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Comparative Analysis of Filtering Techniques on Images of Building Structures with Cracks

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Abstract

The presence of noise causes image distortion which can be eliminated by image filtering. In recent years, it has been proven that noise has a significant effect on the accuracy of performance evaluation which has motivated many researchers in the field of image processing and computer vision to use various filtering techniques. This paper therefore looked into the three most used filters (Averaging, Median and Wiener filters) by researchers in this field so as to have a comprehensive comparative analysis of the filters on images of building structures with cracks. These three different filters were applied on 100 images of building structure with cracks, after which thresholding operation was performed in order to segment the crack from the background image. The Area Under Curve (AUC) shows that the median filter outperformed the other filters. The median filter value is 0.77778, Averaging filter value is 0.77641 and Wiener filter value is 0.77503.

1.0 Introduction

The appearance and development of cracks on building structure surface are one of the earliest ways of degradation of structures which require prompt attention as regards maintenance, otherwise a continuous exposure will seriously affect the safe use of the structure and will lead to severe damage to the environment [1, 2]. Hence, crack inspection and detection should be done on a regular basis to ensure durability and safety of lives and properties [3]. Manual crack detection methods are carried out by experienced human inspectors who manually sketch crack patterns and note the conditions of the irregularities. However, manual detection methods are expensive and lacks objectivity in the quantitative analysis [2, 4]. An alternative to the manual crack detection is the automated crack detection that utilizes digital image processing techniques. Researchers have done a lot of research about crack detection using digital image processing techniques, such as in [1, 5, 6, 7], with promising results. In order to achieve a better result using digital image processing technique, there are various steps involved in the processing of the image before the final output is obtained. These steps include; image acquisition, image pre-processing, image segmentation and image analysis [8]. Segmentation plays an important role in image processing techniques [8] as it helps to identify the region of interest known as cracks in this research. Before image segmentation is done, image enhancement technique or filtering is first employed in order to achieve a better result during the segmentation of the image. Image filtering has been employed on crack images to enhance or give better performance evaluation regarding

the building structures. Researchers have addressed the noise in crack images using different filtering techniques to avoid an unreliable result such as in [2, 9, 10]. Some commonly used filtering techniques are Median filter, Wiener filter and Averaging filter. These filters have been analyzed and compared to give instances on how noise can be eliminated. Therefore, a properly selected filter with an image segmentation operation gives a better performance [8].
This paper is geared towards comparative analysis of filtering techniques on images of building structures with crack which would help to give researcher proper selection of filters to be used in the field of crack detection in building structures.

2. Methodology

2.1 Image Acquisition
Image acquisition is the problem domain in which data set to be processed are being collected. The dataset for this research work is obtained from Zhong Qu and contains 100 images of building cracks.

2.2 Conversion of Red, Green and Blue (RGB) Image to Grayscale Image
The acquired images of building structure with cracks were converted to grayscale by forming a weighted sum of the R, G, and B components [11].

$$\text{Grayscale} = 0.2989R + 0.5870G + 0.1140B \quad (1)$$

2.3 Image Filtering Technique Implementation
The three different filtering techniques were applied to the output of the converted images. In general, it is to convolve the original building structure image I(x,y) of size m x n with a mask to obtain an output building structure image O(x,y).
The Wiener filter is a linear filter. It is an adaptive low pass filter; it uses pixel wise adaption. Therefore, this technique is also called an adaptive filtering technique. The method used in this filter is based on the statistics estimated from a local neighbourhood of each pixel and defined in the Fourier Domain as [11]:

$$G(\mathrm{u,v}) = \frac{H^*(\mathrm{u,v})}{|H(\mathrm{u,v})|^2 + \frac{\mathrm{Pn(u,v)}}{\mathrm{Ps(u,v)}}} \quad (2)$$

where, H(u,v) is the degradation function, H*(u,v) is the Complex conjugate of degradation function, P_n(u,v) is the power spectral density of noise and P_s(u,v) is the power spectral density of un-degraded image.

The Median filter value is the middle or center pixel in an image when arranged in either ascending or descending order of magnitude [8]. The median filtering output is given as [8]:

$$O_m(x,y) = median\{I(x-i, y-j), i, j \in W\} \quad (3)$$

where *I(x,y)* is the original image at the location (x,y), x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, *W* is the mask, with *i* and *j* an element of *W*.

The Averaging (Mean) operates by moving through the image, pixel by pixel replacing each value with the average value of neigbhouring pixels, including itself [8]. It is mathematically represented as [8]:

$$O_a(x,y) = \frac{1}{M} \sum_{(i,j)\in W} I(x-i, y-j) \quad (4)$$

where, *M* is the total number of pixels in the neighbourhood *W*.

