

POTHOLE DETECTION IN ROAD USING IMAGE PROCESSING

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ABSTRACT

Automatic detection and characterization of cracks in road surfaces, which is used to detect and characterize the type of cracks and find the severity level of cracks, used to reduce errors in manual calculation. Road pavement images are converted into non overlapping image blocks and then features of image blocks such as mean and standard deviation are obtained. Then connected component algorithm is applied to detect the crack blocks. Using Otsu thresholding, severity level of cracks is identified. To improve performance, connected component algorithm is applied to features of images.

KEYWORDS: Otsu Thresholding, Severity Level of Crack, Mean, Standard Deviation, Connected Component Algorithm

I. INTRODUCTION

A crack is the separation of an object or material into two, or more, pieces under the action of stress. Depending on the substance which is cracked, the crack reduces the strength of the materials in most cases, e.g. building walls, roads, etc. This cracks become worsen to pavement which increases with load of the vehicles travelling on it. There are three types of cracks: transversal crack, longitudinal crack, miscellaneous crack. Large holes are formed, making the road more dangerous, if these early small cracks are left untreated. Remedy for these large holes, such as fixing potholes or laying new road will cost about 10 to 20times more than the cost of resealing small cracks.

At the beginning, humans were used in detecting these cracks. However, detecting a crack manually is a very difficult one and time consuming process. With the advance of science and technology, automated systems with intelligence are used to detect cracks instead of humans. By using the automated systems, the time consumed and the cost for detecting the cracks reduced and cracks are detected with more accuracy. These automated system's features overcome manual errors providing better outcome comparatively. Numerous algorithms have been proposed and developed in the field of automated systems, but the algorithm given below improves the efficiency in the detection of cracks than the previously developed techniques.

Images obtained for crack analysis are preprocessed. Acquired images may be of different dimensions. Image resizing algorithm is applied on the images, which in turn convert them into a square image. Intensity Normalization process corrects nonuniform background illumination and eliminates the background lighting variations. Pixel saturation eliminate bright pixel which is not a crack pixel mainly occurs due to specular reflection.

A global perspective, cracks are salient long continuous curves in pavement images. However, the intensity along a crack may not always be lower than the surrounding pavement background because the depth and severity of a crack varies along the crack curve. Therefore, using feature extraction process, mean and standard deviation of image blocks are obtained and then clustering technique is applied to them. By applying connected component algorithm, crack type is identified and using Otsu's grey thresholding, the severity level of crack is identified. This paper is structured as follows.

After this, Section II presents an overview of the relevant literature. Section III describes the proposed crack detection approach. Section IV presents the proposed crack type characterization and severity level assignment strategy. Experimental result is discussed in Section V, and Section VI draws conclusion.

II. LITERATURE REVIEW

The number of recently published papers dealing with crack detection and characterization of pavement surface distresses shows an increasing interest in this area. A recent publication a hierarchical method present in [1], which deals with detection of roads and slopes. In this paper, a novel framework is proposed for segmenting road images in a hierarchical manner that can separate the following objects: road and slopes with or without collapse, sky, road signs, cars, buildings and vegetation from the images. The experiments show that the approach in this paper can achieve a satisfied result on various road images. The roads are unstructured, which are more complex than the structured roads.

In [2] multiscale approach based on Markov random field is proposed to segment fine structures (cracks) in road pavement surface images. Cracks are enhanced using a 1-D Gaussian smoothing filter and then processed by a 2-D matched filter to detect them. A total of 64 road pavement surface images representing several crack types are considered for experimentation, producing a qualitative evaluation. Details on image characteristics or the type of sensor used to capture them are not provided. Another paper [3] evidences the difficulty of detecting cracks of less than 3 mm width when using edge detectors. A non subsampled contour let transform is adopted in [4] to detect cracks, wherein a limited set of experimental results is presented.

A complete methodology to automatically detect and characterize pavement defects is proposed in [5], using grayscale images captured by line scan cameras illuminated by lasers during road surveys performed using a high-speed image acquisition system. Crack detection uses a conditional texture anisotropy measurement to each image, and defect characterization uses a multilayer perceptron neural network with two hidden layers. The results presented are promising, but the experimental evaluation does not support the distinction of multiple cracks in the same image. In paper [6], Neural network method is used. The automated pavement defect detection can only identify crack type defects. To classify defect, a multi layer perceptron's neural network (MLPNN) is used. Neural network is used to classify the images into four classes: defect-free, crack, joint and bridged. Experimental results are performed on real road images which are labelled by human operators.

