Automatic Road Crack Segmentation Using Thresholding Methods

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Abstract—**The maintenance of roads is essential to ensure not only for transportation purposes but to safeguard against the unnecessary road accidents and fatalities. Roads is an essential element in the everyday lives of people as well as important to facilitate an economic growth and sustainability. Road cracks are one of the key indicators that show the degradation of road surfaces. Likewise, the inspection of road surfaces is to identify the degradation in the form of cracking and it takes a considerable amount of time and effort. Therefore, an automatic road crack segmentation using thresholding methods is proposed in this study to reduce the amount of time and effort for road inspection. Accordingly, ten road crack images were initially pre-processed followed by applying the normalisation techniques which is L1-Sqrt norm onto the images to reduce the variation of intensities that skewed to the right. The Otsu and Sauvola thresholding methods were adopted to binarize the images. The outcome of the experiments of the road crack images found out that the normalisation technique, L1-Sqrt norm helped to increase the performance of road crack segmentation using the Otsu and Sauvola methods with F-measures of 86.5287 and 98.7453 respectively compared to without using L1-Sqrt norm with F-measure 78.5465 for Otsu method and F-measure is 98.5446 for Sauvola method. The results further showed that the Sauvola method has outperformed the Otsu method in detecting road cracks.**

Keywords—**Road crack segmentation, Thresholding, Otsu method, Sauvola method, Normalisation.**

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I. INTRODUCTION

Machine vision technology (MVT) has rapidly grown over the past few years thanks to huge benefits it offers to the manufacturers, such as increased quality, productivity and flexibility. It is particularly useful in pavement, highway and transportation engineering, in making intelligent transportation systems more useful. MVT can importantly detect cracks on roads or pavement images so that perforated road problems can be detected at an early stage of deterioration.

Recent research has focused on crack detection, not only on pavements but in glass, ceramics, tiles and tunnels [1-7]. Some of the most commonly used edge detection methods have been the Canny method, Sobel method, Prewitt method and the Robert method. The modification of such methods as in [8], [9] have been undertaken in order to obtain accurate detection. Besides using edge detection methods, thresholding methods also play major role in crack detection. The most important phase in using these methods has been the pre-processing phase. The design of the pre-processing phase has been developed in such a way that the image noise, is reduced in order to enhance or sharpen the linear features of the raw images, which are usually associated with the crack features. Typically, the approach commences and consists of the pre-processing step coupled with the distress or road crack detection method. However, these types of systems still provide incorrect reports and results regarding on cracking at the boundaries which correspond to the non-crack elements like patches, joints, and road markings. Therefore, to prevent these false crack detection occurred, there is a needs to have a specific non-crack features stage which masks the portions of the images where the detection of non-crack features occur [10].

As mentioned earlier, roads has contribute to the development and the sustainability of the economy; and are likewise important towards the growth and the advancement of the community. Moreover, road transportation is frequently, if not regularly used as a means of transporting people, goods and other materials (i.e. for construction). Roads also enable access for people in order to socialite, travel to work and school, to visit hospitals, etc., and it make road networks crucial. Although, continuous use of roads have regretfully exposed road infrastructure to certain distresses and deterioration [11]. Cracks in pavement surfaces, loss of asset value, reduced or declining access to remote areas and poor quality of service are some examples of distresses. To help overcome and alleviate these problems, good road maintenance policies are needed, as these will help to provide sufficient structural maintenance, repair and rehabilitation of road infrastructure.

In order to maintain the condition of road surfaces, periodic assessment and inspection of road surfaces are manually performed. Roadwork's officers visually observe cracks along the road and mark the location of the cracks once they are found. The observation process is notoriously long, arduous, inaccurate and labour intensive [12]. Hence, this method of inspection is ineffective. Furthermore, it is mostly based on the judgment of certain officers, and accordingly, the different officers will often give different results [13]. Thus, the slow and inaccurate process of inspection needs to be replaced by employing an intelligent automated crack detection system that is fast and providing accurate crack analysis [14]. The system should also be able to measure the condition of road surfaces and facilitate the maintenance of the road network to avoid significant costs [13].

