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**Submission date:** 08-Dec-2017 09:43AM (UTC+0700)

**Submission ID:** 892362794

**File name:** B\_3\_Analysis\_of\_Digital\_Image\_using.pdf (356.23K)

**Word count:** 2301

**Character count:** 12144



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Advanced Science Letters  
Vol. 21, 3565 – 3568, 2015

## Analysis of Digital Image using Pyramidal Gaussian Method to Detect Pavement Crack

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Examination of road condition, especially pavement crack, needs to be done regularly. With regular checks, road conditions can be maintained to keep it comfortable for road users. Currently, the examination was carried out manually where the officers observe all pavement road and then take notes and mark the existence of cracks. This conventional method takes a long time, labour intensive and low consistency due to the human factor. To overcome the problem, this research proposes the use of digital image processing technique to detect the existence of cracked road surface. The detection technique is developed using Gaussian Pyramid method to create multiscale images and extraction of histogram and black-white area features. Linear discriminant analysis is then used to classify the crack and non-crack images. Based on experiment results, the method produces the accuracy of 92.8571% with 1.50 seconds of computation time per image. In conclusion, the proposed method successfully increase the accuracy of cracks detection on pavement surface.

**Keywords:** Pavement crack detection, image analysis, pyramidal Gaussian.

### 1. INTRODUCTION

According to the UU Republik Indonesia No. 38 tahun 2004 concerning road infrastructures, the road has an important role in realizing development of nation because it supports the rate of economic growth. It can be inferred that the road is very important for human beings and the road condition has to be maintained periodically. Road maintenance is done through the inspection of the road condition, especially road damages. According to Manual Pemeliharaan Jalan Bina Marga No. 03/MN/B/1983, the road damage is classified as crack, distortion, disintegration, polish aggregate, bleeding or flushing, and decline in the former quarry/planting utilities. This research only focuses on detection of the existence of cracks, without distinguishing the type of the cracks.

The current methods that used in checking the road condition is the conventional method, where the officers observe the pavement road and check the existing of cracks manually. This evaluation method is not effective because it requires a long time, a lot of manpower and less precise due to the human subjectivities. In addition, the conventional method is not safe for officers especially when the inspection is conducted on a highway with high traffic. Therefore, there is a problem on this method that needs further research to solve it.

Researchers have reported their findings to overcome the conventional inspection method using various image

processing techniques. Chambon and Moliard<sup>1</sup> summarized the application of image processing techniques for crack detection in five approaches, i.e. histogram, morphology, training-testing, filtering and modelling. Histogram approach is implemented based on assumption that the intensity of crack region and background is separated. This approach is usually continued by applying thresholding technique to segment between 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 image to significantly improve the segmentation process<sup>4,5,6,7</sup>. Generally, this approach produces better results than histogram technique.

Riyadi et al<sup>4</sup> apply a method that combines thresholding, morphological closing and median filtering technique to detect the present of crack on surface pavement. Thresholding technique is applied to perform crack segmentation from background image. Several values are selected and tried to obtain the optimal threshold value. Crack image obtained from this segmentation looks containing noise or background part that is segmented as crack. Therefore, they apply a median filter and morphological closing technique to improve the quality of crack images. Although median filter significantly increases the accuracy result, it remains problem because the filter works only on the local region or window. Local region processing is effective for detail

task but sometimes it is not proper to represent the apparent of the whole image.

Image processing technique introduced a pyramidal image analysis to observe the pyramidal apparent of images. Using this analysis, images can be evaluated from coarse to fine view<sup>8,9</sup>. The objective of this paper is to use a pyramidal technique to detect the present of crack on pavement surface. A Gaussian filter is implemented combined with the pyramidal approach.

## 2. METHOD

The stages of research that has been implemented are presented in the following flowchart:

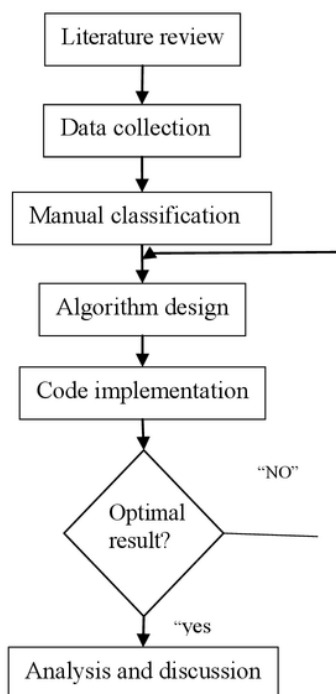


Fig. 1. Flowchart of overall research stages

1. Literature review  
This stage aims to obtain the state of art on the topic and related theory and implementation of image processing techniques.
2. Data collection  
The image data are collected on pavement road in Wates, Kulonprogo, Yogyakarta. Digital camera is positioned perpendicular to the angle of 90 degrees with height of 1 meter from the road. A number of 86 images were captured where 43 image is with crack and the rest is non crack.
3. Manual classification

