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Road crack detection using adaptive multi resolution thresholding techniques

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Abstract

Machine vision is very important for ensuring the success of intelligent transportation systems, particularly in the area of road maintenance. For this reason, many studies had been focusing on automatic image-based crack detection as a replacement for manual inspection that had depended on the specialist's knowledge and expertise. In the image processing technique, the pre-processing and edge detection stages are important for filtering out noises and in enhancing the quality of the edges in the image. Since threshold is one of the powerful methods used in the edge detection of an image, we have therefore proposed a modified Otsu-Canny Edge Detection Algorithm in the selection of the two threshold values as well as implemented a multi-resolution level fixed partitioning method in the analysis of the global and local threshold values of the image. This is then followed by a statistical measure in selecting the edge image with the best global threshold. This study had utilized the road crack image dataset that were obtained from Crackforest. The results had revealed the proposed method to not only perform better than the conventional Canny edge detection method but had also shown the maximum value derived from the local threshold of 5x5 partitioned image outperforming the other partitioned scales.

Keywords: *edge detection, fixed partitioning, machine vision, multi-resolution level, road crack detection*

1. Introduction

The machine vision technology has been growing rapidly owing to the many benefits it offers to the manufacturers such as the automation of quality monitoring and providing the advantage of a more accurate evaluation system. For this reason, the application of computer vision techniques had been proven to be particularly useful for the transport and highways departments in automatically detecting and assessing patches, potholes and road pavement cracks. There had been many studies conducted on crack detection, not only on pavements, but also in glass, ceramics, tiles and tunnels [1–7]. Some of the most commonly edge detection techniques used are the Canny, Sobel, Prewitt and Robert methods. The pre-processing stage is considered to be one of the key steps in the distress detection system, where it eases the cracking detection through noise suppression and the sharpening of the linear features in the raw images that are usually associated with the crack features. In general, the basic approach is made up of a pre-processing step along with the distress or road cracks detection module. However, these systems tend to provide incorrect reports on the cracking of the boundaries that correspond to non-crack elements such as joints, patches and road markings. As such, to prevent these false crack detections from taking place, a specific non-crack features stage is required to mask the region of the images where non-crack features have been detected [8].

Edge detection is an image processing technique for finding the boundaries of objects within images by detecting the intensity discontinuities in a digital image. This method is commonly used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision. In the case of image thresholding, it is a simple, yet effective way of partitioning an image into a foreground and background and can be regarded as a type of image segmentation that isolates objects by converting the greyscale images into

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binary images. There had been studies conducted on both edge-based and threshold-based segmentation such as the Canny edge detection and Otsu thresholding methods [9–11]. The Otsu method is based on grey level histograms that are deduced by using the least square method and is currently regarded as the most stable technique used for image threshold segmentation. From a statistical perspective, this method also generates the best threshold value [12], which is one of the key factors that greatly affect the performance of the traditional Canny Operator. As such, this research had followed the method used from previous studies such as [12–18], which is to provide an improved self-adaptive threshold Canny Operator that inherits the merit of Otsu method in choosing the low threshold (L_t) and high threshold (H_t) values adaptively.

The selection of a threshold value is vital in ensuring that an accurate edge is given, which not only produces a clear image of the cracks, but also to filter out the cracks from other layers as layerwise instead of laminate-wise. The length and location of each individual crack is then measured from the filtered images by using a simple heuristic procedure [7]. In cement, the crack patterns are detected by using a combination of threshold and filter-like edge detection methods, which is similar to the method Sobel had used in detecting cracks within a binary image. By utilizing a suitable threshold binary image, the pixels are categorized into the foreground and the background image and the residual noise is eliminated through the use of Sobel's filtering. After undergoing the filtering process, the Otsu method is then used to detect the major cracks. This detection method had been discussed earlier in [2].

The modified Canny edge detection algorithm had been used in a few studies such as [19]. Since edge preserving filters are used in the applications of road cracks detection, this algorithm was therefore tested on randomly chosen pavement images data. While the traditional Canny edge detection method had provided a relatively simple but precise methodology for edge detection problem, the Gaussian filter that was used to smooth the images, however, had caused the loss of edge information during noise suppression. As such, the Mallat wavelet transform was therefore proposed to reinforce the weak edges of the input images and quadratically optimising the genetic algorithm to obtain a suitable threshold in self-adapting standard when performing the Canny algorithm steps. As a result, this newly improved Canny model had met the needs for real-time road cracks detection and had compensated the disadvantages of a traditional Canny algorithm by effectively and rapidly identifying road cracks in a short amount of time.