Automatic road crack segmentation is an extremely challenging problem as some of the problems are due to the existence of low contrast and light between the cracks and the surrounding pavement area. In homogeneity of intensity and the occurrence of shadows with similar intensity have been identified as the main problems in crack detection [15]. As a result, researchers have proposed different methods in the field of automated crack analysis. With the emergence of image processing techniques, the detection and recognition of road cracks have become increasingly more efficient. In 2009, Oliviera and Correia [11] proposed thresholding methods for road crack segmentation where they used two dynamic threshold values. The first value was used to identify dark pixels and the second value was applied onto the entropy block matrix. The classification system classified the images as to whether they contained horizontal, vertical, and miscellaneous or no cracks. Next, they extended their work [16] by including two separate stages where outstanding crack seeds were selected, followed by adopting an efficient segmentation method. This step minimize the detection of false positives. Then, every pixel was classified interactively either as a crack or non-crack and extending the seeds until the crack shape was identified entirely.

Another thresholding method used by [17] was based on the neighboring difference histogram method where they constructed an objective function used for maximizing the difference between the two classes. They also compared their work with leading-edge methods to justify their findings. Research conducted by [18] used topological properties to classify cracking types into line or alligator cracking. For line cracking, they were further classified into longitudinal or transverse cracking, according to the chain code of the cracking in the image.

Recent work carried out by [19] applied a method of Gabor filters as an invariant to rotation which could help to detect cracks in any direction. The parameters used in the work were optimized using the differential evolution method which helped to improve the accuracy of detection of 95.27%. Also, [14] proposed the CrackForest method that assimilates the complementary features from multiple levels. In this case, structured information based on crack patches was used providing several advantages towards crack detection. Using this method, integral channel features were introduced as crack tokens, and the random structured forest has used the structured tokens to predict patch cracks. Structured tokens are aggregated across the image and used as crack descriptors, classifying the cracks from noise.

Zhang et al. [20] presented an automatic crack detection method by classifying the crack for safety monitoring of a subway tunnel, using a distance histogram based shape descriptor for the feature extraction process. The histogram efficiently gave the descriptors of the difference of spatial shapes between the cracks and other objects. Notably, the work has been tested and proven effective for the Beijing Subway (Line 1). In the research undertaken by [15], a fully automatic crack detection system named CrackTree was proposed where it began with developing a geodesic shadow removal algorithm. Next, the probability map for crack detection was then built using tensor voting, and a graph model was generated from a set of crack seeds. To identify desirable cracks, the researchers conducted recursive tree edge pruning.

Accordingly, the objective of this study is to have a automatic segment road cracks by using thresholding methods. Pre-processing of images is first carried out showing a significant amount of noise. Then, using the normalisation method, the L1-Sqrt norm is used to reduce the variation of intensity values that exist due to the occurrence of shadows. The thresholding methods used to binarize the final image were the Otsu [21] and Sauvola [22] methods.

The remainder of this paper is organised as follows: Section II describes the theoretical background of the methods used. Section III presents the experimental results which are followed by Section IV which discusses and concludes this paper.

II. THEORETICAL BACKGROUND

The experimental work commenced with the pre-processing steps beginning with median filtering, Gaussian filtering, adjusting intensities and image sharpening. Median filtering is performed where the value of each output pixel is the median value for a 3 3 neighborhood for a corresponding pixel in the input image. It is importantly used for reducing noise and keeping useful details in an image. Gaussian filtering is also used to remove noise and to blur the image by using a Gaussian kernel that is:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{x^2}{2\sigma^2}} \tag{1}$$

where σ is the standard deviation of the distribution.

Adjusting intensities are also used in the pre-processing step where new values of each pixel are generated. Finally, each image is been sharpened where it increases the contrast along the edges between the colours.