2.4 Image Segmentation of Building Structure with Crack

Image segmentation of building structure with crack is to segment the crack from the entire image in order to locate the boundaries of the cracks known as foreground or region of interest from the background image. In other to achieve this region of interest, thresholding technique is applied to the image. The thresholding technique segments an image based on the intensity of the pixels' value and produce a binary image from the gray level image [12]. The crack which is the region of interest is being represented by value one (1) which is the white colour and the background with value zero (0) which is the black colour of the segmented image. The thresholding segmentation technique is mathematically represented [8]:

$$S_{th}(x,y) = \begin{cases} 1 & if \quad O(x;y) \; > \; T \\ 0 & otherwise \end{cases} \tag{5}$$

where T is the threshold image, and O(x,y) is the output of the filtered image

2.5 Post Processing

The areas of the connected components were computed because of the noise in the binarized image. The connected component with the maximum area was considered as the foreground (crack).

2.6 Performance Evaluation

The thresholding-based segmentation technique is the simplest
and useful segmentation technique that segments an image
based on the intensity of the pixels value
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and useful segmentation technique that segments an image
based on the intensity of the pixels value
The performance evaluation is based on the following statistical criteria namely; Accuracy, Sensitivity, and Specificity [13]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{7}$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \tag{8}$$

where, TP is known as the True Positive and it is when the positive pixels in the ground truth image is correctly identified as positive pixels in the segmented image, TN is known as the True Negative and it is when the negative pixels in the ground truth image is correctly identified as negative pixels in the segmented image, FP is known as the False Positive and it is when negative pixels in the ground truth are observed as positive pixels in the segmented image and FN is known as False Negative and it is when the positive pixels in the ground truth are observed as negative pixels in the segmented image.

2.6.1 Receiver Operating Characteristic (ROC) Curve

ROC curve in machine learning is used in evaluating and comparing algorithms [14]. To compare the algorithms, a common method is to calculate the area under ROC curve, abbreviated as AUC. The value of AUC will always be between 0 and 1 [14]. The higher the AUC value, the better the performance of the model in distinguishing between positive and negative classes [14].

$$Sensitivity\ (True\ Positive\ Rate) = \frac{\text{Number of TP}}{\text{Number of TP +Number of FN}} \tag{9}$$

$$Specificity\ (False\ Positive\ Rate) = \frac{\text{Number of TN}}{\text{Number of TN +Number of FP}} \tag{10}$$

$$Specificity\ (False\ Positive\ Rate) = 1 - \text{Sensitivity} \tag{11}$$

3. Results and Discussion

3.1 Results

Table 1: Conversion of RGB Image to Grayscale Image

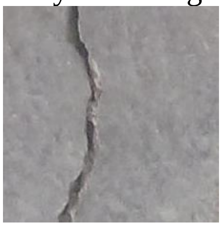
RGB Image	Grayscale Image
 a	 b

Table 1 shows the conversion of the RGB image to Grayscale image. The original image (Table 1a) is a gray colour (RGB) image that has three channels. It is converted to grayscale image that has a single channel (Table 1b).

Table 2: Quantitative result of the Wiener Filter on crack image

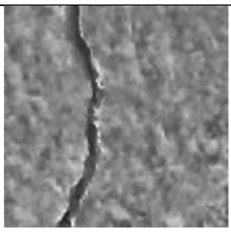
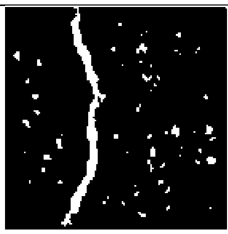
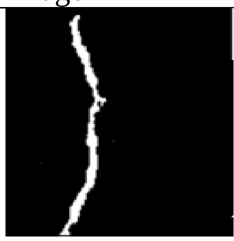
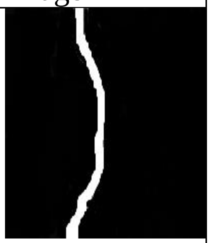
RGB Image	Wiener Filter Image	Segmented Image	Post Processed Image	Groundtruth Image
 a1	 b1	 c1	 d1	 e1

Table 3: Quantitative result of the Average Filter on crack image

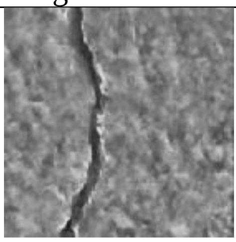
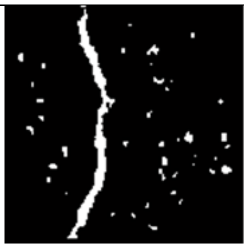
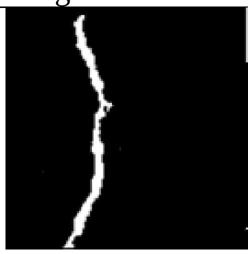
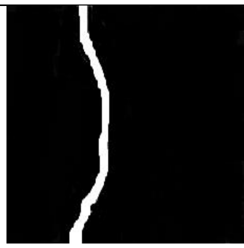
RGB Image	Average Filter Image	Segmented Image	Post Processed Image	Groundtruth Image
 a2	 b2	 c2	 d2	 e2

