Detection of Pavement Surface Crack Based on Image Processing using Wavelet Features Extraction Technique

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Abstract Evaluation of road pavement is an important part of maintaining its quality. In a traditional way, human checks the asphalt by walking along the road. This traditional method it is less efficient because it requires substantial costs, takes a long time, exposed to safety issues such as the high intensity of vehicle passing by, the subjective factor, and the fatigue factor. With digital image processing technique, pavement evaluation will be safer for surveyor. Pavement's cracks are captured on a picture and then processed with some algorithm. This paper explains the principle of Discrete Wavelet Transform (DWT). The image is filtered by the low-pass filter and a high-pass filter and decomposed into four sub-bands to perform feature extraction to extract unique features of the picture. These extracted features are then applied to classification method using linear discriminant analysis (LDA), and the accuracy is about 92.8%.

Keywords: crack detection, feature extraction, image processing, discrete wavelet transform.

1. Introduction

The primary infrastructure used to deliver necessities like food and clothes are ground transportation. Therefore, the road becomes an important function not only to connect one place to another but also has a role in the development of a region**.** Roads material have a certain lifespan and durability. There are many factors affecting road damage. Such as material quality, natural factors, and overload usage. These conditions could disrupt and endanger road users. Accidents often occur because the driver cannot control vehicle while anticipating the damage of the road. According to the Bina Marga Roads Manual No.03/MN/B/1983, the road damage is classified into cracking, distortion, surface effects (disintegration), polish aggregate, bleeding & flushing, and utility planting. This research only focused on the examination to detect a presence of cracks, regardless of the fracturing.

Currently, examination of the road still uses the traditional way of manual observation using sensory vision. This traditional method it is less valuable because it needs substantial costs, takes a long time, exposed to safety issues such as the high intensity of vehicle passing by, the subjective factor, and the fatigue factor [1]. Automated pavement crack detection has undoubtedly improved the assessment process of road pavement condition [2].

The Federal Highway Administration (FHWA), Road Inventory Program (RIP) for the National Park Service (NPS), collects roadway condition data on asphalt paved surface. The FHWA RIP is implemented based on the premise that an accurate pavement surface condition assessment can be accomplished using automated crack detection technology as applied to digital images [3].

Photogrammetric approach considered to be very effective in the detection of cracks but on other hands, there is a lack in this study because the camera was used has unique specifications at relatively expensive and complicated operation [4]. The cracks are well detected using continuous wavelet transform with more or less noise according to the texture, but there is some noise due to a high texture [5].
Based on the problems discussed above, research is needed to find the new method that can detect cracks with a more affordable, reliable, and simple operation device. The method used to detect the presence of cracks on the road is wavelet feature extraction. Selected features briefly characterise the statistical properties of the proposed features. All the features extracted from the database can be represented in a vector, usually called feature vector [6].

2. Methodology

Figure 1 shows the procedure of detection process for pavement's surface cracks. First to get the images data, we have to make data acquisition. Then the data was resized and converted to grayscale image mode. After that, we processed the image and extracted the feature using statistical properties extraction. This study used mean and standard deviation values as statistical properties extraction. Finally, linear discriminant was applied to the images to classify them as "crack" or "non-crack". Discriminant lines make images separated by its class. This result then compared to visual initialization images to get the percentage of accuracy.

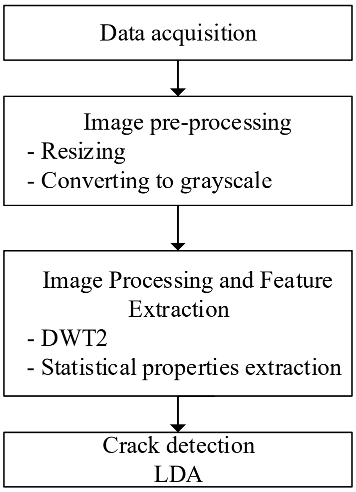


Figure 1. Crack detection diagram

2.1 Data Acquisition

The treatment is done while data retrieval are as follows:

1. The camera was positioned is perpendicular to the road.
2. Camera and road surface distance should not be too close or too far so the image obtained can be processed well.
3. Data was collected at certain hours when it is not too dark and have enough light intensity.

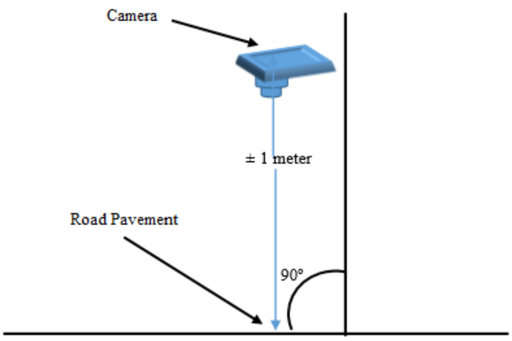


Figure 2. The image acquisition setup

2.2 Image Pre-processing

Pre-stage image process aims to unify the input image before it is processed using wavelet transformation method. First, Resizing the RGB image into 480x640 dimension. Second, converting the image into grayscale image mode. The aim of simplifying the input image is to reduce the processing time.

