International Journal of Computer Techniques – Volume 4 Issue 2, Mar – Apr 2017

RESEARCH ARTICLE OPEN ACCESS

Classification and Detection of Highway Crack Using SBIR

Minu Inba Shanthini W.B[1], Vignesh. R[2], John Shajio.T[3] , Vijay Raj.D [4]

[1,2,3,4] (Information Technology, Loyola Institute of Technology, Chennai)

------------------------------------*************************-------------------------------

Abstract:

Crack detection in road pavements and objects has been a constant field of research in pavement management. Conventionally, humans were engaged to detect cracks in the pavements and they used to present report sheets based on their assessment. But, this process was a time consuming one and was costlier too. So, researchers were trying for minimizing the human involvement and at the same time detecting the cracks precisely. This gave way to numerous automated techniques for the detection of cracks. In the below paper, an automated technique to detect cracks in road pavements by means of digital image processing is proposed . In Some conditions such as complex texture, bad illumination, and non-uniform background in images may influence the accuracy of the automatic system. In this technique we propose a automated detection of crack area in the road pavement from the road surface video footage. First, the images required are processed by gray scale morphological processing. The result is received by filtering the images and then applying the edge detection operators. Based on applying shape based image retrieval algorithm, the particular defective area can be retrieved. These results are simulated through computer software tool using MATLAB VERSION 7.9.

Keywords— **ACD, SBIR, MP, LRIS**

------------------------------------*************************-------------------------------

I. INTRODUCTION

A crack is the separation of an object or material into more, pieces under the action of stress. Depending on the substance which is cracked, the crack decreases the strength of the materials in most cases, e.g. Constructing walls,roads, etc. At the starting , humans were used in detecting these cracks. However, detecting a crack manuallyis a very intricate and time consuming process. With the advance of science and technology, automated systems with intelligence were used to detect cracks instead of humans. By using the crack detected automated systems, the time consumed and the cost for detecting the cracks reduced and cracks are detected with more accuracy. The accurate detections of minute cracks has enabled for the better design for critical projects. These automated systems features overcomes manual errors providing better outcome comparatively. Numerous algorithms have been proposed and developed in the field of automated systems, but the proposed algorithm improves the efficiency in the detection of cracks than the previous developed techniques. Figure1 illustrates some road pavement image samples

(a) (b) (c)

Figure 1: pavement image samples: (a) longitudinal crack, (b)transversal crack, (c) alligator crack.

In this paper, after the problem position and a brief presentation of pavement surface images, we expose a new approach for automation of crack detection using a shape based image retrival image processing method. The results shown are analyzed. Finally, results and perspectives are given.

A.PROBLEM POSITION

Pavement crack detection is a difficult edge detection problem due to various pavement textures that can be encountered on pavement surface images. A way to reduce the texture effect is to use low spatial resolution images. But low resolution tends to erase thin crack signatures. So, they won't be detected by image segmentation. Consequently, we have chosen to work with images whose spatial resolution is between 1 and 2 mm per pixel. If we look forward to the final on road operational system, such spatial resolution seems to be realistic, due to available technologies on the market. Because of the road pavement image nature, crack detection methods, in literature, were based on "stable" characteristics of cracks. We can give the two following characteristics of cracks [1], [4]:

crack pixels are darker than neighbors.

crack is continuous or could be formed by various continuous segments. Its length is greater than its width and than granulate size.

Usually, crack pavement detection methods can be divided into four sequential stages: pre-processing, and segmentation, post-processing and classification. According to [5], in most of existing methods, classification step is trivial due to the easy task consisting in separating different crack types (longitudinal, transversal and alligator). Most of approaches, in literature, use brightness characteristic of crack for segmentation followed by a post processing step, which uses connectivity characteristic to connect crack segments and to eliminate noises.

In the next part, we propose a new method which takes into account simultaneously intensity and crack form features for segmentation step.