As mentioned earlier, the Otsu method is generally used in the conventional Canny method to adaptively find the high and low threshold values. Much research has been done on the modification of the Canny method by using the Otsu method such as the fixed partitioning technique that was used for the global and local threshold analysis of the image. By using this approach, the image is divided into several equal portions, where the local histogram for each of the respective part is then calculated. One of the main advantages of using this method is that it provides an additional input to the histogram as a way of obtaining the spatial distribution of the image content [20]. This proposed method had used a comprehensive technique in generating edge images. [21] had discussed how the Salient Detection method can be utilised for crack detection. Visually, salient regions are more conspicuous because they are in contrast with the surroundings. Although the current methods had illustrated their efficacy for the detection of salient areas in the Berkeley database [22], they had demonstrated poor performance in terms of the continuity and completeness of the detected crack. In [15], since the modified Canny method had demonstrated effective detection within the Berkeley database, this algorithm was adopted for this study but with certain modifications.

This paper had proposed an algorithm for finding edge images within the CrackForest dataset [21] through the use of an adaptive threshold approach, which is based on a local value after the fixed partitioning of the image in five different levels. While the high threshold value (H_t) was obtained through the use of Otsu method, the low (L_t) threshold value on the other hand, was determined by halving the high threshold value. Contrary to [14], the three statistical measures, namely the minimum, maximum, and mean values from all the L_t and H_t are generated. These are the measurements from the best obtained edge images that had been compared with the ground truth images provided by the dataset. The outcomes from the experiment were then compared against the results obtained from the Canny method. Based on the comparison results, it was revealed that the proposed method had provided edge images with the best accuracy level. The following sections of this paper will provide a detailed discussion on the materials and methods used for the research, an explanation of the experimental and comparison results as well as the conclusion of the study conducted.

2. Materials and Methods

This paper had proposed a road crack detection algorithm that consisted of the following steps: image retrieval and pre-processing, road crack detection and finally, the analysis of the performance measurement shown in Figure 1.

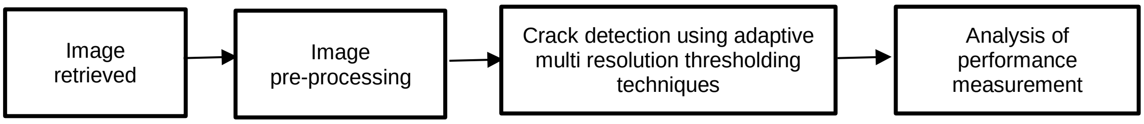


Figure 1. Flowchart of the proposed road crack detection algorithm

2.1 Image Pre-Processing

Here, the algorithm of the pre-processing phase in [23] is adopted to get a clearer crack edge of road images. At this stage, the image will undergo several manipulations such as pixel smoothing, normalisation, white line detection and saturation before the crack is detected. Figure 2 shows the original image and the pre-processed image with its grey level histogram.

