

# AUTOMATIC LOCAL SEGMENTATION TECHNIQUE FOR DETECTION OF ROAD SURFACE CRACK

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**Abstract-** Image processing technique has been implemented to detect the crack on road surface. However, the accuracy of the detection is still low due to the difficulties in segmentation between crack and non-crack area. This research proposes the implementation of Sauvola technique to perform automatic local segmentation of crack. The methodology involves pre-processing, image segmentation, feature extraction and classification step. In segmentation step, in addition to Sauvola, other techniques, i.e. manual thresholding, Otsu and Bernsen, are also implemented for comparison purpose. The result shows that Sauvola technique produces consistent segmentation results on high, medium and low quality images. Sauvola method also perform the best accuracy detection of 96% among them.

**Keyword-** Image Processing, Road Surface Crack, Segmentation, Sauvola Technique, Thresholding

## I. INTRODUCTION

Periodic evaluation of road is important to maintain the condition of a road surface. The evaluation is performed by observing the presence of surface cracks. Currently, the observation is done manually where the officers observe the surface crack visually along the road and then they make marks on the road when the crack was founded. This conventional method is not effective since it requires long inspection time, labor intensive and not accurate. It is also dangerous when the inspection is performed in the high traffic way.

To overcome the above problem, researchers offer methods to detect the presence of cracks by utilizing camera and image processing techniques. As summarized by Chambon and Moliard<sup>1</sup>, various techniques based on image processing for detection of crack are categorized into five approaches, i.e. histogram, morphology, training-testing, filtering, and modeling. Histogram approach is implemented based on an assumption that the intensity of crack region and background is separated. This approach is usually continued by applying thresholding technique to segment between the crack region and background<sup>2,3,4</sup>. Histogram and thresholding technique are selected mostly because of their simplicity and efficient computation process. The other approach is morphology that modifies intensity pixel of an image to significantly improve the segmentation process<sup>4,5,6,7</sup>. This approach produces better results than histogram technique.

The steps of image processing methods for crack detection are pre-processing, image segmentation, features extraction and classification step. In this paper, we focus only on the image segmentation, which is a step to differentiate between the crack and background image. The conventional method for

image segmentation is thresholding technique. This technique selects a threshold value to differentiate between crack object that usually has lower pixel intensity compared to the surface pixel intensity. The selection of the threshold value might be manual or automatic whereas the value might be constant or dynamic value.

Riyadi et. al.<sup>4</sup> apply a constant global threshold value to convert images from grayscale to binary number. Several values were previously selected by observing histogram of overall images data and then implemented to obtain the optimal one. The pixels with gray level below than the threshold value are segmented as crack and pixels value higher than the threshold value are considered as background. The result showed that the segmented images still contain noise or background part that is considered as crack whereas the other result, a part of crack is detected as background.

Instead of the manual global threshold value, an automatic global threshold value is also popular that firstly introduced by Otsu<sup>8</sup>. Otsu method assumed that the image intensity is a bi-modal histogram, i.e. object, and background. Then, the method calculates the threshold value so that the intra-class variance is minimal and the inter-class variance is maximal. The main drawback of global thresholding technique, either manual or automatic, is the fact that the real images are not bi-modal then the threshold value could not be precisely implemented on overall images data.

To overcome the global threshold problem, researchers proposed automatic local thresholding techniques, such as Bernsen technique. This technique is popular as fairly fast since it has a mechanism to reduce complex computation and does not need to compute images histogram. Other popular

automatic local thresholding technique was proposed by Sauvola. This technique has an ability to segment texts precisely in a document with noise, illumination and many degraded sources. The objective of this paper is to implement the automatic local thresholding technique by Sauvola to detect the presence of crack on road surface images. Other segmentation techniques, which are manual thresholding technique, Otsu method, and Bernsen, are also evaluated for comparison purpose.

**II. METHODOLOGY**

The methodology of this research is presented in the flowchart of Fig. 1. The flowchart involves pre-processing step, image segmentation, feature extraction and classification step. The first step is pre-processing. In this step, the image is resized and converted from RGB to grayscale format to reduce the computation complexities. A Gaussian filter is also implemented to enhance the quality of the image.

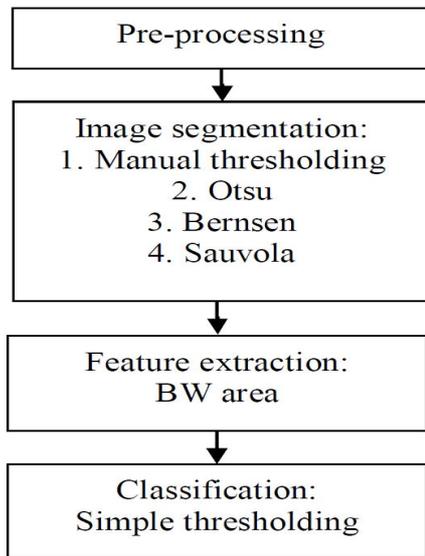


Fig. 1 Methodology of research

In the segmentation step, four segmentation techniques are implemented, i.e. manual thresholding, Otsu, Bernsen and Sauvola method. Manual and Otsu method are global segmentation techniques whereas Bernsen and Sauvola are local segmentation techniques.