II. SYSTEM ARCHITECTURE

The proposed automatic method is a video based system can able to record the pavement up to 100 km/h. The recorded video is then inspected off-line at speed of 20 km/h. Main advantages of an automated system is faster , more reliable, more accurate. In this novel methodology propose a automated detection of crack area in the road pavement from the road surface video footage. First, images are processed by gray scale morphological processing. Subsequently, then the result is obtained by filtering the images (Gaussian filter) and then applying the edge detection operators (sobel).finally by applying shape based image retrieval algorithm, the particular defective area can be retrieved,

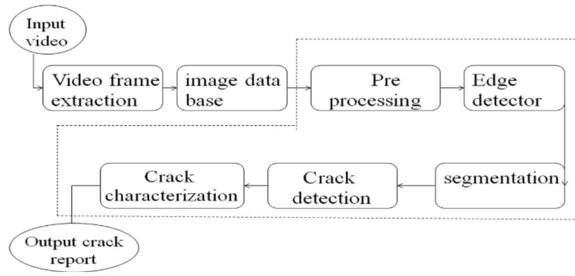


Figure 2:proposed solution for crack detection and classification

A. HIgh Speed Image Acquisition

Automatic systems for road pavement surface distress data acquisition and processing is an active research field. Despite the performance improvements of recent equipments, some problems still remain, for instance related with implementation costs, processing speed or accuracy . In a present Laser Road Imagery System (LRIS) is a capable of acquiring pavement surfaces images during road surveys at speeds that can surpass 100 km/h. The LRIS system is composed by two high speed/high resolution line scan cameras (each one acquiring half road lane images) in conjunction with high power lasers, see Figur1. The cameras and the projectors are aligned in the same plane in a symmetrically crossed optical configuration. This configuration increases the visibility of very small cracks since the incident illumination angle of the laser causes the projection of shadows in crack areas.

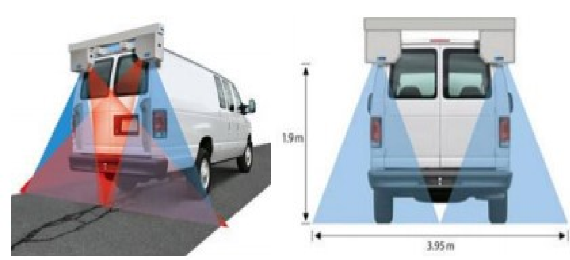


Figure 3: Schematics of LRIS system [7]

As an alternative, human observation is commonly used to gather information about pavement surface distresses, during road surveys made by inspectors. Usually, digital photos of defects are also taken during such surveys. Two samples of the human observation image database considered in the scope of this paper, are shown in Figure 4.

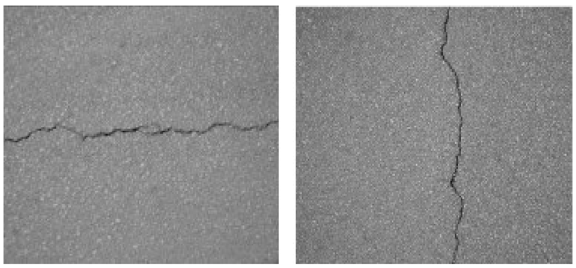


Figure 4: Two sample original images from the database acquired during a human observation survey

Pre-processing

First, a preprocessing step to correct the measured brightness levels along the images is presented. At the beginning of the process, the gain and the exposure time of every camera is adjusted individually to a 128 average grey level. Nevertheless, brightness measured along a given line is not constant due to the fact that the lighting and viewing conditions are not exactly the same at every point. Every time a new image is transferred, the average pixel value for each column is recalculated to adapt to the sheet reflection changes. An image acquired by LRIS and the corresponding preprocessed image by the algorithm developed can be seen in Figure 5

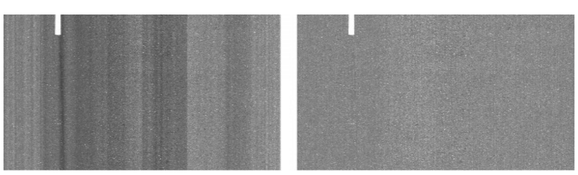


Figure 5: (a) Image acquired by LRIS. (b) Preprocessed image

B. *Edge Detection*

(i)Canny Method:

The Edges are areas in an image with sharp intensity gradients. The objective of edge detection algorithms is to seek out these points of rapid intensity changes. There are a number of edge detection algorithms, including the Sobel edge detector, the Laplacian of Gaussian method, the Canny edge detector, the fast Fourier transform, the zero-crossing method, the Prewitt method, and the Roberts method. Of all the edge detection algorithms, the Canny edge detector seems to be the most effective in detecting object edges, and the most widely used. The Canny edge detector detects edges by finding the pixel points where the gradient magnitude is a maximum in the direction of the gradient, that is, in the direction of maximum intensity change. However, the image is first smoothed with a Gaussian filter to remove noise, which is a convolution operation. The following steps are give details of edge detection methods.