There are more additional filters required for this system. In paper [7], Vision-based approaches are used to address functionalities such as lane marking detection, traffic sign recognition, pedestrian detection, etc. This system is possible to detect the free road surface ahead of the ego-vehicle using an on board camera. Novelty Method is used for both Shadowed and non- shadowed regions which provide highest performance. Road detection algorithm is devised by combining the illuminant invariant feature space and likelihood based classifier. The defect of this system is under-saturation by improving image acquisition system.

In paper [8], A neural network based technique for the classification of segments of road images into cracks and normal images. The features are passed to a neural network for the classification of images into images with and without cracks. Another approach [9] extracts linear features (cracks) using two methodologies: one based on holistic thresholding and the second employing the Otsu algorithm.

III. POT HOLE DETECTION

The road images are labelled as transversal, longitudinal, miscellaneous by extracting block wise features from the images. The block wise features are extracted based on mean and standard deviation of the block. If the particular block is detected as crack, the pixels within the particular block are converted to one. The pixels in the non-crack regions are converted into zero. The query image is divided into blocks. Mean and standard deviation features are extracted from the blocks. The distance is calculated between the extracted features with the plain road features. If the distance is minimum with the crack regions, the regions are labelled as cracks while the other regions are labelled as normal regions. The pixels that are identified as cracks are denoted with different representations (ones). Then the type of crack present in the image is identified with the help of the different type of ranges of the features. Finally the performance of the process is measured. This method is useful to overcome some of the identified limitations, performing a (fast) block-based crack detection capable of identifying the presence of multiple cracks in a given image and providing a detailed quantitative evaluation of the results obtained, highlighting which blocks in each image contain cracks, identifying the type of each detected crack, and assigning its severity level. This complete process is explained in flow diagram as follows.

Preprocessing

The road images have higher pixel value in crack parts than other non crack parts. But sometimes it has higher pixel value in non crack region. This occurs because of specular reflection. To reduce this, average of image pixels is generated and it is taken as threshold value. Pixels which have higher value than this value, are replaced by this value. This process is called pixel saturation. To reduce non uniform background illumination, image enhancement is necessary. To achieve this intensity normalization method is used.

Feature Extraction

Query images are separated into image blocks. Mean and Standard deviation value is obtained for each block. After that feature normalization is done. Then Kmean clustering algorithm is applied for two features mean and standard deviation.