Next, normalisation techniques are used to reduce the variation of intensity values. L1-Sqrt norm is used as in [23] where;

$$L1 - Sqrt = \sqrt{v/(\|v\|_1 + \varepsilon} \text{ where } \|v\|_1 = \Sigma|x_n| \cdot \tag{2}$$

The normalisation techniques made the feature space narrower thereby eliminating the domination of certain values, and LI-Sqrt norm is used to reduce the values of intensities that are skewed to the right. Next, the Otsu [21] and Sauvola [22] methods are applied to the images.

A. Otsu method

The Otsu method is one of the global thresholding techniques which is considered to be one of the best threshold selection methods for general real-world images with regards to uniformity and shape measures [21]. Moreover, it is used between-class variance criteria to automate threshold selection. However, differences of class variances resulted in this method is not able to binarize an image efficiently. Therefore, the obtained threshold is biased towards the larger class variance component. The misclassification of pixels will also occur because pixels belong to a class will be classified into the other class having a smaller variance. Researchers in [24] have shown that by maximising between-class variance,

$$\sigma_B{}^2(t) = \max(\sigma_B{}^2(t)) \text{ for } 1 \le t \le L \tag{3}$$

and L = the number of grey levels; the optimal threshold t can be obtained.

Global thresholding techniques are very fast and provide good results. However, if the illumination of the image is not uniform, global thresholding techniques tend to add noise to the resultant images. Hence, in order to overcome the problems, local thresholding techniques are proposed.

B. Sauvola method

The Sauvola method is a local thresholding technique to estimate a different threshold for each pixel according to the greyscale information of the neighbouring pixels [22]. The threshold value $T(x, y)$ is computed using the following formula:

$$T = m\left(1 - k\left(1 - \frac{\sigma}{R}\right)\right) \quad (4)$$

where m is the mean value, R is the grey level, k is set to 0.2 as a default value and σ is the standard deviation.

The Sauvola method is used to solve the problem of black noise [25]. This depends on the value of the standard deviation in the range of grey level values used. However, the Sauvola method will fail to segment if small contrasting occurs between the foreground and background. Figure 1 shows the overall process of the experimental work.

III. EXPERIMENT AND RESULTS

A standard database by [14] was used in the experiment where 10 images were chosen from the database to test the experiment. To evaluate the performance of this work, several metrics were used, namely; Precision, Recall, F-measure and the Misclassification Error.

These metrics are calculated as follows:

$$\text{Precision (P)} = \frac{TP}{TP+FP} \quad (5)$$

$$\text{Recall (R)} = \frac{TP}{TP+FN} \quad (6)$$

$$\text{F- measure (FM)} = \frac{2 \times \text{recall} \times \text{precision}}{\text{recall} + \text{precision}} \times 100 \quad (7)$$

where TP = true positive, FP = false positive, FN = false negative. F-measure shows the percentage accuracy of the binary image.

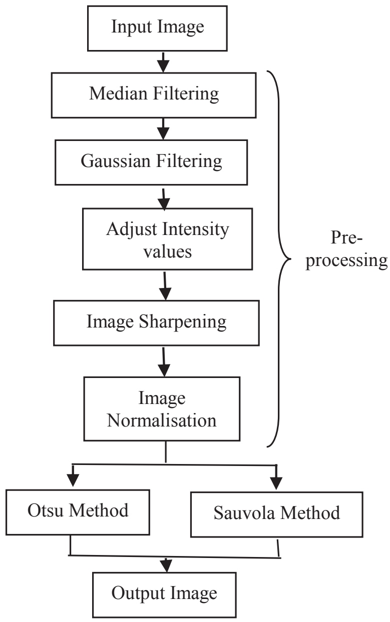


Fig. 1 Flow of the process

Another quality measurement of the segmentation result is the misclassification error (ME) which is formulated as shown below;

a. $$ME = 1 - ((|B_O \cap B_T| + |F_O \cap F_T|)/(|B_O| + |F_O|)) \quad (8)$$

| . | shows the cardinality of the set. The lower ME values indicate better quality of the obtained image and the range of ME is between 0 and 1. Table I displays the results obtained for the 10 images when employing the Otsu method and Table II shows the results obtained for the 10 images when using the Sauvola method.