(i) smooth image by convolving with an appropriate
Gaussian filter to reduce image details;
(ii) at each pixel, determine gradient magnitude and
gradient direction along maximum intensity change;
(iii) mark the pixel as an edge if the gradient magnitude
at the pixel is greater than the pixels at both sides of it
in the gradient direction;
(iv) remove the weak edges by hysteresis thresholding

(ii) Sobel method:

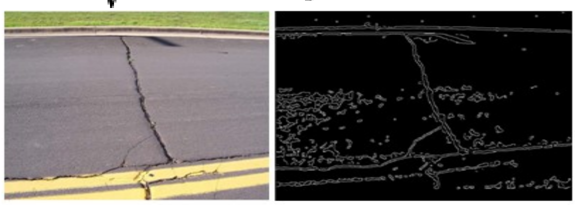
Similar to the Canny method, the Sobel edge detector is also a gradient-based method. It detects edges by searching for maxima and minima in the first derivative of the image. However, the Sobel method does not do any pre smoothening of the image; therefore, it is more susceptible to noise, but is computationally less expensive and faster. The Sobel edge detector performs a 2-D spatial gradient calculation on a gray-scale image; two 3×3 convolution masks are used to calculate gradients, one along the x-direction, and the other along the y-direction. The operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives - one for horizontal changes, and one for vertical.

$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * A \quad \text{and} \quad G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * A$$

(1)

Since the Sobel kernels can be decomposed as the products of an averaging and a differentiation kernel, they compute the gradient with smoothing. The resulting gradient approximations can be combined to give the gradient magnitude. (2)

$$\mathbf{G} = \sqrt{\mathbf{G}_x^{\,2} + \mathbf{G}_y^{\,2}}$$



(a) (b)

Figure 6: (a) original image. (b) Canny edge detected image

(a) (b)

Figure 7: (a) original image. (b) sobel edge detected image

C. Segmentation by thresholding

Thresholding is one of the simplest and computationally faster segmentation procedures, being selected to identify crack regions present in the pavement surface images taken during road surveys. A dynamic threshold value, Th1, unique for each image, is then computed according to the expression:

$$Th_1 = Th(Ot) - 0.5 \times std(\mathrm{Img}) \quad (3)$$

where Th(Ot) is the threshold value computed according to a modified Otsu method using only the intensity levels lower than the mean intensity level for each image. This provides the increased immunity to noise. std(Img) is the standard deviation of all image pixel intensities. The output of the thresholding operation assigns label ‘0’ to pixels whose value is above the threshold Th1, and ‘1’ to potential crack pixels, those with intensity below Th1.

.

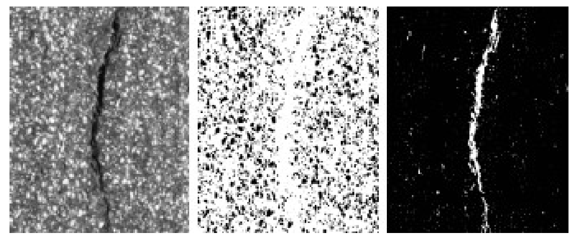


Figure 8:original image(left),after thresholding image(right)

D. Identify relevant connected components

Candidate crack pixels are then grouped using a connected components algorithm, to form a set of connected component objects(cco).The right image of Figure 7 reveals the presence of very small and ccos ,many of them not corresponding to real road cracks .In fact, only ccos respecting a set of conditions should be selected by the system as crack regions.

To be kept as a candidate crack region a cco should have (i)major than 90% of eccentricity for an ellipse fitted to it;(ii)width higher than or equal to 2 mm(computed dividing the number of pixels in cco by the number of pixels in the skeleton);(iii)major axis of a fitted ellipse longer than 25 pixels. Figure 9 presents sample results after removal of the less connected components.