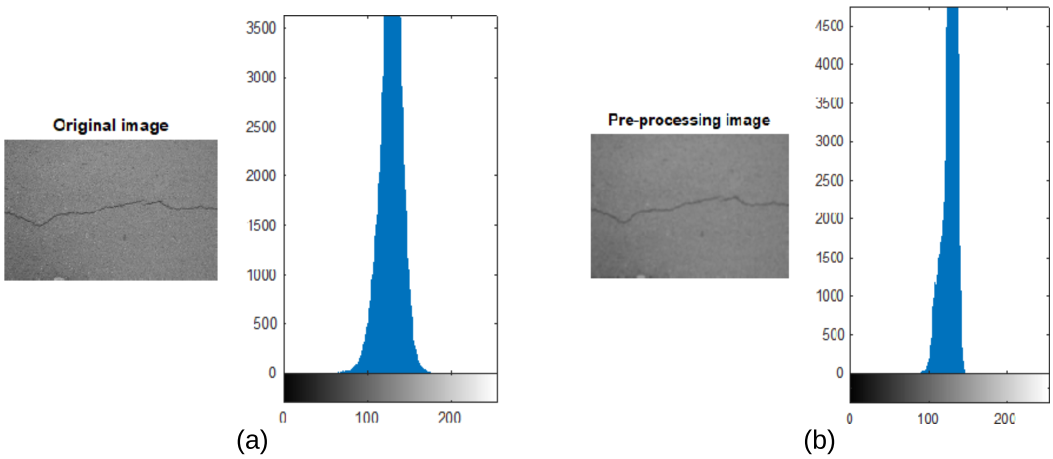


Figure 2. Sample of the (a) original image and (b) the smoothed image with its grey level histogram

2.2 Crack Detection Using Adaptive Multi Resolution Thresholding Techniques

After the original images had been retrieved in grey level image format and subjected to the pre-processing phase, the fixed partitioning is then carried out to separate the image into five different levels. While implementing the Canny edge detection [24], the Otsu method [9] is adopted in the selection of the threshold values. However, a few changes had to be made in order to obtain the best low threshold (L_t) and high threshold values (H_t) as shown in [14, 15] through the utilisation of different image resolutions. At this stage, the global and local spatial values will be selected from the variance values depicted in the 2x2 partition (CO2x2), 3x3 partition (CO3x3), 4x4 partition (CO4x4) and 5x5 partition (CO5x5). Next, the local threshold values for each of the partition are used to generate a global edge image shown in Figure 3. Unlike the previous studies, the global threshold values from CO2x2, CO3x3, CO4x4 and CO5x5 are then applied into the statistical measures to determine the portion that gives the most accurate minimum (min), maximum (max) and average (mean) values.

Let's assume the fixed partitioning for each of the resolution as such:

$$L_{1,1} \in \text{COG} \tag{1}$$

$$L_{2,1}, L_{2,2}, L_{2,3} \text{ and } L_{2,4} \in \text{CO2×2} \tag{2}$$

$$L_{3,1}, L_{3,2}, L_{3,3}, L_{3,4}, L_{3,5}, L_{3,6}, L_{3,7}, L_{3,8} \text{ and } L_{3,9} \in \text{CO3×3} \tag{3}$$

$$L_{4,1}, L_{4,2}, L_{4,3}, L_{4,4}, L_{4,5}, L_{4,6}, L_{4,7}, L_{4,8}, L_{4,9}, L_{4,10}, L_{4,11}, L_{4,12}, L_{4,13}, L_{4,14}, L_{4,15} \text{ and } L_{4,16} \in \text{CO4×4} \tag{4}$$

$$L_{5,1}, L_{5,2}, L_{5,3}, L_{5,4}, L_{5,5}, L_{5,6}, L_{5,7}, L_{5,8}, L_{5,9}, L_{5,10}, L_{5,11}, L_{5,12}, L_{5,13}, L_{5,14}, L_{5,15}, L_{5,16}, L_{5,17}, L_{5,18}, L_{5,19}, L_{5,20}, L_{5,21}, L_{5,22}, L_{5,23}, L_{5,24} \text{ and } L_{5,25} \in \text{CO5×5} \tag{5}$$