TABLE I: RESULTS OF CRACK SEGMENTATION USING OTSU METHOD

Image	Otsu				L1-Sqrt + Otsu			
	Precision	**recall**	**F-measure**	**ME**	**Precision**	**recall**	**F-measure**	**ME**
001.jpg	0.9993	0.7304	84.3980	0.2668	0.9989	0.7951	88.5437	0.2033
002.jpg	0.9959	0.7624	86.3629	0.2329	0.9934	0.9063	94.7895	0.0964
003.jpg	0.9931	0.5065	67.0849	0.4891	0.9931	0.637	77.6379	0.3613
004.jpg	0.9991	0.7747	87.2703	0.2230	0.9982	0.9476	97.2276	0.0533
005.jpg	0.9998	0.6040	75.3068	0.3916	0.9993	0.6623	79.6640	0.3343
006.jpg	0.9979	0.5912	74.2512	0.4054	0.9969	0.6720	80.2846	0.3263
007.jpg	0.9994	0.6560	79.2107	0.3411	0.9991	0.7780	87.4812	0.2206
008.jpg	0.9987	0.6771	80.7066	0.3183	0.9981	0.8522	91.9431	0.1468
009.jpg	0.9992	0.5905	74.2373	0.4044	0.9976	0.7351	84.6481	0.2631
010.jpg	0.9994	0.6214	76.6363	0.3741	0.9989	0.7109	83.0679	0.2861
Average	0.9981	0.6514	78.5465	0.3446	**0.9973**	**0.7696**	**86.5287**	**0.2291**
Standard deviation	0.0021	0.0855	6.3164	0.0851	0.0022	0.1060	6.6471	0.1045

