, while the section between M and E

is acutely, so the images after M are the potential distressed images, then how to get the position of M is the nature of this method. Let N be the images number, and the corresponding cracking index after ascending sortation is $C_{I,k}$, ($k \in [1,2\dots N]$). Let M' is the random point in this C_I curve, g ($g \in [2\dots N-1]$) is the image serial number of M' , then there will be resulted in two line segments $\overrightarrow{SM'}$ and $\overrightarrow{M'E}$, if the absolutely variance between C_I curve points and the corresponded line points are $\Delta_{VL,k}$ (by the left hand of M') and $\Delta_{VR,k}$ (by the right hand of M'), then the total variance S_g according to M' can be described as follows:

$$S_g = \sum_{k=1}^{k=g} |\Delta_{VL,k}| + \sum_{k=g+1}^{k=N} |\Delta_{VR,k}| \quad (10)$$

according to the above description, the threshold value g_t which minimize the S_g can sieve the distressed pavement images from massive images, the mathematical description is as follows:

$$g_t = \underset{g \in [2\dots N-1]}{\text{Arg Min}} \{S_g\} \quad (11)$$

4. EXPERIMENTAL ANALYSIS

To demonstrate the accuracy and efficiency of the proposed method and the process procedure, three kinds of experiments are executed in this paper such as distresses statistical procedure, accuracy and efficiency analysis. Due to page limitations, only several representational pavement images with distresses are discussed in this paper. Figure 4 and 5 illustrated the pavement images distresses statistical procedure, column(a) are original pavement images, column(b) are the segmented images based on the proposed multi-scale segmentation method, column(c) are the images after scale transformation on column(b), column(d) are the result images with weighted value on different distress density regions.

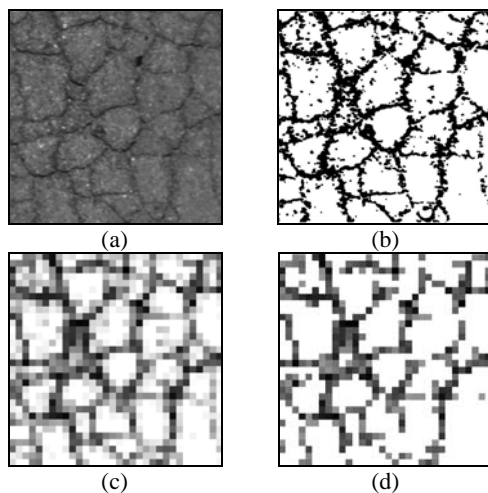


Figure 4. Coarse texture pavement image distresses

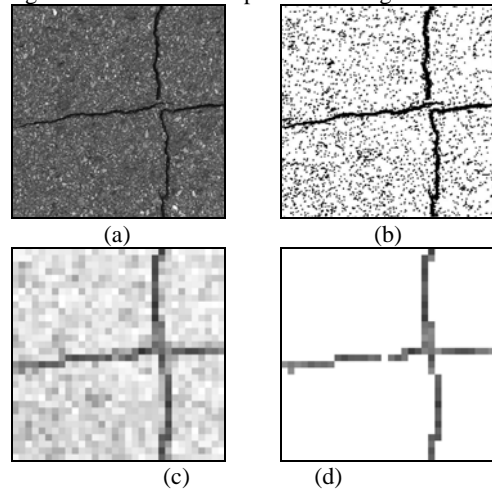


Figure 5. Fineness texture pavement image distresses

Ten groups of pavement images with different pavement texture structure are selected to validate the proposed method, and with the same texture structure in each images group. Table 1 illustrated the statistical results with the proposed method. In this table, i is the group serial number, N_i is the images number, n_i is the potential distressed images number, M_i is the real distressed images number contained in N_i , and $n_{M,i}$ is distressed images number missed by the proposed method, then $1 - \frac{n_i}{N_i}$ and $1 - \frac{n_{M,i}}{M_i}$ are the sieving rate and accuracy rate separately.

| i | N_i | n_i | M_i | $n_{M,i}$ | $1 - \frac{n_i}{N_i}$ | $1 - \frac{n_{M,i}}{M_i}$ |
|-------|-------|-------|-------|-----------|-----------------------|---------------------------|
| 1 | 100 | 8 | 5 | 0 | 0.920 | 1.000 |
| 2 | 200 | 29 | 16 | 1 | 0.855 | 0.938 |
| 3 | 300 | 23 | 12 | 0 | 0.923 | 1.000 |
| 4 | 400 | 31 | 19 | 1 | 0.923 | 0.947 |
| 5 | 500 | 57 | 32 | 2 | 0.886 | 0.938 |
| 6 | 600 | 53 | 27 | 1 | 0.912 | 0.963 |
| 7 | 700 | 63 | 36 | 2 | 0.910 | 0.944 |
| 8 | 800 | 126 | 69 | 3 | 0.843 | 0.957 |
| 9 | 900 | 99 | 54 | 2 | 0.890 | 0.963 |
| 10 | 1000 | 92 | 57 | 3 | 0.908 | 0.947 |
| Total | 5500 | 581 | 327 | 15 | 0.897 | 0.954 |

Table 1. Experimental results on sieving rate and accuracy

The results indicated in this table demonstrated that the proposed method can achieved an average sieving rate more than 89.7% , and an average accuracy rate more than 95.4%, which means that it can separated the potential distressed images from massive images accurately and efficiently, and the efficiency comparison between the classical method and the proposed method is executed, the comparison results illustrated in Figure 6.

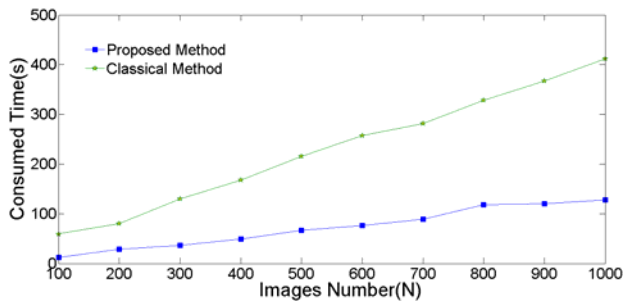


Figure 6. Efficiency comparison between the classical method and the proposed method

On the basis of guaranteeing the sieving accuracy, the comparison results in Figure 6 indicated that: (1) the consumed time increased with the tested images number on the linearity trend; (2) the proposed method can lead an much higher efficiency than that of the classical method, and the farther experimental results demonstrated that the time consuming is less than one third of the classical method.

5. CONCLUSIONS AND DISCUSSION

In this paper, a novel pavement images segmentation and distresses statistical method based on a two stage multi-scale is proposed and experimented. At the beginning part of this paper, the limitations of the conventional distress detection method which dealing with each image through single algorithm and under single scale are reviewed at first. Then the architecture of the proposed method is described. The proposed method is based on the facts that: (1) the crack pixels in pavement images are darker than their surroundings and continuous; (2) images associated with the same road section with the consistence of pavement texture structure. A lot of experiments are implemented to demonstrate the priority of the proposed method, and the results indicated that it can really achieve a much higher efficiency than the classical method on the basis of guaranteeing the sieving accuracy, and the time consuming is less than one third of the classical method while the missing detection rate not exceed five percent.

The thresholding value T_C in this paper which used to separate the potential distressed pixels from background pixels after binary image scale transformation is decided under experience, so how to get the value automatically is our future working direction.

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ACKNOWLEDGEMENT

We would like to acknowledge the supports from the National Natural Science Foundation of China under Grant No. 40571134, and the supports from the Special Funds for Major State Basic Research Programs of China under Grant No. 2006CB705500.

