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## COMPUTERIZED HIGHWAY DEFECTS RECOGNITION AND CLASSIFICATION SYSTEM

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### Abstract

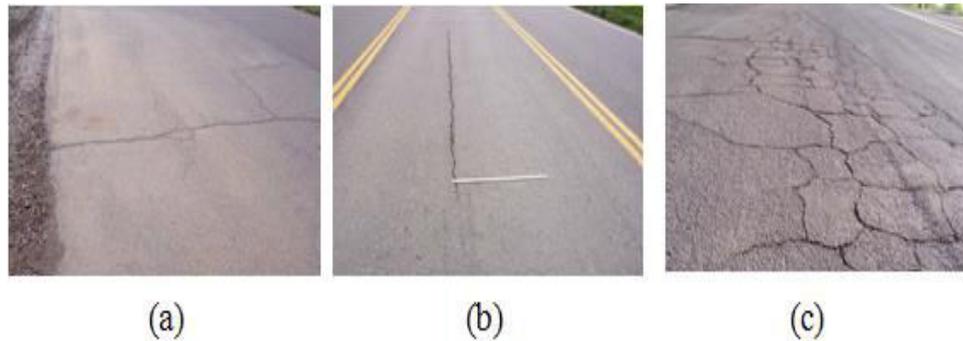
Crack detection in road pavements and objects has been a constant field of research in pavement management. Conventionally, humans were engaged to detect cracks in the pavements and they used to present report sheets based on their assessment. But, this process was a time consuming one and was costlier 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 this paper, an automated technique to detect cracks in road pavements by means of digital image processing is proposed. Some conditions such as complex texture, bad illumination, and non-uniform background in images may influence the accuracy of the automatic system. In this novel methodology propose a automated detection of crack area in the road pavement from the road surface video footage. First, the images are processed by gray scale morphological processing. Subsequently, then the result is obtained by filtering the images and then applying the edge detection operators. Finally by applying shape based image retrieval algorithm, the particular defective area can be retrieved. These are simulated through computer software tool using MATLAB VERSION 7.9.

**Keywords:** Automated Crack Detection, shape based image retrieval, morphological processing, road surface video footage.

### I. Introduction

A crack is that the separation of Associate in Nursing object or material into a pair of, or more, things beneath the action of stress. depending on the substance that's cracked, the crack reduces the strength of the materials in most cases, e.g. building walls,roads, etc. At the beginning, humans were used in detection these cracks. However, detection a crack manually is a awfully tangled and time intense methodology. With the advance of science and

technology, automatic systems with intelligence were accustomed observe cracks instead of humans. By practice the automated systems, the time consumed and so worth for detection the cracks reduced and cracks unit detected with plenty of accuracy. The right detections of minute cracks has enabled for the upper vogue for very important comes. These automatic systems choices overcomes manual errors providing higher outcome comparatively. varied algorithms are projected and developed at intervals the sector of automatic systems, but the projected rule improves the efficiency at intervals the detection of cracks than the previous developed techniques. Figure1 illustrates some road pavement image samples



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

During this paper, when the matter position and a quick presentation of pavement surface pictures, we tend to expose a brand new approach for automation of crack detection employing a form primarily based image retrieval image process methodology. Some results are shown and analyzed. Finally, conclusion and views are given.

## II. Problem Position

Pavement crack detection may be a troublesome edge detection downside attributable to varied pavement textures which will be encountered on pavement surface pictures. A way to reduce the texture impact is to use low abstraction resolution pictures. But low resolution tends to erase skinny crack signatures. So, they won't be detected by image segmentation. Consequently, we have chosen to figure with pictures whose abstraction resolution is between 1 and 2 mm per pixel. If we glance forward to the ultimate on road operational system, such abstraction resolution looks to be realistic, due to accessible technologies on the market. Due to the road pavement image nature, crack detection strategies, in literature, were supported "stable" characteristics of cracks. We will provide the two following characteristics of cracks [1], [4]: Brightness: crack pixels are darker than their neighbors.

-Form: crack is continuous or may be fashioned by varied continuous segments. Its length is bigger than its dimension and then granulate size. Usually, crack pavement detection strategies can be divided into four ordered stages: pre-processing, segmentation, post-processing and classification.