Image data are manually classified between image with crack and non-crack. This stage is done visually by an expert and the result is considered as the ground-truth that will be used to validate or compute the accuracy of proposed method.

### 4. Algorithm Design

The algorithm consists of the following steps: pre-processing, pyramidal Gaussian, features extraction and classification task as shown in Fig. 2. In the pre-processing, the image is resized and converted from RGB to grayscale format to reduce computation complexities. After that, the pyramidal Gaussian is then implemented to obtain different scale views of image. Scale 1 represents the image with original size, scale 2 is a half size of original image whereas scale 3 is a half size of scale 2 image.

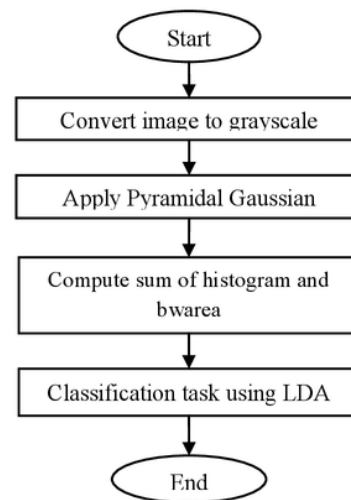


Fig. 2. Flowchart of algorithm design

In each scale view, two features are then extracted, i.e. sum of histogram and black-white area (bwarea). Sum of histogram is selected as a feature to represent crack because based on histogram observation, histogram of image containing crack is relatively distributed on the left region compare to image without crack as shown in Fig. 4(c) and (d). Therefore, sum of histogram feature is computed for several ranges of histogram to determine the optimal one. The second feature is bwarea that is computed by sum of black pixels in the segmented grayscale image. Black pixels represents the crack in the image whereas the white pixels represents the background image.

These two features are used for classification task using linear discriminant analysis (LDA) method. LDA training obtains linear discriminant function following formula:

$$y(x_1, x_2) = K + L_1 x_1 + L_2 x_2$$

where  $y$  is linear discriminant function,  $x_1$  and  $x_2$  are sum of histogram and bwarea, respectively, and  $K$ ,  $L_1$  and  $L_2$  are constant values obtained from LDA training. LDA training uses 30 set of images whereas the testing process involves 53 images. Finally, the accuracy of crack detection is computed using LDA testing.

5. Implementing program.

Program is created using the MATLAB software.

3. RESULT AND DISCUSSION

The total of images used in this study was 86 images, where 43 data are images with crack and the rest are non crack. A number of 30 images were used for LDA training and 56 ones were used for testing. Fig. 3(a) and (b) shows an example of original image with crack and non-crack, where Fig. 3(e) and (f) are the images of Fig. 3(a) and (b) after conversion from original to grayscale.

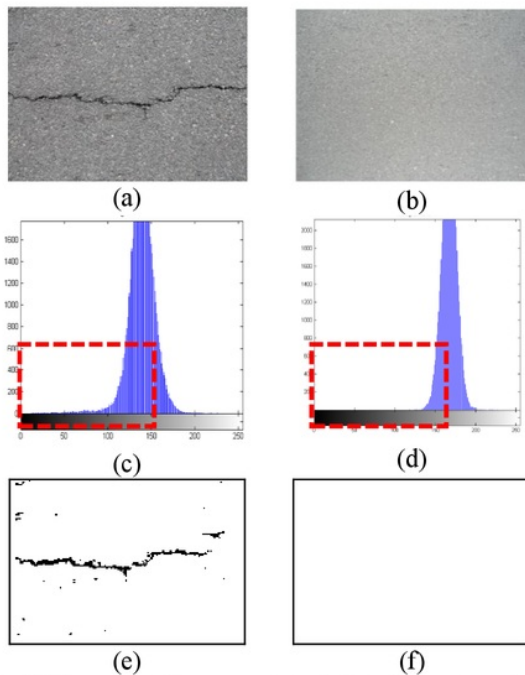


Fig. 3. Example of images: original (a) with crack and (b) non-crack, histogram of images (c) with crack and (d) non-crack, grayscale image (e) with crack and (f) non-crack