Table 4: Quantitative result of the Median Filter on crack image

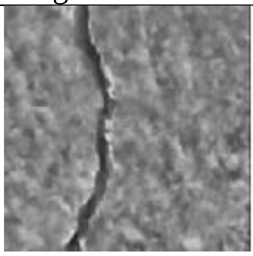
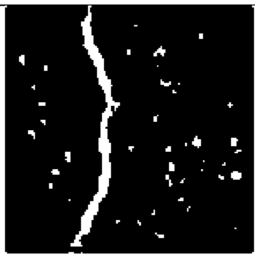
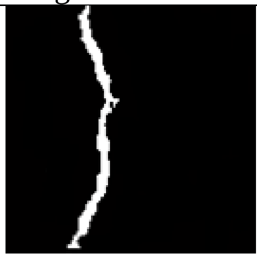
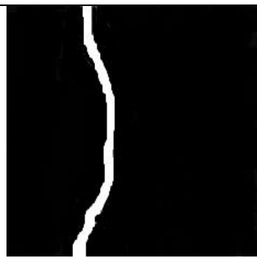
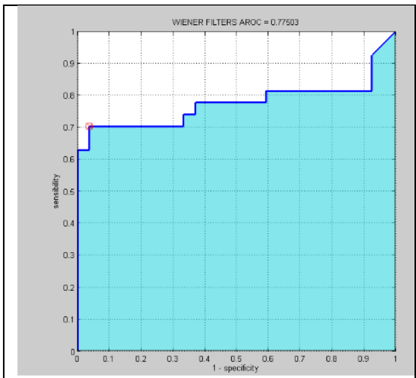
RGB Image	Median Filter Image	Segmented Image	Post Processed Image	Ground-truth Image
 a3	 b3	 c3	 d3	 e3

Table 2 shows the quantitative result of the Wiener filter on crack RGB image. Table 3 shows the quantitative result of the Averaging filter on crack RGB image. Table 4 shows the quantitative result of the Median filter on crack RGB image. Images a1, a2, and a3 are same images. Then, images b1, b2, and b3 are the images obtained after the application of the Wiener, Averaging and Median Filters respectively. c1 (Wiener output), c2 (Averaging output) and c3 (Median output) are the segmented results after thresholding the images b1, b2, b3 respectively. Images c1, c2 and c3 are binarized images with noise (the white dots) therefore, area of the connected components in c1, c2, c3 were computed to obtain the maximum area of the images d1, d2, d3 for Wiener, Averaging and Median filters respectively. Images d1, d2, and d3 are the images obtained after the post-processing stage. This is done in order to have a better image to use for comparison. Images e1, e2 and e3 are the ground truth images and are the same images. These ground truth images are used for comparison purpose.

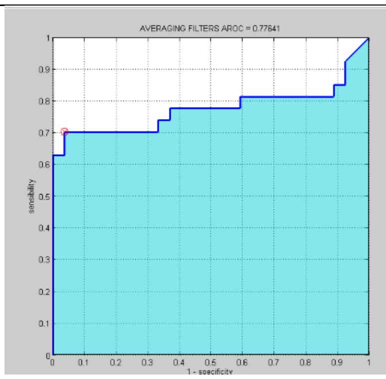
Table 5: Mean Metrics of Each Filter Performance on the 100 Crack Images

Filter Type	**Accuracy**	**Sensitivity**	**Specificity**
Wiener	0.638184	0.051838	0.74476
Averaging	0.638254	0.0517892	0.744858
Median	0.638254	0.0517892	0.744858

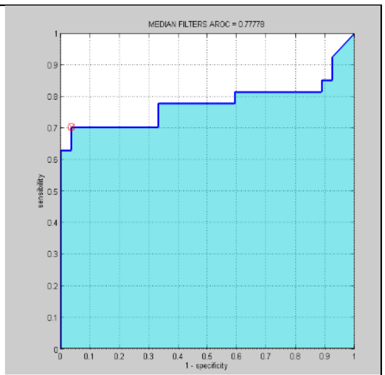
Table 5 shows the mean metrics of each filter performance on the 100 crack images. The statistical criteria (Accuracy, Sensitivity and Specificity) were computed for the 100 crack images for the three filters. It is observed from Table 4 that the accuracy value for Averaging (0.638254) and Median (0.638254) Filter are the same and outperformed the Wiener (0.638184) Filter. Furthermore, the sensitivity and specificity criteria were used to plot the ROC based on the AUC.



(a) Wiener Filter



(b) Averaging Filter



(c) Median Filter

(AUC = 0.77503)	(AUC = 0.77641)	(AUC = 0.77778)

Figure 3: ROC curve for the three filters

Figure 3 shows that ROC curve for the three filters. The AUC for the Wiener, Averaging and Median filters are 0.77503, 0.77641 and 0.77778 respectively. The AUC shows that the three filters have good measure of separability as their values tend to be close to 1. An excellent model has AUC near to the value 1, which means it has a good measure of separability. However, it also shows that Median filter outperforms the other two filters.

4. Conclusion

In this paper, the three most used filtering techniques were selected and discussed. Furthermore, a comparative analysis of the filtering techniques; wiener filter, mean filter and median filter was done on building crack images. The paper shows that the filters are closely related but median filter has higher denoising capabilities as its AUC is the closest to 1. The higher the AUC, the better the model.

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