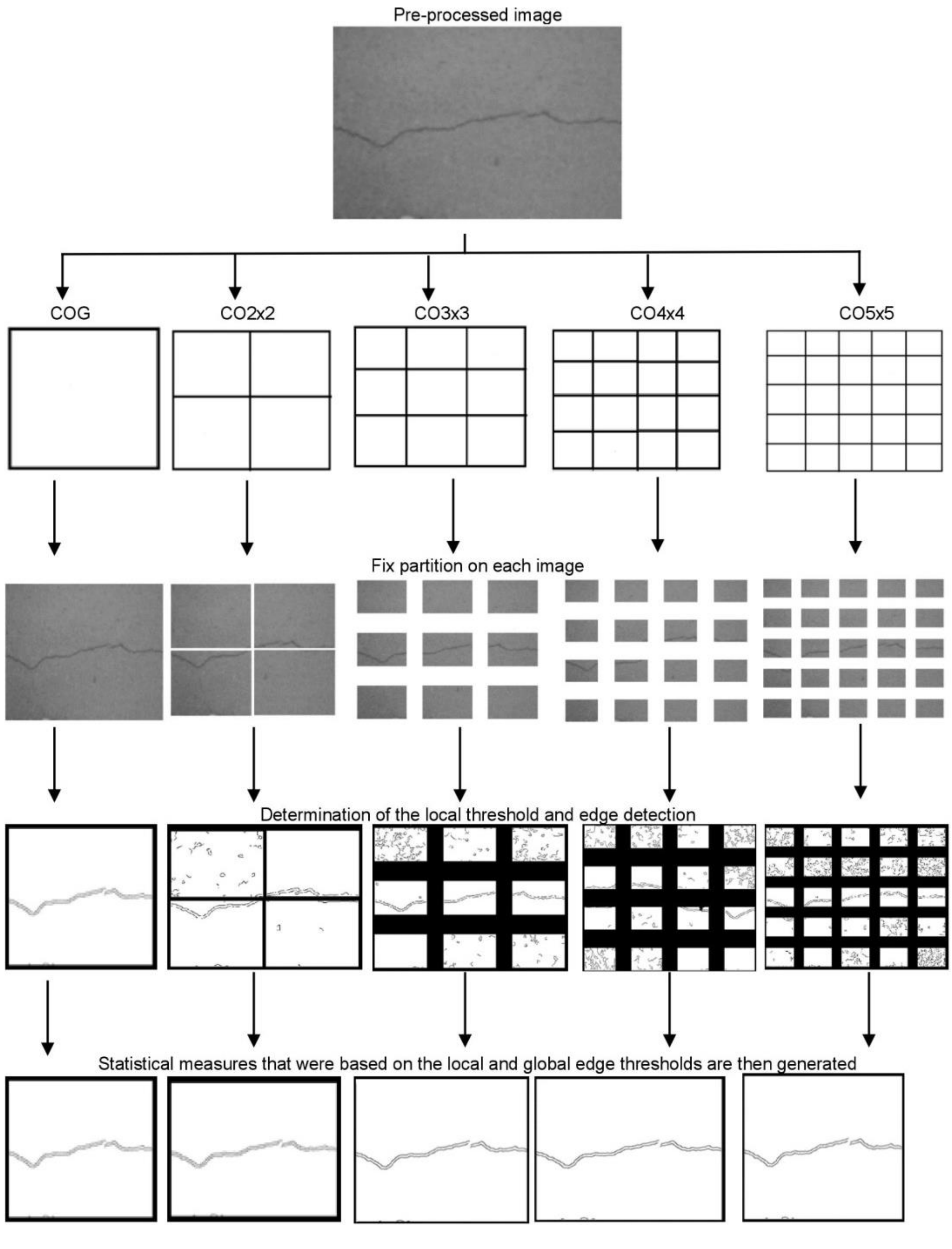


Figure 3. The process used in the adaptive multi-resolution thresholding technique for edge detection

here, each of the fixed partitioning is represented as $L_{i,j}$ with $i = \text{partition involved}$ and $j = 1, 2, \ldots, i^2$. The statistical measures for each of the resolution level at high (*RH_t*) and low threshold values (*RL_t)* for min, max and mean are defined as such:

$$\mathrm{RH_t} = \frac{1}{\mathrm{n}} \times \text{arg max}(\mathrm{H_t} \in \mathrm{L_{i,j}}) \text{ and } \mathrm{RL_t} = \frac{1}{\mathrm{n}} \times \text{arg max}(\mathrm{L_t} \in \mathrm{L_{i,j}}) \tag{6}$$

$$\mathrm{RH_t} = \frac{1}{\mathrm{n}} \times \text{arg min}(\mathrm{H_t} \in \mathrm{L_{i,j}}) \text{ and } \mathrm{RL_t} = \frac{1}{\mathrm{n}} \times \text{arg min}(\mathrm{L_t} \in \mathrm{L_{i,j}}) \tag{7}$$

$$\mathrm{RH_t} = \frac{1}{\mathrm{n}} \times \text{mean}(\mathrm{H_t} \in \mathrm{L_{i,j}}) \text{ and } \mathrm{RL_t} = \frac{1}{\mathrm{n}} \times \text{mean}(\mathrm{L_t} \in \mathrm{L_{i,j}}) \tag{8}$$

where weight $n = 1,2,3, \ldots ,10$.