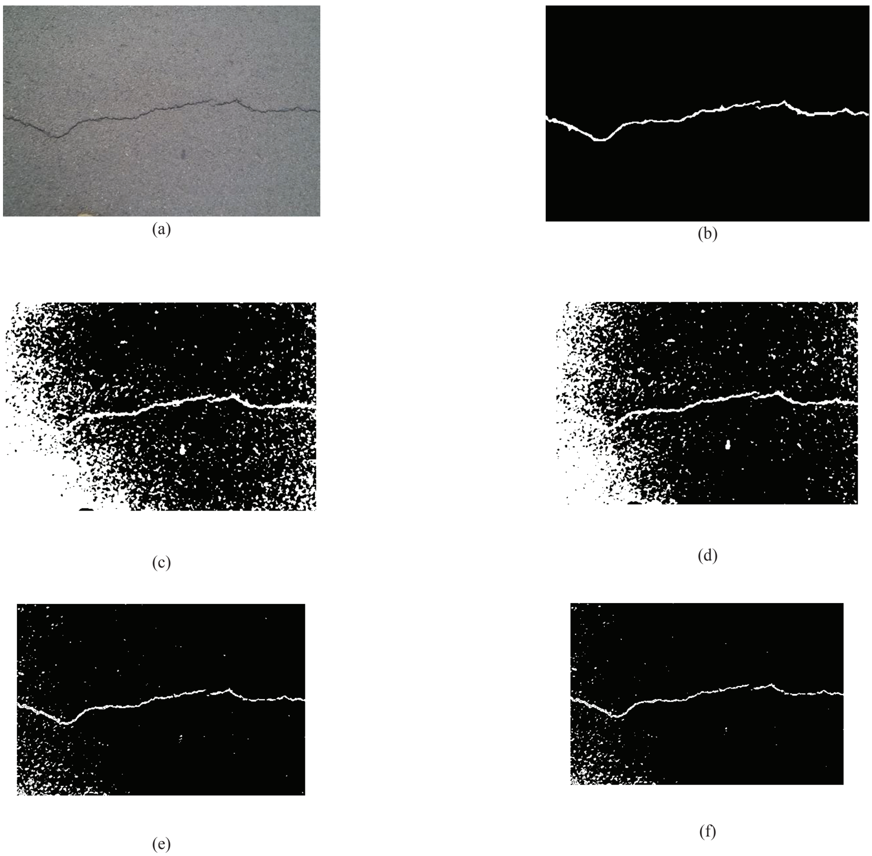
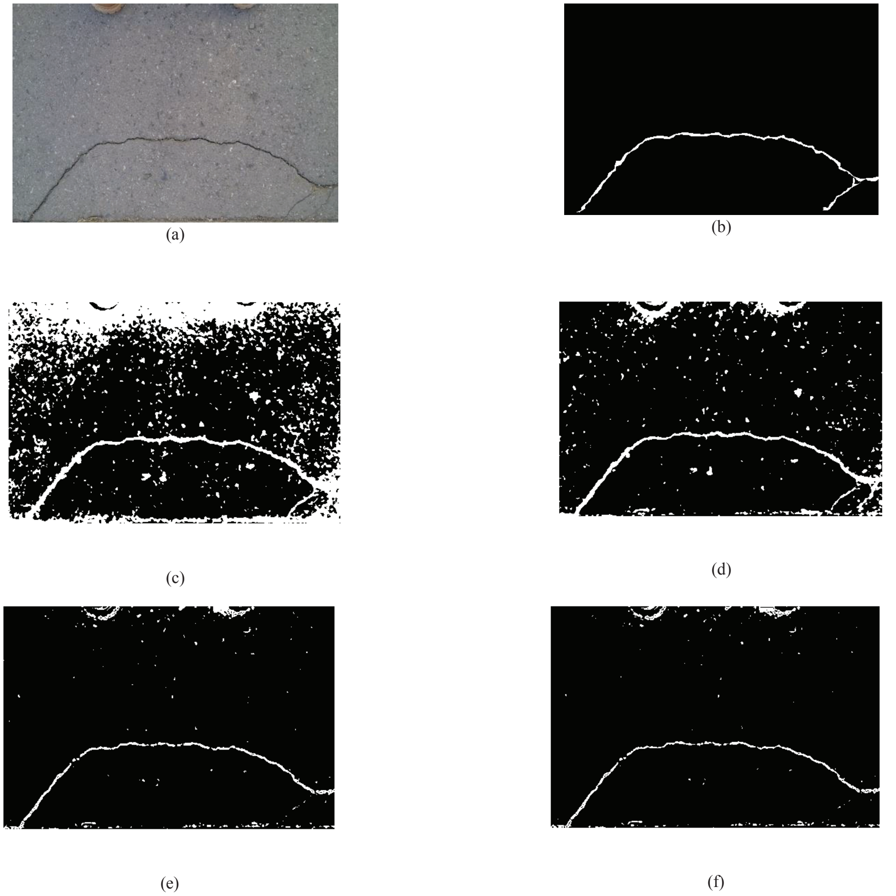


Fig. 2 Crack segmentation of image 001.jpg (a) Original image (b) Ground truth image (c) Otsu method (d) L1-Sqrt + Otsu method (e) Sauvola method (f) L1-Sqrt + Sauvola method.