Consistent with [5], in most of existing strategies, classification step is trivial attributable to the simple task consisting in separating completely different crack sorts (longitudinal, crosswise and alligator). Most of approaches, in literature, use brightness characteristic of crack for segmentation followed by a post process step that uses property characteristic to attach crack segments and to eliminate noises.

In the next half, we tend to new methodology that takes into account at the same time intensity and crack type options for segmentation step.

### III. System Architecture

The projected automatic methodology may be a video primarily based system will able to record the pavement up to 100 km/h. The recorded video is then inspected off-line at speed of twenty km/h. Main benefits of an automatic system is quicker, a lot of reliable, a lot of correct. During this novel methodology propose a automatic detection of crack space within the road pavements from the paved surface video footage. First, the photographs are processed by grey scale morphological process. After, then the result obtained by filtering the photographs (Gaussian filter) so applying the sting detection operators (sobel). Finally by applying form primarily based image retrieval rule, the actual defective space is retrieved,

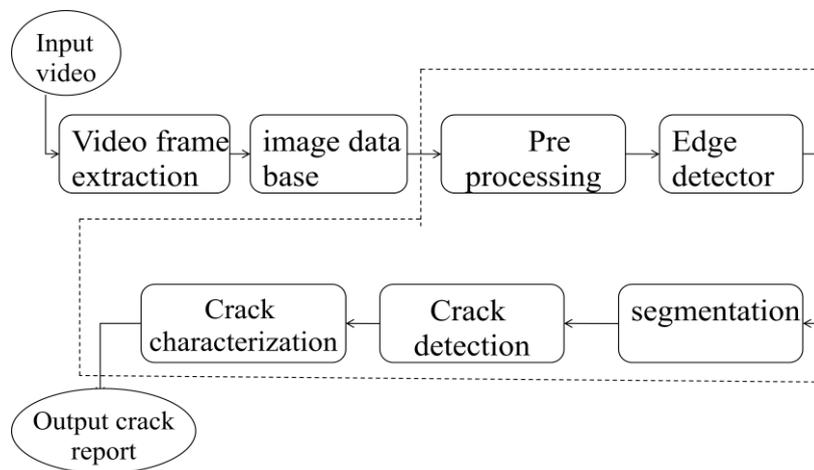
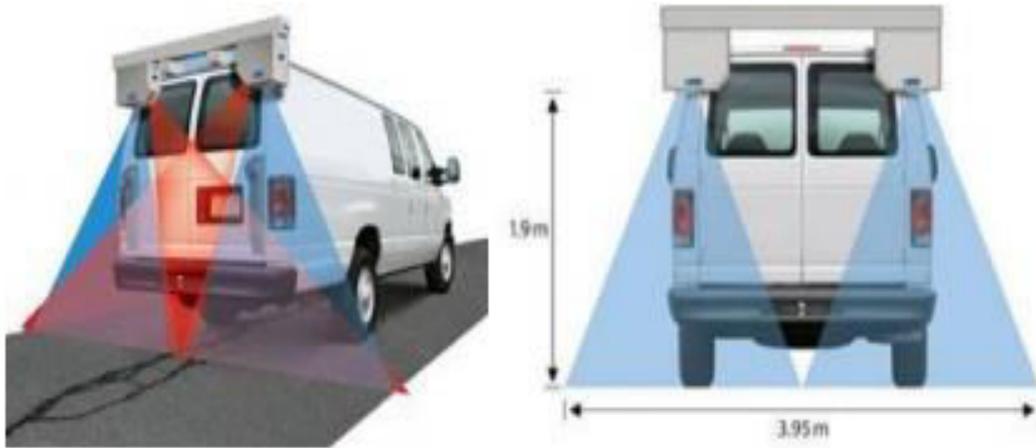


Figure 2:proposed answer for crack detection and classification.