**a. Manual Thresholding**

Manual thresholding technique is performed by determining a threshold value manually by observing the histogram of images. If the value T is determined, then each pixel value is segmented to be two group using the following formula.

$$\begin{cases} 1; & \text{if } f(x,y) > T \\ 0; & \text{if } f(x,y) < T \end{cases}$$

**b. Otsu**

Otsu method computes the threshold value based on the image histogram. It analyzes the discriminant of two classes of the histogram, i.e. crack, and background. The method finds the threshold value by minimizing the intra-class variance  $\sigma_w^2$

$$\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$

where  $\omega_i$  are the probability of two classes separated by t and  $\sigma_i^2$  are variances of the classes, and maximizing the inter-class variance  $\sigma_b^2$

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = \omega_1(t)\omega_2(t) [\mu_1(t) - \mu_2(t)]^2$$

where  $\mu_i$  are the class means.

**c. Bernsen**

In the Bernsen technique, the threshold value is determined for each window, which is called local threshold. The local threshold is the mean value of the maximum and minimum pixel intensity in the window as long as the contract value L is sufficient. Otherwise, the global threshold value (GT) will be used as a local threshold value.

$$T_{window} = \begin{cases} (I_{max}+I_{min})/2 & \text{if } I_{max}-I_{min} > L \\ GT, I_{max}-I_{min} < L \end{cases}$$

**d. Sauvola**

Sauvola technique calculates the local threshold value for each window using the formula

$$T(x,y) = m(x,y) * (1 + (k * ((s(x,y)/R) - 1)))$$

where  $T(x,y)$  is the threshold value in each window,  $m(x,y)$  is mean of window intensity,  $s$  is its standard deviation,  $k$  and  $R$  are constant values.

Segmentation step produces an image in binary format, the 0 value is the crack part, and the 1 value is the background. After segmented, a feature represented the presence of crack is then extracted. In this research, a simple feature that is a total of black pixels is computed. Then we use a classification threshold value to differentiate between crack and non-crack images. The classification threshold value is determined by observing the total of black pixels of representative images.

**III. RESULTS AND DISCUSSION**

In this section, the result of crack segmentation is discussed. We implement the proposed technique on 100 images, which consist 80 images with crack and 20 non-crack images. The images are categorized into three groups, i.e. high, medium and low-quality data.

We categorized high-quality image if an image has high contrast and we could easily differentiate between crack and non-crack images by visual. Fig. 2 (a) shows the example of a high-quality image, where

the Fig. 2(b), (c), (d) and (e) are the segmentation result using manual threshold, Otsu, Bernsen and Sauvola method, respectively. It can be seen that four methods are successful in detecting the presence of crack accurately.

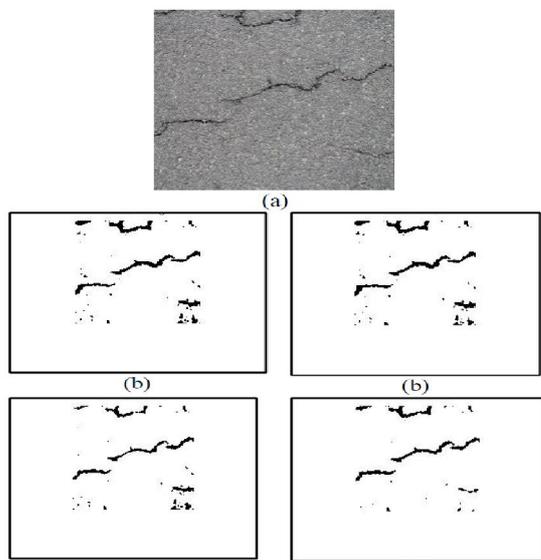


Fig. 2 (a) original high-quality image and segmentation result using (b) manual thresholding, (c) Otsu, (d) Bernsen and (e) Sauvola

Medium-quality data consists of images with low contrast and it is rather difficult to detect the presence of crack visually. When manual thresholding and Bernsen method were implemented on this category of data, they produce fail segmentation. Almost all of crack part could not be detected by both methods. Otsu method yields over detected area so some background part is detected as crack. Sauvola result looks the best compared to others. The example of original medium quality image and the segmentation results are shown in Fig. 3.