2.3 Wavelet Transformation

Wavelets are the foundation for representing images in various degrees of resolution. In particular, this material is used in this book for image data compression and for pyramidal representation, in which images are subdivided successively into smaller regions [7]. The Wavelet transform is a mathematical means to perform signal analysis when signal frequency varies over time. For certain classes of signals and images, wavelet analysis provides more precise information about signal data than other signal analysis techniques. The image that has been converted to grayscale in the image pre-processing stage was then transformed into sub-band frequency in which component was produced by a decreased level of decomposition. Implementation of discrete wavelet transform (DWT) can be done by passing a high frequency (high-pass filter) and low frequency (low-pass filter) signal. In this case, we used *haar* mother wavelet transformation to extract the feature of images, a process of smoothing (averages) to get a piece of the low-frequency image and do the reduction process (differences) to get a piece of the high-frequency picture [8]. *Haar* filter bank is shown in Figure 3.

$$A^{n} = \frac{1}{2}\begin{bmatrix} 1 & 1 & & & & & & & & \\ & & 1 & 1 & & & & & & \\ & & & & \ddots & & & & & \\ & & & & & & 1 & 1 & & \\ & & & & & & & & 1 & 1 \end{bmatrix}$$

$$B^{n} = \frac{1}{2}\begin{bmatrix} 1 & -1 & & & & & & & & \\ & & 1 & -1 & & & & & & \\ & & & & \ddots & & & & & \\ & & & & & & 1 & -1 & & \\ & & & & & & & & 1 & -1 \end{bmatrix}$$

Figure 3. Haar filter bank

If an image transformations process is carried out with two-dimensional discrete wavelet decomposition level one as shown in Figure 4, it will generate four sub-bands, namely:

1. Coefficient Approximation (CA) or LL sub-band.
2. Coefficient Horizontal Detail (CH) or HL sub-band.
3. Coefficient Vertical Detail (CV) or LH sub-band.
4. Coefficient Diagonal Detail (CD) or LH sub-band HH.

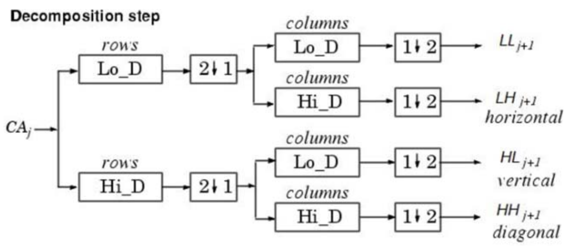
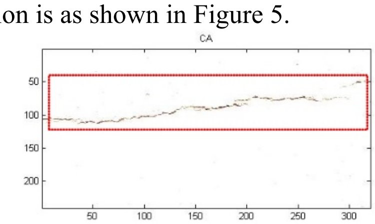
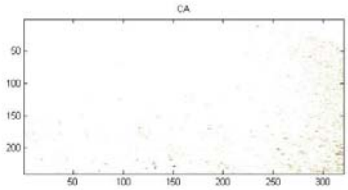


Figure 4. Decomposition step

In this case, this algorithm has been applied to the previously step. The resulting image of CA after decomposition is as shown in Figure 5.



(a)



(b)

Figure 5. CA transformation result
(a) crack images (b) non-crack images.

2.4 Statistical Feature Extraction

Feature extraction is the process that raises the unique characteristics of an object in the form of value that will be used for analysis. Coefficient approximation (CA) is component that represents the original image which has been filtered by using a low-pass filter (LL). Next, coefficient approximation (CA) was processed and computed further using basic statistical properties. The computed statistical properties are; x_1 represents mean computed using equation (1) and x_2 represents standard deviation computed using equation (2).

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_1 \quad (1)$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x}_i)^2} \quad (2)$$

2.5 Linear Classification

Classification method used in this research is Linear Discriminant Analysis (LDA). Linear Discriminant Analysis is a method used in statistics, pattern recognition and machine learning to find a linear combination of the characteristic or separating two or more classes of objects or events. Classification is divided into two classes, namely "crack" and "non-crack". Having these distinct features, crack detection is made simple and thus there is no need for a complex classifier [9]. This classification method uses two inputs, namely the values of feature extraction results in the previous step. Equation of linear discriminant analysis that we used is as follows

$$Y = K + L(1)*X_1 + L(2)*X_2 \quad (3)$$

In the case of mean-STD feature extraction, it is as shown in Figure 6.