TABLE II: RESULTS OF CRACK SEGMENTATION USING SAUVOLA METHOD

Image	Sauvola				L1-Sqrt + Sauvola			
	Precision	**Recall**	**F-measure**	**ME**	**Precision**	**Recall**	**F-measure**	**ME**
001.jpg	0.9965	0.9831	98.9840	0.0199	0.9961	0.9853	99.0705	0.0182
002.jpg	0.9824	0.9876	98.5036	0.0290	0.9811	0.9901	98.5658	0.0278
003.jpg	0.9883	0.9682	97.8181	0.0425	0.9876	0.9734	98.0510	0.0380
004.jpg	0.9950	0.9866	99.0817	0.0180	0.9944	0.9885	99.1494	0.0167
005.jpg	0.9967	0.9894	99.3100	0.0135	0.9964	0.9917	99.4052	0.0117
006.jpg	0.9948	0.9447	96.9138	0.0594	0.9946	0.9553	97.4565	0.0493
007.jpg	0.9963	0.9761	98.6096	0.0272	0.9953	0.9827	98.9015	0.0216
008.jpg	0.9932	0.9881	99.0677	0.0182	0.9924	0.9908	99.1667	0.0163
009.jpg	0.9934	0.9682	98.0684	0.0376	0.9931	0.9755	98.4256	0.0307
010.jpg	0.9961	0.9856	99.0891	0.0178	0.9961	0.9891	99.2615	0.0145
Average	0.9932	0.9777	98.5446	0.0283	**0.9927**	**0.9822**	**98.7453**	**0.0244**
Standard deviation	0.0045	0.0140	0.7496	0.0143	0.0048	0.0114	0.6191	0.0119



(a) (b) (c) (d) (e) (f)

Fig. 3 Crack segmentation of image 004.jpg (a) Original image (b) Ground truth image (c) Otsu method (d) L1-Sqrt + Otsu method (e) Sauvola method (f) L1-Sqrt + Sauvola method.

From observing Table I, it can be seen that by using the Otsu method with the normalisation technique, L1-Sqrt norm, the results are better in recall, F-measure and misclassification error that are 0.7696, 86.5287 and 0.229, respectively. The results are being compared to using only the Otsu method with recall is recall is 0.6514, F-measure is 78.5465 and misclassification error is 0.3446. This is also supported as shown in Table II, where the results using the Sauvola method with L1-Sqrt norm are better with recall is 0.9822, F-measure is 98.7453 and misclassification error is 0.0244 compared to using only the Sauvola method with recall is 0.9777, F-measure is 98.5446 and misclassification error is 0.0283. In this case, L1-Sqrt norm can help to reduce the variation of intensity values that skewed to the right. These results support the findings as in [23].

By comparing the Otsu and Sauvola methods for crack segmentation, it is evident that the Sauvola method gives better results. In this case, the value of recall, F-measure and misclassification error are 0.9822, 98.7453 and 0.0244 respectively when using L1-Sqrt norm with Sauvola method. These values are much higher compared to using L1-Sqrt norm with the Otsu method. The results of using Sauvola method only also can be seen higher with its F-measure is 98.5466 compared to using Otsu method only with its F-measure is 78.5465. Hence, it can be concluded that by using Sauvola method, crack segmentation can be done more effective compared to using Otsu method. This can also be seen in Fig. 2 and Fig. 3. In Fig. 2, a significant amount of noise can be seen in Fig. 2 (c) and Fig. 2 (d). While in Fig. 2(e) and Fig. 2(f), the noise becomes significantly less. The same results are also shown in Fig. 3. Although, in Fig. 3(e) and Fig. 3(f), it can be seen that the junction at the bottom right-hand corner cannot be detected which appears that over threshold occurred using the Sauvola method.

For standard deviation, the standard deviation for most of the measures can be seen using the Sauvola method, which is significantly less compared to using the Otsu method. Therefore, it shows that by using the Sauvola method, the results are more robust and stable.

IV. CONCLUSION

In conclusion, the results show that by using the Sauvola method, crack segmentation can be performed effectively and outperform the Otsu method because the Sauvola method is a local thresholding method. Moreover, it can overcome the problems that cannot be solved by global thresholding methods such as; varying levels of noise and multiple illumination levels that occur in the crack images. Some of the advantages of local thresholding are that they are reasonably easy to implement, and in most cases, they provide high performance. However, in some cases, some parameters need to be manually tuned to obtain more good results.

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