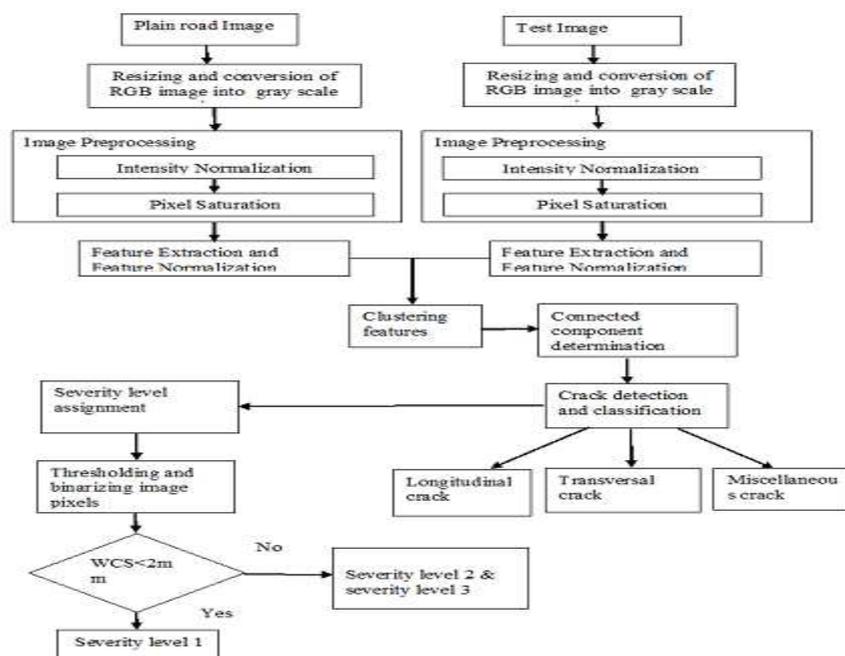


Figure 1: Flow Diagram of Pothole Detection in Road Using Image Processing

All the measurements (mean and standard deviation of gray level values within a block) for each image compose a pattern vector x , representing a sample of the random variable X , taking values on a sample space X . For each element x_i of the pattern vector x , one possible class y_i is assigned, where Y is the class set. Thus, the feature set is

$$F = \{(x_1, y_1) \dots (x_n, y_n) : x_i \in \mathbb{R}^2; y_j \in \{c_1, c_2\}\} \quad (1)$$

Where n is the number of points for the pattern vector x , and j is the number of classes, with x_i being the feature values extracted from an input image. Only two classes are considered: 1) blocks without cracks, labeled as class c_1 ; and 2) blocks with cracks, labeled as class c_2 . The calculated features are clustered and the cluster centroids are identified.

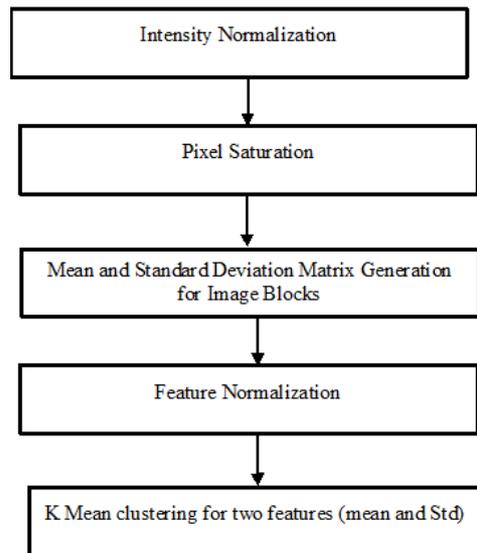


Figure 2: Preprocessing and Feature Extraction

IV. CRACK TYPE CHARACTERIZATION

Crack Detection

Using subtraction of standard deviation matrix of database image from query image standard deviation matrix, the crack region is identified and using contouring the boundary of crack region is separated from no crack region.

Severity Level Assignment

For severity level assignment, Otsu's gray thresholding method is used. Two threshold values are taken (i.e. threshold1 and threshold2) from Database image crack blocks and query image crack blocks. The values are compared. If check the condition $\text{threshold1} < \text{threshold2}$, threshold1 is selected as threshold else threshold2 is selected as threshold. Then this threshold is applied to query image and binary image is obtained and the connected components are identified. Then the short crack pixels are removed using region opening process. Next, using morphology method the skeleton image of cracks is computed. Then crack width is calculated using formula,

$$WCS = \frac{\text{Total number of pixels in a crack}}{\text{Total number of pixels in the crack's skeleton}} \quad (2)$$

Severity level assignment process is explained in following Figure 3.