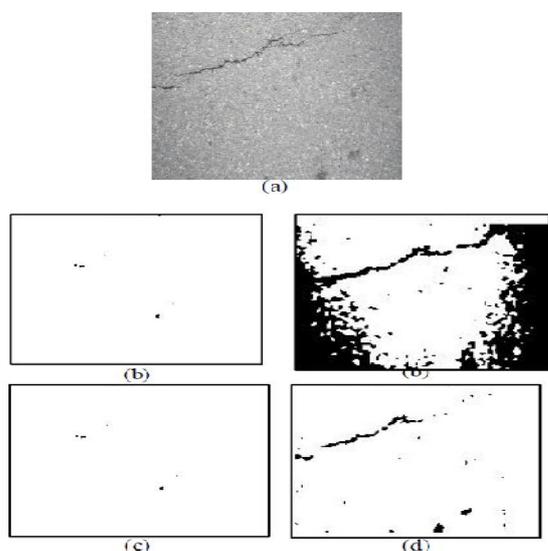


Fig. 3 (a) original medium-quality image and segmentation result using (b) manual thresholding, (c) Otsu, (d) Bernsen and (e) Sauvola

Fig. 4(a) shows the example of low-quality image. The image is a blur, low contrast and very difficult to detect the crack visually. According to the segmentation results shown in Fig. 4(b), (c), (d) and (e), among the methods, Otsu produces the worst segmentation, whereas the others still have the ability to detect the crack.

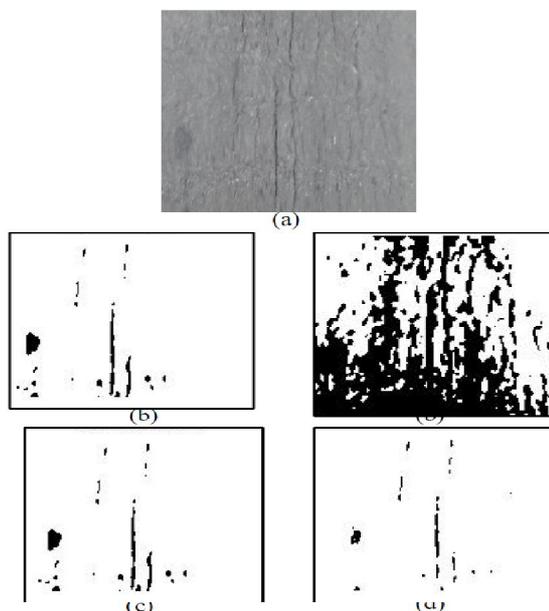


Fig. 4 (a) original low-quality image and segmentation result using (b) manual thresholding, (c) Otsu, (d) Bernsen and (e) Sauvola

In addition to visual evaluation of the segmentation results, we present detection results based on each segmented image. The detection of crack was performed based on the total number of white area. An image with totally white area which is more than 19.100 area pixels is classified as a non-a crack image, while an image with a total of the white area is less than 19.000 pixels is classified as crack image. The classification threshold value is determined by observing the total number of white area of representative images. Finally, Table 1 shows that Sauvola performed the best classification between the crack and non-crack with an accuracy of 96%, while Otsu performed the worst one.

Table 1. Accuracy of crack detection

Method	Manual	Otsu	Bernsen	Sauvola
Accuracy(%)	88	80	88	96

### CONCLUSION

The implementation of Sauvola method to perform automatic local segmentation of crack was conducted. The method produces consistent segmentation result for high, medium and low-quality images. It also yields the best accuracy of detection compared to manual thresholding, Otsu, and Bernsen method.

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## REFERENCES

- [1] Sylvie Chambon and Jean-Marc Moliard. 2011. Automatic road pavement assessment with image processing: review and comparison. *International Journal of Geophysics* Vol. 2011.
- [2] E. Teomete, V. R. Amin, H. Ceylan, and O. Smadi, "Digital image processing for pavement distress analyses," in *Proceedings of the Mid-Continent Transportation Research Symposium*, p. 13, 2005.
- [3] H. Elbehiery, A. Hefnawy, and M. Elewa, "Surface defects detection for ceramic tiles using image processing and morphological techniques," in *Proceedings of the World Academy of Science, Engineering and Technology (PWASET '05)*, vol. 5, pp. 158–162, 2005.
- [4] Slamet, Riyadi, Azyumarridha A. Riza, Ramadoni Syahputra, Tony K. Hariadi. "Detection of Road Surface Crack based on Image Processing using Combination Techniques of Thresholding, Median Filter dan Morphological Closing". *Simposium Nasional Teknologi Terapan* 2014.
- [5] M. Coster and J.-L. Chermant, "Image analysis and mathematical morphology for civil engineering materials," *Cement and Concrete Composites*, vol. 23, no. 2, pp. 133–151, 2001.
- [6] A. Ito, Y. Aoki, and S. Hashimoto, "Accurate extraction and measurement of fine cracks from concrete block surface image," in *Proceedings of the Annual Conference of the Industrial Electronics Society*, vol. 3, pp. 2202–2207, 2002.
- [7] S. Iyer and S. K. Sinha, "A robust approach for automatic detection and segmentation of cracks in underground pipeline images," *Image and Vision Computing*, vol. 23, no. 10, pp. 921–933, 2005.
- [8] Nobuyuki Otsu (1979). "A threshold selection method from gray-level histograms". *IEEE Trans. Sys., Man., Cyber.* 9 (1): 62–66
- [9] Bernsen J., Dynamic thresholding of grey-level images, *Proceedings 8th International Conference on Pattern Recognition*, Paris, pp. 1251-1255, 1986.
- [10] J. Sauvola and M. Pietikainen, Adaptive document image binarization, *Pattern Recognition* 33 (2000) 225-236

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