2.3 Performance Measurement

At this stage, each of the obtained edge detection images will be compared against the ground truth image. The measurements as discussed in [25] are then used in the result's analysis:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive + False Negative}} \tag{9}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive + False Positive}} \tag{10}$$

$$\text{FMeasure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}} \tag{11}$$

3. Experiment and Results

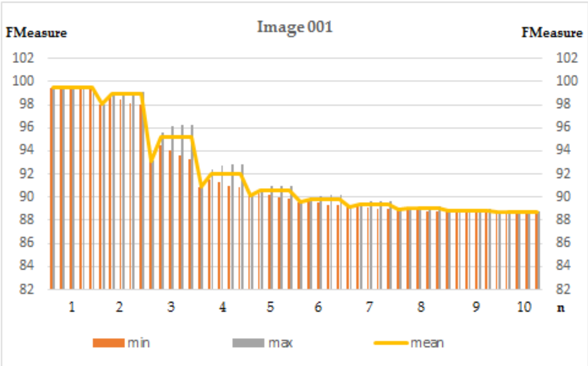
This study had utilized the provided CrackForest dataset [21] and ground truth edge images. The FMeasure results that are shown in Figure 4 had been obtained by using [14, 15] algorithms after the pre-processing phase [23]. There were fifty results obtained for each of the statistical measure, namely, min from (6), max from (7) and mean from (8), for each of the n used. As shown in Figure 4 (a)(i), Figure 4 (b)(i), Figure 4 (a)(ii) and Figure 4 (b)(ii), the corresponding CrackForest dataset results from $n = 1$ and the max value from (7) had yielded dominant values for each of the edge image generated.

Table 1 shows the FMeasure results of the 10 images used, where the value for CO5x5 was shown to be higher than the conventional Canny method and the other levels of resolution used. Although the edge image that was obtained for image 001 shown in Figure 5 had generated noise by using the Canny method, it did not display any visible differences from the edge images obtained in COG, CO2x2, CO3x3, CO4x4 and CO5x5. The average results from the dataset used had also shown the accurate edge image generated by CO5x5 shown in Table 2. In Figure 6, by comparing the edge image obtained from the Canny method, there is a clear indication that the image produced by the proposed method had been similar to the ground truth image. From all of the obtained images and results for road cracks, we have found (12) to provide the most favourable result:

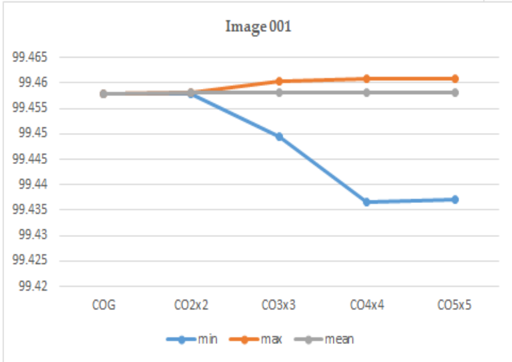
$$\mathrm{RH_t} = \text{arg max}(\mathrm{H_t} \in \mathrm{L_{i,j}}) \quad \text{and} \quad \mathrm{RL_t} = \text{arg max}(\mathrm{L_t} \in \mathrm{L_{i,j}}) \tag{12}$$