#### A. High Speed Image Acquisition

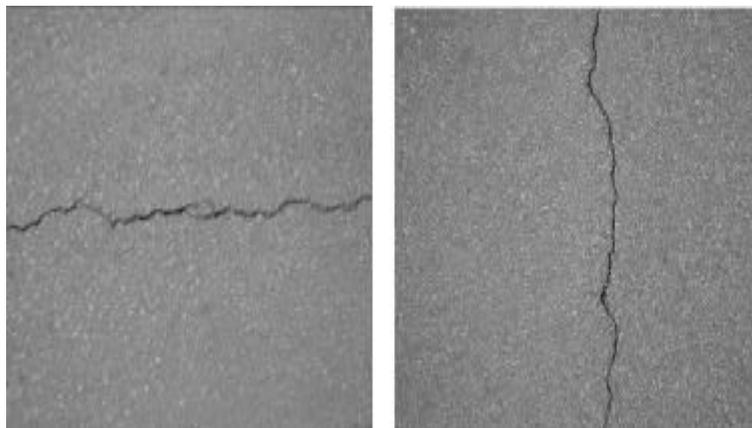
Automatic systems for road pavement surface distress information acquisition and process is an active analysis field. Despite the performance enhancements of recent equipments, some issues still stay, as an example connected with implementation prices, process speed or accuracy . In an exceedingly gift laser road device imagination System (LRIS) may be a capable of exploit pavement surfaces pictures throughout road surveys at speeds which will surpass one hundred km/h. The LRIS system is consists by 2 high speed/high resolution line scan cameras (each

one exploit [\*fr1] road lane images) in conjunction with high power lasers, see Figur1. The cameras and therefore the projectors are aligned within the same plane in an exceedingly symmetrically crossed optical configuration. This configuration will increase the visibility of terribly tiny cracks since the incident illumination angle of the optical device causes the projection of shadows in crack areas.



**Figure 3: Schematics of LRIS system.**

As an various, human observation is usually used to assemble data concerning pavement surface distresses, during road surveys created by inspectors. Usually, digital photos of defects are taken throughout such surveys. 2 samples of the human observation image information though-about within the scope of this paper, are shown in Figure four.

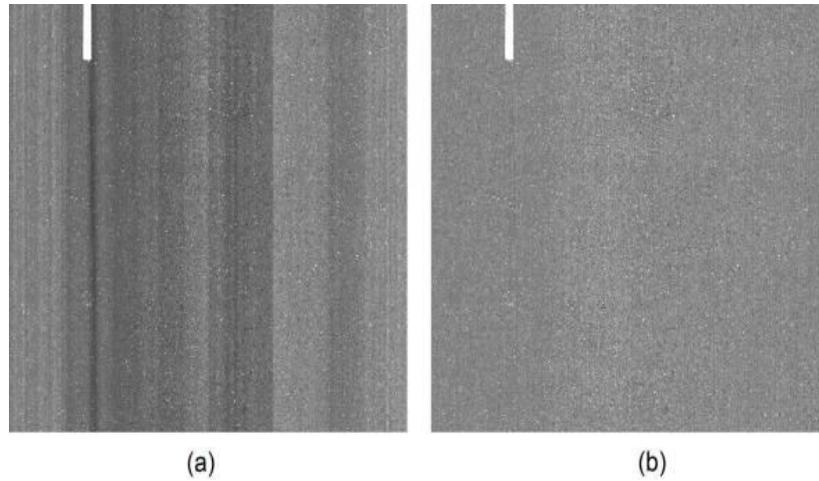


**Figure 4: Two sample original pictures from the information noninheritable throughout a person's observation survey**

### **Pre-processing**

First, a preprocessing step to correct the measured brightness levels on the photographs is conferred. At the start of the method, the gain and also the exposure time of each camera is adjusted severally to a 128 average grey level. withal, brightness measured on a given line isn't constant because of the very fact that the lighting and viewing

conditions are not specifically the same at each purpose . Each time a brand new image is transferred, the average pixel price for every column is recalculated to adapt to the sheet reflection changes. Associate degree image noninheritable by LRIS and the corresponding preprocessed image by the algorithmic program developed can be seen in Figure 5



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

## **B. Edge Detection**

### **(i) Canny Method:**

The Edges are areas in a picture with sharp intensity gradients. The target of edge detection algorithms is to hunt out these points of fast intensity changes. There are variety of edge detection algorithms, together within the Sobel edge detector, the Laplacian of Gaussian methodology, the canny edge detector, the quick Fourier remodel, the zero-crossing methodology, the Prewitt methodology, and also the Roberts methodology. Of all the sting detection algorithms, the Canny edge detector appears to be the foremost effective in sleuthing object edges, and also the most generally used. The Canny edge detector detects edges by finding the pixel points wherever the gradient magnitude may be a most within the direction of the gradient, that is, within the direction of most intensity amendment. However, the image is initial ironed with a Gaussian filter to get rid of noise, that may be a convolution operation. The subsequent steps are give explicate of edge detection stratgies.