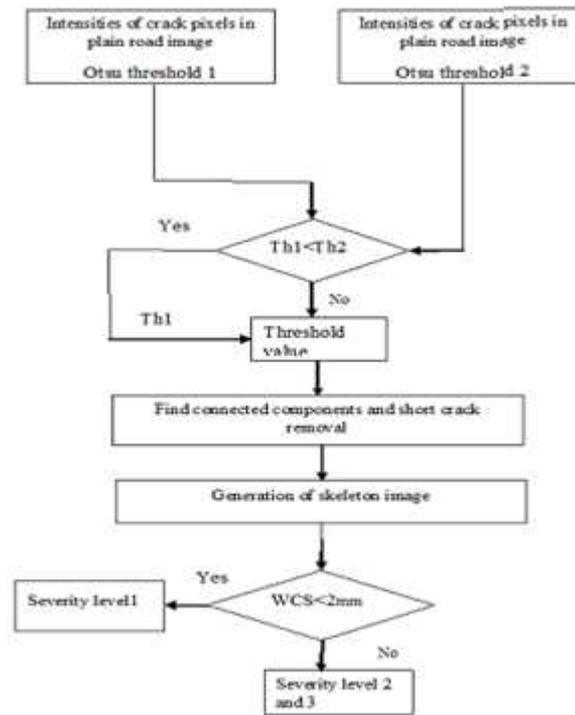


Figure 3: Severity Level Assignment

V. EXPERIMENTAL RESULTS

Image samples of each type are collected. Totally 50 samples are collected of Longitudinal, Transversal and Miscellaneous cracks which are given in Table 1. Images are converted into non overlapping image blocks and using gridlines, blocks are shown as separated. Mean and Standard deviation are calculated for each image blocks and matrices of mean and standard deviation are generated.

In preprocessing, using histogram equalization, intensity normalization is obtained. By replacing threshold value to high pixel (non cracks) value, pixel saturation of image is obtained. Query image is resized into 512*512 and then it is separated into non overlapping image blocks of 64*64 pixels or 32*32 or 8*8 pixels. For each blocks, mean and standard deviation matrices are generated. K means clustering is applied for two feature matrices and Fm value is determined.

For crack detection, standard deviation matrix of Database image is subtracted from standard deviation matrix of query image. If the result value is high, that block considered as crack block and pixels in it are replaced by 255(White) and other blocks are replaced by 0 (Black). Contouring is applied on boundaries of crack blocks.

Otsu's gray thresholding is applied on database image and query image blocks and connected components (pixel based) are identified. Using morphological process, short cracks are removed. Then skeleton image for query road image is generated. By dividing number of white pixels in binary query image by number of white pixels in skeleton image, the width of crack is identified. The detection of different type of cracks is shown in figure 4, figure 5, figure 6. It shows that when number of block increases, the result will be more accurate. The identified crack width and corresponding images are shown in Table 2.

Table 1: Database Collection

| Type of Image | Number of Samples |
|--------------------------|-------------------|
| Road image without crack | 10 |
| Transversal cracks | 10 |
| Longitudinal cracks | 7 |
| Miscellaneous cracks | 9 |