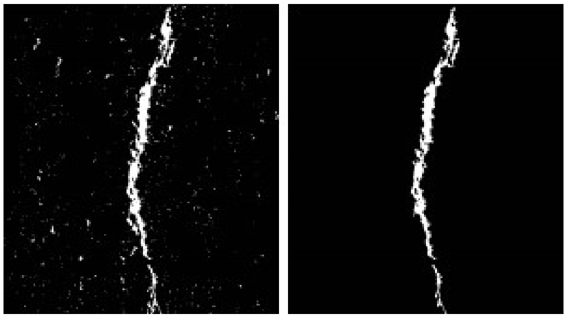


Figure 9: Removal of the less relevant connected components original image (left); processed image (right)

E. Crack classification

The pavement cracks are classified into transverse and longitudinal cracks. The segmentation technique, described in the previous section, provides two binary output images. Transverse cracks are highlighted in one of them, and longitudinal cracks in the other one. Each of these images is analysed independently. Adjacent pixels corresponding to cracks form groups and nearby groups are joined to form a single defect. This processing allows the number of cracks to be counted up, and the features of these cracks to be calculated. This process is applied to both binary images independently, so the cracks detected in every binary image belong to transverse o longitudinal cracks respectively.

III. EXPERIMENTAL RESULTS

The proposed automatic crack detection methodology has been tested on video captured during a real road pavement survey in india. Experimental results are presented using 20 images for which a ground truth is available, provided by a skilled inspector who has manually identified the existing crack regions. The Canny edge detector, and the Sobel method were able to detect cracks more easily on road surfaces, but with a little bit more difficulty for asphalt surfaces. However, the Canny method generally proved better on asphalt surfaces. It is also observed that despite the noisy output of the Sobel method, crack edges could be detected on closer examination as may be seen in Figures 5 and 6. For images with no cracks. the Sobel method still suffers from the effects of noise when the images have lots of irregularities present, as is the case for asphalt concrete surfaces. For images with less irregularities, such as the road surfaces, crack detection is more effective, and easily comparable to results from the Canny method; for road surfaces with no cracks, the Sobel method gives outputs with less noise, which is better. Overall, the Canny edge detector performed better than the Sobel method for asphalt surfaces, and slightly better for road surfaces. The ground truth information is used to evaluate the system performance (see Table 1), by computing a overall error-rate (classification error for the detection of regions with and without crack pixels), a crack error-rate (1 minus the Recall value), Precision (pr), Recall (re) and a Performance Criterion (PC) metric, reflecting the overall classifier performance:

$$pr = \frac{\text{Number of regions correctly classified as cracks}}{\text{Total number of crack regions detected}}.$$

$$re = \frac{\text{Number of regions correctly classified as cracks}}{\text{Total number of crack regions (ground truth)}}.$$

$$\mathrm{PC} = \frac{2 \times pr \times re}{pr + re}.$$

The evaluation results are show that the proposed methodology achieves better Precision results than the technique reported in existing methodologies. Also the overall system perform (PC) is better, using the proposed methodology (89% and 95% against 60.5% and 94.7% for comparing previous results, respectively). In terms of Recall (viewed as the most important metric for this type of application, where missing crack areas must be more penalized), the proposed methodology achieves a significantly better value for crack images (94.8% against 61.7%). Although the results for existing methodology are not better than those described (95.6% against 97.0%), the gain in system robustness leads to the conclusion that the proposed methodology's global performance is quite good. In terms of crack classification, 100% recall and precision were obtained for all classes of detected cracks, which reveals a very good overall system performance.

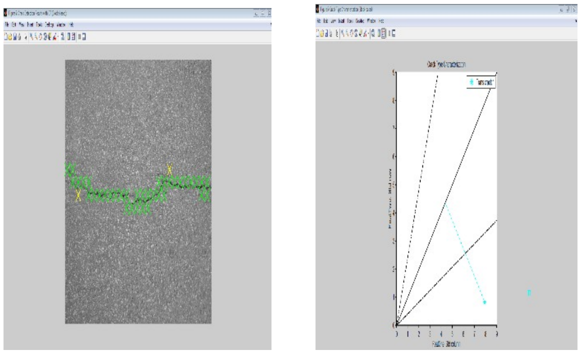


Figure 10: automatic crack detection result: (a) crack detection (c) crack characterization.

Moreover, the proposed methodology presents faster processing times, when compared to those reported in [10]. Using the same hardware and software platforms, u the proposed system takes 5 seconds/image against the 31 seconds reported in [10].