- (i) Sleek image by convolving with associate degree acceptable Gaussian filter to cut back image details;
- (ii) At every pixel, verify gradient magnitude and gradient direction on most intensity change;
- (iii) Mark the pixel as a foothold if the gradient magnitude at the pixel is bigger than the pixels at either sides of it in the gradient direction;
- (iv) Take away the weak edges by physical phenomenon threshold

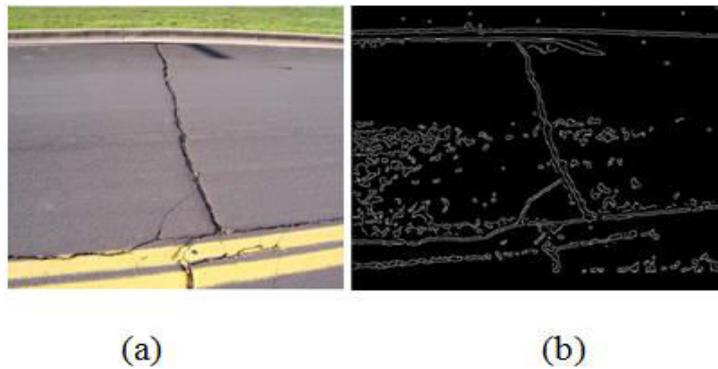
**(ii) Sobel method:**

Similar to the canny methodology, the Sobel edge detector is additionally a gradient-based methodology. It detects edges by looking for maxima and minima within the reckoning of the image. However, the Sobel methodology doesn't do any pre smoothing of the image; thus, it's additionallible to noise, however is computationally less costly and quicker. The Sobel edge detector performs a 2-D spatial gradient calculation on a gray-scale image; 2 3×3 convolution masks are accustomed calculate gradients, one on the x-direction, and also the alternative on the y-direction. The operator uses 2 3×3 kernels that are convolved with the first image to calculate approximations of the derivatives - one for horizontal changes, and one for horizontal changes and one for vertical.

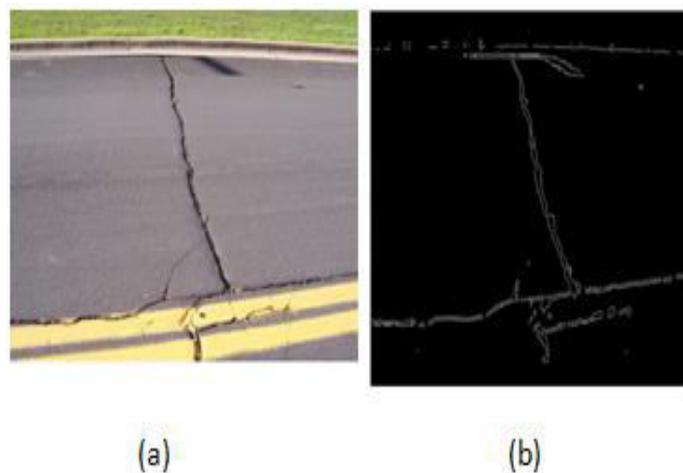
$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * A \text{ and } G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * A$$