Table 1. F-Measure Max Results on 10 Images from Crackforest Dataset

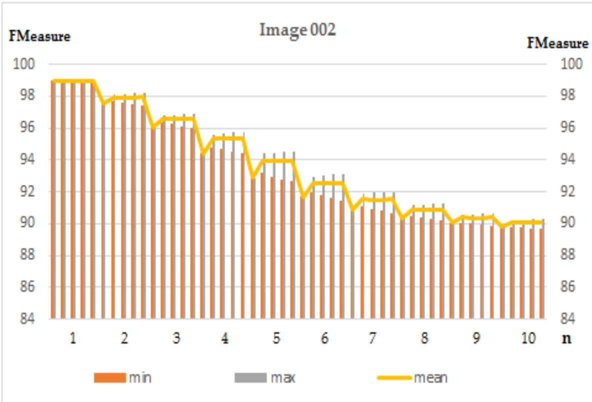
Method	Canny	COG	CO2x2	CO3x3	CO4x4	CO5x5
001	86.35352	99.45778	99.45812	99.46042	99.46075	9 .46075
002	88.56953	98.98639	99.00228	99.00448	99.01731	99.01731
003	88.4293	99.43131	99.44877	99.45173	99.45173	99.45173
004	89.52685	99.3298	99.3298	99.33016	99.34008	99.34008
005	89.55255	99.43277	99.44134	99.44233	99.44299	99.44299
006	86.88847	99.19375	99.30702	99.33511	99.30702	99.33511
007	88.23459	99.4437	99.46317	99.46415	99.46449	99.46449
008	89.09414	99.31765	99.31865	99.31898	99.31931	99.32427
009	87.2423	99.09312	99.1823	99.2214	99.22239	99.22239
010	87.91355	99.443	99.44465	99.44597	99.44597	99.46378



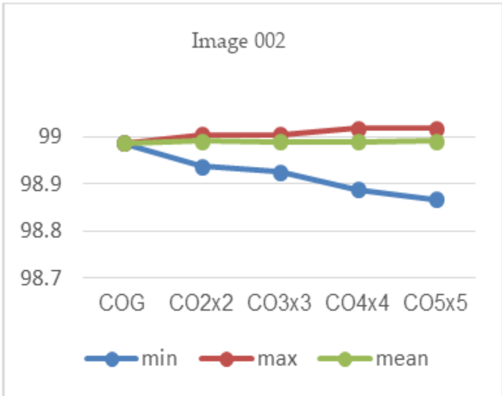
(a)(i)



(a)(ii)

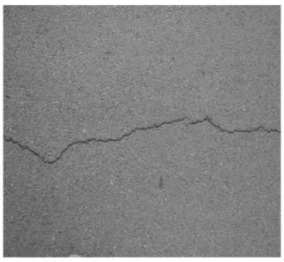


(b)(i)

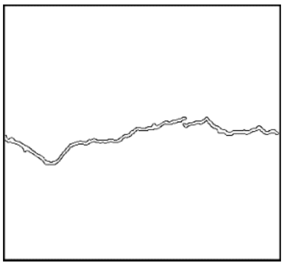


(b)(ii)

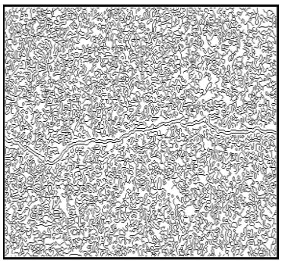
Figure 4. Results obtained on two images: (a) image 001 and (b) image 002, Results (i) for $n = 1,2,3 \ldots,10$ and (ii) for min, max and mean for $n = 1$ only



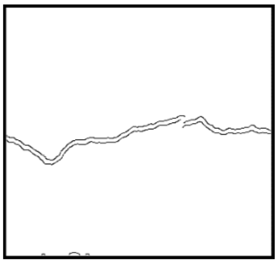
(a)



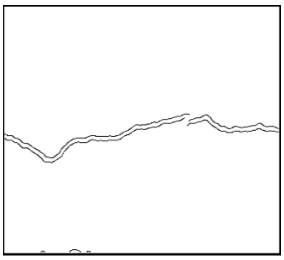
(b)



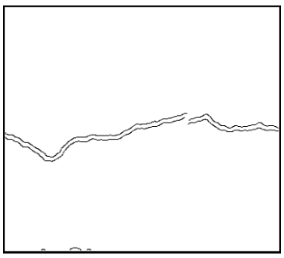
(c)



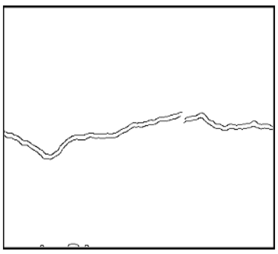
(d)