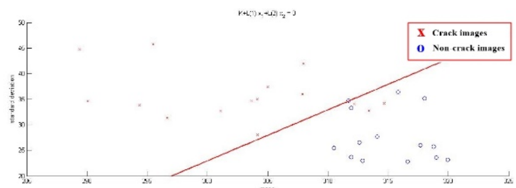
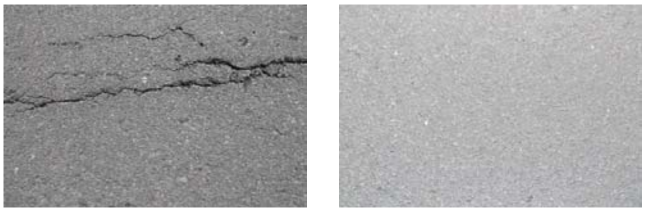


Figure 6. Scatter plot feature extraction (sum-std) and its linear discriminant line

A total of 56 testing images were classified by quality into good, middle, and low. This qualification based on manual perception. Good quality images are images that can be processed properly and produce a right decision according to manual classification. This good image has to crack that easy to detect because of high contrast between object and background. The sample of good images is shown in Figure 7



(a) (b)

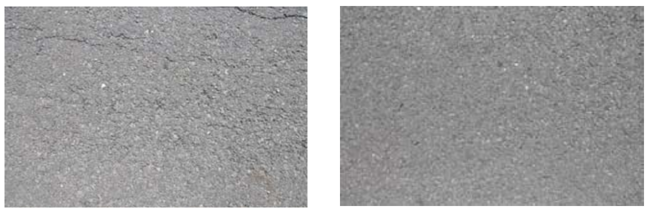
Figure 7. Good quality images (a) crack, (b) non-crack

Middle-quality images have cracked that less obvious, so it is difficult to recognise because have almost the same colour between object and background and non-crack images displays a less smooth. The sample of middle-quality images is shown in Figure 8

(a) (b)

Figure 8. Middle quality images (a) crack, (b) non-crack

Bad quality images are images that can't be processed properly and produce a false decision according to manual classification. This image isn't clear with the same colour between object and background, so it's difficult recognised. The sample of bad quality images is shown in Figure 9



(a) (b)

Figure 9. Bad quality images (a) crack, (b) non-crack

3. Result

In this case, a total 30 images consist of crack and non-crack classes were used for training to determine the discriminant function and another 56 images were used for testing. The images for training (crack and non-crack) were classified and used as a reference for expert visual labelling. Next, the rest of images were classified using the linear discriminant function obtained in training session shown in equation (3).

$$y = -74.5443 + 0.2691 * x_1 + (-0.2699) * x_2 \quad (3)$$

To discriminate the image as crack or non-crack, we implemented the following rules base:

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    If y <= 0 then image = crack, else
image = non-crack
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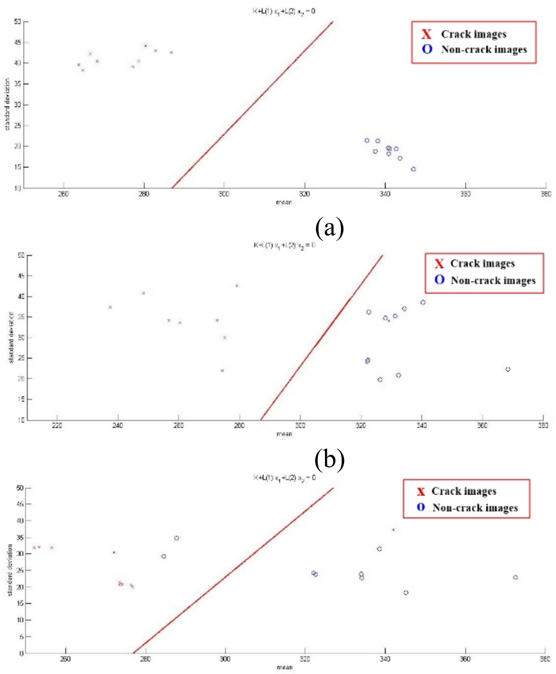
These images were tested using linear discriminant analysis. The result of tested images is shown in Figure 7.



(a)

(b)

(c)

Figure 7. Scatter plot of tested images by quality, (a) good, (b) middle, (c) low

Scatter plot result quality images are shown in Figure 7 with "x" as crack images and "o" as non-crack. From scattering plot result can be observed that both of crack and non-crack images separated by red lines linear equation. It's mean that testing on good quality images Figure 7(a) scores up to 100% accuracy. Scatter plot of middle-quality images Figure 7(b) can be observed that some images cross the red lines equation, scores up to 94.7% accuracy. Scatter plot of bad quality images Figure 7(c) can be observed that some images cross the red lines. This type crack and non-crack images difficult to distinguish from the background scores up to 94.7% accuracy. The classification results of 56 testing images filtered by quality; good, middle, and low is shown in Table 1.

Table 1. Result of pavement cracks detection

Images Quality	Images		Error	Accuracy
	Crack	Non-crack		
Good	9	9	0	100 %
Middle	9	10	1	94.7 %
Low	10	9	3	84.2 %

4. Conclusion

Based on this study, we can conclude that the use of wavelet transforms and feature extraction to perform pavement surface crack detection based on image processing has successfully extracted features to detect road image. A mean value and standard deviation (STD) value can be used properly to create a pavement surface crack detection. The system developed in this study can detect pavement crack with 92.85% optimal accuracy. Read error occurs due to the lighting intensity, while data acquisition affects the image feature extraction.

5. References

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