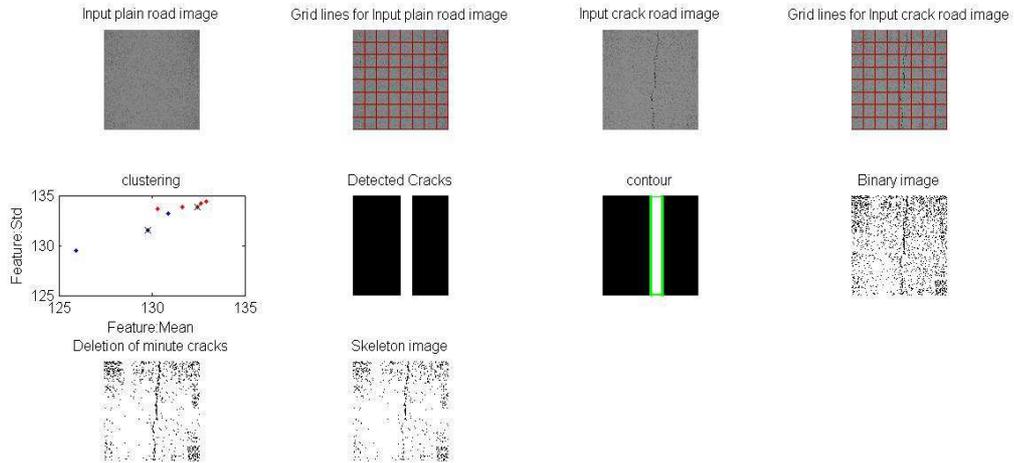


Figure4: Longitudinal Crack Road Crack Detection for 8*8 Image Block

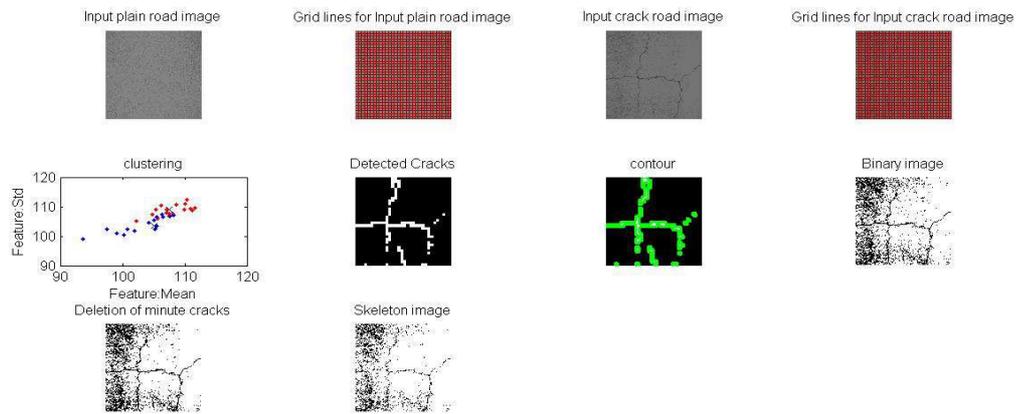


Figure 5: Miscellaneous Crack (Road Crack Detection for 32*32 Image Block)

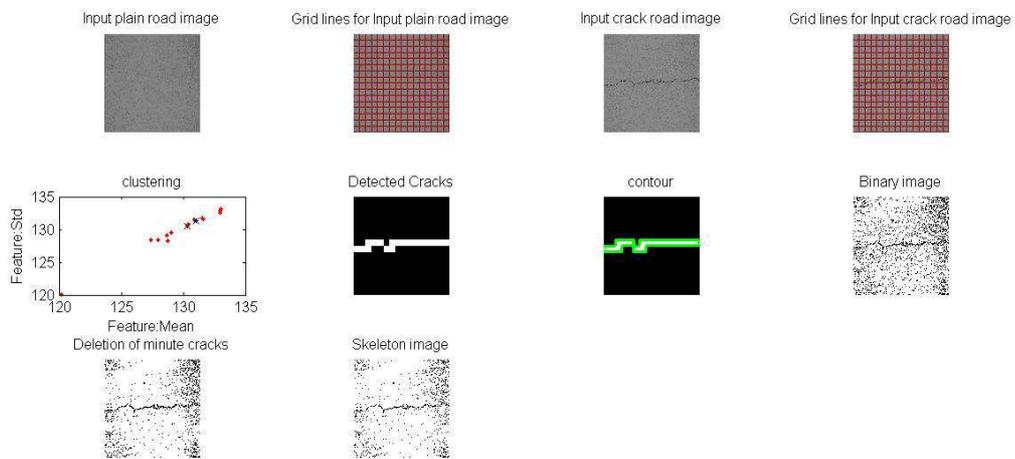
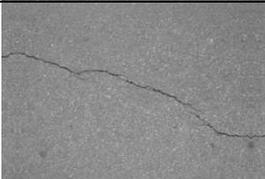
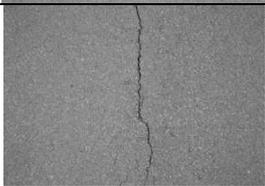
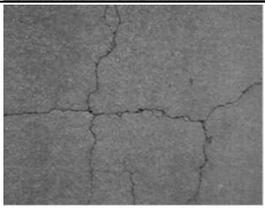


Figure 6: Transversal Crack (Road Crack Detection for 32*32 Image Block)

Table 2: Crack Images and their Width of Crack Segment

| Sample Images | Type of Crack | WCS (mm) |
|---|---------------------|----------|
|  | Transversal Crack | 3.025 |
|  | Miscellaneous crack | 3.59 |
|  | Longitudinal crack | 3.4 |
|  | Miscellaneous crack | 5.2 |
|  | Longitudinal crack | 7.79 |
|  | Longitudinal crack | 11.2613 |
|  | Miscellaneous crack | 4.6642 |

VI. CONCLUSIONS

This paper gives view about image-processing method for the crack detection of road pavement. A different method for the detection of road cracks has been introduced. We have presented a new evaluation and comparison method for automatic detection of road cracks. It considered pixels as for detection of cracks. The dimension of the distressed area such as width in case of longitudinal, transverse cracks, and miscellaneous cracks are digitally and manually measured.

VII. REFERENCES

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