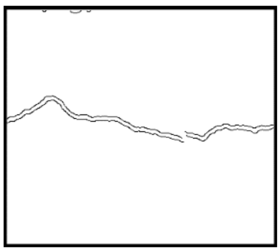
(e)



(f)



(g)



(h)

Figure 5. (a) Original image, (b) Ground truth image, which is followed by the edge image generated by (c) Canny method, (d) COG, (e) CO2x2, (f) CO3x3, (g) CO4x4 and (h) CO5x5

Table 2. The F-Measure Values that were Obtained from the Average Max

Method	Average
Canny	87.80299
COG	99.29134
CO2x2	99.31586
CO3x3	99.3238
CO4x4	99.32689
CO5x5	99.33232

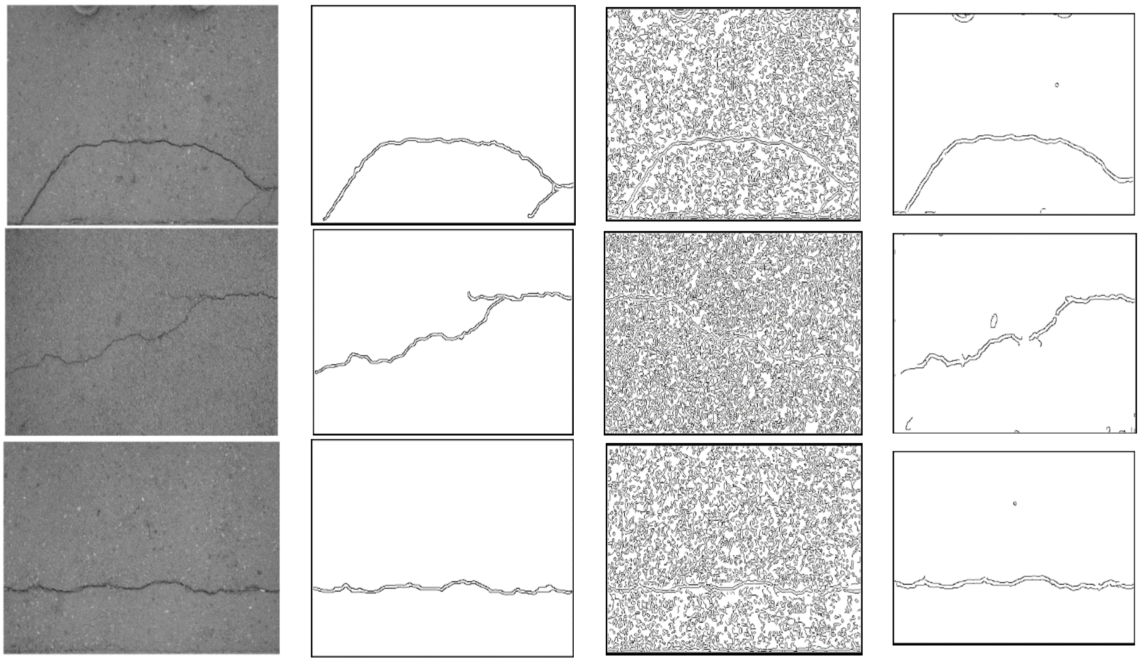


Figure 6. (a) Original image, (b) Ground truth image, which is followed by the edge image generated by (c) Canny method and (d) the proposed method

4. Conclusion

This study had proposed a new crack detection method through the application of Otsu-Canny Edge Detection Algorithm as well as incorporating calculations in the global and local threshold analysis of the fixed partitioned images at multiple resolution levels. To obtain the optimal threshold value, a sampling approach was utilised in the calculation of statistical measures, namely the minimum, maximum and mean values from the class variance of each partitioned image. The most accurate image is then selected based on the resolution level, statistical measure and the weight used.

Based on the results obtained from the CrackForest image datasets, the proposed method was found to perform better than the Canny method in terms of its edge image results and the F-Measure values. In this study, although the modified version of the Canny method had resulted in the detection of unwanted edges, it was still selected as the edge images had provided the most complete edge boundaries. The local spatial adaptive approach through the use of Otsu method was also proven to enhance the edges by eliminating the noise acquired from the conventional Canny method. The results had reflected more accurate edge images as it had taken in the foreground image of interest and ignored the background regions.

Acknowledgements

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