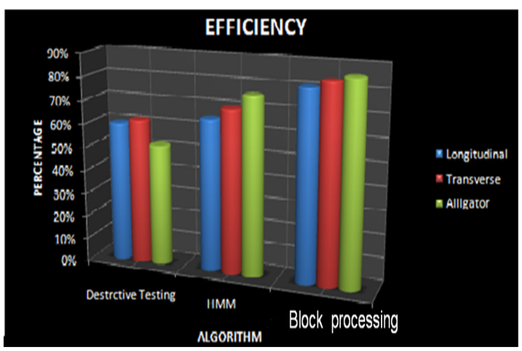


Figure 11: Comparison Result Chart

IV. CONCLUSION AND FUTURE WORK

In this paper a simple unsupervised system for crack detection and classification into several classes is proposed. Sample videos were taken from various places of India and the cracks were detected. This method displays promising result of detecting cracks in every feasible direction. The end result of the system was accomplished by integrating shape based image retrieval algorithm. This algorithm process the images in sequential manner and provide sequence of images like binary image, filtered image and cracks in image. The system achieves distress quantification more effectively when compared to the traditional methods. Techniques to determine the depth and intensity of the cracks using soft computing methods will also be proposed in the future. Also in future development will consider the usage of additional filtering techniques to further reduce the variance of pixel intensities in road surveys image databases..

REFERENCES

[1] F. Liu, G. Xu, Y. Yang, X. Niu, and Y. Pan, "Novel approach to pavement cracking automatic detection based on segment extending.inProc. IEEE Int. Symp. KAM, Wuhan, China, 2008, pp. 610–614 .

[2] A. Ayenu-Prah and N. Attoh-Okine, "Evaluating pavement cracks with bidimensional empirical mode decomposition,"EURASIP J. Adv. Signal Process., vol. 2008, no. 1, pp. 861701-1–861701-7, 2008.

[3] Q. Li and X. Liu, "Novel approach to pavement image segmentation based on neigbhboring difference histogram method," inProc. IEEE CISP,Sanya, China, 2008, pp. 792–796.

[4] Y. Sun, E. Salari, and E. Chou, "Automated pavement distress detectionusing advanced image processing techniques," inProc. IEEE Int. Conf.Electro/Inf. Technol., Windsor, ON, Canada, 2009, pp. 373–377

[5] C. Ma, W. Wang, C. Zhao, F. Di, and Z. Zhu, "Pavement cracks detectionbased on FDWT," inProc. IEEE Int. Conf. CiSE, Wuhan, China, 2009,pp. 1–4.

[6] T. Nguyen, M. Avila, and B. Stephane, "Automatic detection and classification of defect on road pavement using anisotropy measure," inProc.17th EUSIPCO, Glasgow, U.K., 2009, pp. 617–621

[7] Laser Road Imaging System (LRIS), INO, Quebec City, QC,Canada,Jan.2012.[Online].Available:http://www.ino.ca/enca/achievements/description/project-p/laser-road imaging.html

[8] Y. Huang and Y. Tsai, "Enhanced pavement distress segmentation algorithm using dynamic programming and connected component analysis,"inProc. 90th Meeting Transp.Res.Board,2011

[9] R. Gonzales and R. Woods, Digital Image Processing 3th edition, Pearson International Edition, USA,2008.

[10] H. Oliveira and P. L. Correia, "Supervised Strategies for Crack Detection in Images of Road Pavement Flexible Surfaces", Proc. 16th European Signal Processing Conference (EUSIPCO), Lausanne, Switzerland,25-29,2008.

[11] Henrique Oliveira, Paulo Lobato Correia, "Automatic Road Crack Detectionand Characterization inProc. IEEEtransc. on intelligent transportation system, pp.155–168,feb2013.

[12] P.Ekdahl,Routine Measurements of Pavement Surface Cracks,RamböllRST,Malmo,Sweden.[Online].Available:http://carbon.videolectures.net/2008/contrib/surf08_portoroz/ekdahl_rmopsc/surf08_ekdahl_rmopsc_01.pdf.

[13] C. Rasse, V. Leemans, M.-F. Destains, J.-C. Verbrugge, Application of image analysis to the identification and rating of road surface distress, Bearing Capacity of Roads, Railways and Airfields, Correia & Branco 2002, 61–68.

[14] H. D. Cheng and M. Miyojim, "Automatic Pavement Distress Detection System", Journal of Information Sciences 108, ELSEVIER,pp.219-240,1998.