Since the Sobel kernels are often rotten because the product of associate degree averaging and a differentiation kernel, they work out the gradient with smoothing. The ensuing gradient approximations are often combined to provide the gradient magnitude, using:

$$G = \sqrt{G_x^2 + G_y^2} \rightarrow (2)$$



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



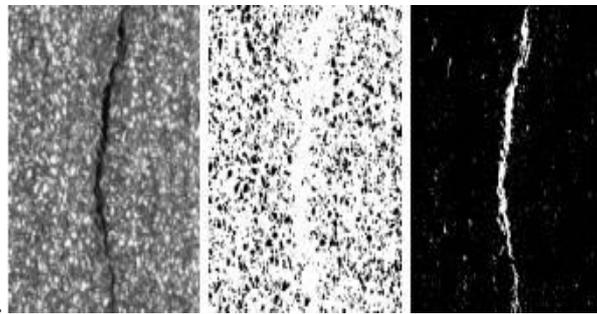
**Figure 7: (a) original image. (b) sobel edge detected image.**

### C. Segmentation by threshold

Threshold is one of the simplest and computationally quicker segmentation procedures, being chosen to determine crack regions present within the pavement surface pictures taken throughout road surveys. A dynamic threshold value,  $Th_1$ , distinctive for every image, is then computed consistent to the expression:

$$Th_1 = Th(ot) - 0.5 \times std(Img) \rightarrow (3)$$

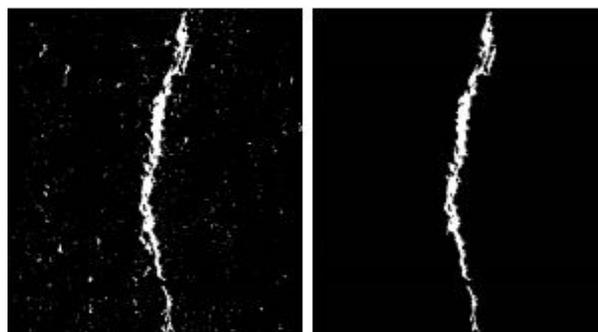
wherever  $Th(Ot)$  is that the threshold value computed consistent with to a modified Otsu methodology victimization only the strengths under the mean intensity level for every image. This provides increased immunity to noise  $std(Img)$  is that the variance of all image pixel intensities. The output of the threshold operation assigns label '0' to pixels whose value is higher than the threshold  $Th_1$ , and '1' to potential crack pixels, those with intensity below  $Th_1$ .



**Figure 8: original image (left),after threshold image(right).**

### D. Identify relevant connected components

Candidate crack pixels are then sorted using a connected components algorithmic program, to make a set of connected component objects (cco).The right image of Figure 7 reveals the presence of terribly tiny and ccos, Many of them not corresponding to real road cracks .In fact, only ccos respecting a set of conditions ought be chosen by the system as crack regions. To be unbroken as a candidate crack region a cco ought to have (i) major than 90% of eccentricity for an ellipse fitted to it;(ii)width higher than or equal 2 mm (computed dividing the quantity of pixels in cco by the quantity of pixels within 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, represented within the previous section, provides two binary output images. Transverse cracks are highlighted in one amongst them, and longitudinal cracks within the alternative one. Every of those pictures is analysed severally. Adjacent pixels corresponding to cracks type sets and nearby sets are joined to make one defect. This process permits the quantity of cracks to be counted up, and also the options of those cracks to be calculated. This method is applied to each binary pictures severally, thus the cracks detected in every binary image belong to transverse o longitudinal cracks respectively.

## IV. Experimental Results

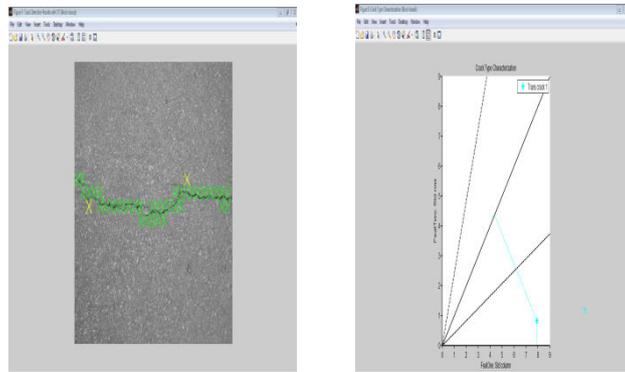
The planned automatic crack detection methodology has been tested on video captured throughout a true road pavement survey in india. Experimental results are conferred using 20 pictures that a ground truth is offered, provided by a talented inspector who has manually known the prevailing crack regions. The Canny edge detector, and also the Sobel methodology were able to notice cracks more easily on road surfaces, however with slightly bit more difficulty for asphalt surfaces. However, the canny methodology usually proved better on asphalt surfaces. It is also determined that despite the noisy output of the Sobel method, crack edges may be detected on nearer examination as could be seen in Figures 5 and 6. For images with no cracks the Sobel method still suffers from the consequences of noise once the pictures have numerous irregularities present, as is that the case for asphalt concrete surfaces. For pictures with few irregularities, like the road surfaces, crack detection is more practical, and easily comparable to results from the Canny method; for road surfaces with no cracks, the Sobel method provides outputs with less noise, that is better. Overall, the Canny edge detector performed higher than the Sobel method for asphalt surfaces, and slightly higher for road surfaces. The ground truth information is employed to judge 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:

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

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

$$Pc = \frac{2 \times Pr \times Re}{Pr + Re}$$

The analysis results are show that the proposed methodology achieves higher Precision results than the technique reported in existing methodologies. Conjointly the system perform (PC) is better, mistreatment the proposed methodology (89% and 95% against 60.5% and 94.7% for comparison previous results, respectively). In terms of Recall (viewed because the most vital metric for this kind of application, wherever missing crack areas should be lot of penalized), the proposed methodology achieves a considerably better value for crack images (94.8% against 61.7%). though the results for existing methodology don't seem to be higher than those represented (95.6% against 97.0%), the gain in system robustness leads to the conclusion that the proposed methodology's global performance is sort of sensible. In terms of crack classification, 100% recall and exactness were obtained for all categories of detected cracks, that reveals a awfully sensible overall system performance.



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

Moreover, the proposed methodology presents quicker process times, once compared to those reported in [10]. Mistreatment the same hardware and software package platforms, the proposed system takes 5 seconds/image against the 31 seconds reported in [10].

## V. Conclusion and Future Work.

In this paper an easy unsupervised system for crack detection and classification into many categories is proposed. Sample videos were taken from varied places of India and therefore the cracks were detected. This methodology displays promising results of detecting cracks in every feasible direction. The top result of the system was accomplished by integrating shape based image retrieval algorithm. This algorithm method the images in successive manner and provide sequence of images like binary image, filtered image and cracks in image. The system achieves distress quantification a lot of effectively when compared to the standard strategies. Techniques to work out the depth and intensity of the cracks mistreatment soft computing strategies will also be proposed within the future. conjointly in

future development can take into account the usage of additional filtering techniques to additional scale back the variance of pixel intensities in road surveys image databases.

## **VI. References**

1. F. Liu, G. Xu, Y. Yang, X. Niu, and Y. Pan, "Novel approach to pavement cracking automatic detection based on segment extending," in Proc. 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 neighboring difference histogram method," in Proc. IEEE CISP, Sanya, China, 2008, pp. 792–796.
4. Y. Sun, E. Salari, and E. Chou, "Automated pavement distress detection using advanced image processing techniques," in Proc. 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 detection based on FDWT," in Proc. 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," in Proc. 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](http://www.ino.ca/enca/achievements/description/project-p/laser-road%20imaging.html)
8. Y. Huang and Y. Tsai, "Enhanced pavement distress segmentation algorithm using dynamic programming and connected component analysis," in Proc. 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. P. Ekdahl, Routine Measurements of Pavement Surface Cracks, Ramböller RST, Malmö, Sweden. [Online]. Available: [http://carbon.videlectures.net/2008/contrib/surf08\\_portoroz/ekdahl\\_rmopsc/surf08\\_ekdahl\\_rmopsc\\_01.pdf](http://carbon.videlectures.net/2008/contrib/surf08_portoroz/ekdahl_rmopsc/surf08_ekdahl_rmopsc_01.pdf).
12. 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.

13. Henrique Oliveira, Paulo Lobato Correia, “Automatic Road Crack Detection and Characterization in Proc. IEEE Trans. on intelligent transportation system, pp.155–168, feb 2013.
14. H. D. Cheng and M. Miyojim, “Automatic Pavement Distress Detection System”, Journal of Information Sciences 108, ELSEVIER, pp.219-240, 1998.

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