The results of pyramidal Gaussian for scale 1, scale 2 and scale 3 are showed in Fig. 4(a), (b) and (c) respectively. Visually, higher scale of pyramid results smaller size of images. The image from scale 1 looks more detail compared to others. Image with more details should not have been proper for detection purpose because it also contains more noise compared to image

with less detail. To determine which scale is the optimal one, each image is then processed in the next step, i.e. computation of sum of histogram and bwarea.

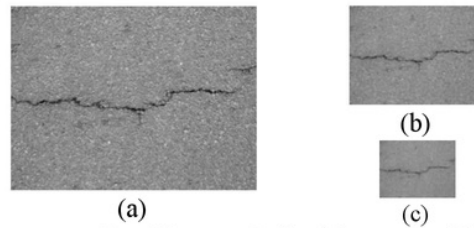


Fig. 4 Images obtained from pyramidal Gaussian (a) scale 1, (b) scale 2 and (c) scale 3

Computed sum of histogram and bwarea are used to determine the linear discriminant function and yields

$$9.4511 + (0.001 * 0.4781)x_1 + (0.001 * -0.9651)x_2 = 0$$

This function is then used to classify the images by defining:

$$y = 9.4511 + (0.001 * 0.4781)x_1 + (0.001 * -0.9651)x_2 = 0$$

If  $y > 0$  then image is classified as image with crack, whereas if  $y < 0$  then image is non-crack.

Using the linear discriminant function obtained, we computed the accuracy of detection as shown in Tabel 1, 2 and 3 for pyramidal Gaussian scale 1, 2 and 3 respectively. For this experiment, we applied three ranges of sum of histogram, i.e. 1:170, 1:175 and 1:180. These values are selected based on visual analysis of histogram as shown in Fig. 4(c) and (d). We also selected three thresholding value, i.e. 0.40, 0.45 and 0.50 when converting grayscale to black-white image.

According to Table 1, for pyramid scale 1 or original size, the result shows that the best accuracy of 87.5000% was obtained at range of histogram 1:170 and thresholding value 0.50 or range 1:175 and thresholding value 0.45. The significant increment to 92.8750% of accuracy was obtained at pyramid scale 2 (Table 2) where sum of histogram computed at range 1:175 and thresholding value 0.45. Other results in Table 3, for pyramid scale 3, all accuracy of detection are smaller than scale 1 and 2 at any range and thresholding value. In conclusion, the optimal accuracy was obtained at scale 2 with range 1:175 and thresholding 0.45. This fact can be explained that pyramid scale 1 produces images with more details and noisy whereas scale 3 produces too smooth images and both scales cause inaccurate segmentation results. In addition, the computation time is about 1.50 seconds per images that can be considered as efficient in time consumed.



Tabel 1 Accuracy result in % for pyramid scale 1

Features		Thresholding of bwarea		
		0.40	0.45	0.50
Range of sum histogram	1:170	85.7143	85.7143	87.5000
	1:175	85.7143	87.5000	82.1429
	1:180	78.5714	80.3571	80.3571

Tabel 2 Accuracy result in % for pyramid scale 2

Features		Thresholding of bwarea		
		0.40	0.45	0.50
Range of sum histogram	1:170	91.0714	89.2857	91.0714
	1:175	71.4286	92.8570	80.3570
	1:180	71.4286	76.7857	82.1429

Tabel 3 Accuracy result in % for pyramid scale 3

Features		Thresholding of bwarea		
		0.40	0.45	0.50
Range of sum histogram	1:170	89.2857	91.0714	91.0714
	1:175	75.0000	85.71429	87.5000
	1:180	64.2857	76.92308	82.1429

#### 4. CONCLUSION

The proposed method for <sup>6</sup> detection of crack on pavement surface has been developed using pyramidal Gaussian method. Based on experiment results, the method successfully produces almost 93% of accuracy with computation time of 1.50 seconds per image. The pyramidal technique shows its ability to significantly increase the accuracy result. For the future, this method should be tested on various data and also involve

automatic selection to determine the optimal values of range of histogram and thresholding.

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