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# Research Journal of Pharmaceutical, Biological and Chemical Sciences

## Image-Based Surface Crack Inspection and Pothole Depth Estimation.

Satyavrat G\*, Neelamegam P, and Rubalya Valantina S.

School of Electrical and Electronics Engineering (SEEE), SASTRA University, Thanjavur-613401, Tamilnadu, India.

### ABSTRACT

Visual technologies for Non-destructive evaluation have been playing a successful role over a decade especially in the engineering fields of civil, transportation and infrastructure. Not only that these technologies reduce labor cost, but they can also be implemented quite effortlessly. The manual inspection of visible deteriorations on several structures and pavement surfaces has found to be time-consuming and inaccurate. In this paper, a vision sensor has been used in order to extract surface crack properties in 2-D mode and estimation of depth of potholes has been done through stereo mode of image processing. The image processing steps involves pre-processing, segmentation and feature extraction in MATLAB environment. The performance of the current methodology in extracting surface crack properties and to estimate depth of potholes is found to be of reasonable accuracy.

**Keywords:** Minoru 3-D Webcam, Un-calibrated Rectification, Image-processing and MATLAB.

*\*Corresponding author:*

## INTRODUCTION

Many engineered and transportation structures pose disastrous threat to human lives due to their irregular and inadequate maintenance. Bridge deck inspection and earthquake post-relief operations are certainly necessary to prevent human race from man-made calamities. There has been nearly 25 bridge surface collapses since 2009 around the world leaving around 100 killed and 200 injured around the globe (Source: Wikipedia).

Surface inspection normally involves surface crack detection and properties retrieval for post-analysis and maintenance. Potholes could prove fatal especially for vehicles on-road due to their dissimilar and multi-form depths.

From the existing literature, [1] Ito et al. developed an automated concrete block inspection system by the method of fine crack extraction. The system uses a high-resolution vision to acquire images, and the cracks are extracted using an integrated image processing technique. [2] Hu and Zhao proposed a local binary pattern method to increase robustness. The work designed for pavement-crack detection (including cracks less than 1 mm wide). They used parameters, which had to be set manually for different types of backgrounds. [3] Sun Zhaoyun, Wang Chaofan, Sha Aimin processed pavement images of cracks captured by the digital camera and classified them based on the chain code of the cracks in the image, the paper estimates the length and width of the line cracks and the area of the rectangular box of the alligator cracking. Yu et al. (2007) determined the length, thickness and orientation of concrete surface cracks by the method of graph search; but, the method carried the start and end points of the cracks. Zhenhua Zhu, Stephanie German & Ioannis Brilakis constructed the crack map and then, the skeleton images of cracks are created through morphological thinning, and the crack properties (width, length, orientation and location) are calculated. The method has been experimented in a CPP based prototype and on a set of real crack images.

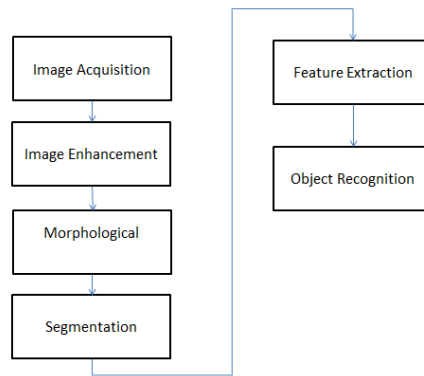
Stereo vision based image-processing techniques; on the other hand, provide three dimensional measurements, such that the geometric features of a pothole can be determined easily. Stereo vision provides information on the depth size of the pothole, without the need for using high cost specialized laser scanners. [4] Ezzatollah Salari, Eddie Chou, and James J Lynch, implemented Machine vision based methods for automatic pothole detection have also been proposed, which only require a camera as input. However, existing approaches rely on the texture of the road surface, resulting in low accuracy. [5] M. Mustaffar, T. C. Ling, O. C. Puan studied in developing a photogrammetric based pavement evaluation approach by utilizing ortho-images and image processing techniques. [6] Ashraf Anwar Fahmy experimented SURF, and implemented Un-calibrated Rectification using inliers to calculate the depth without disparity map. This idea encouraged us to implement it in our paper.

The framework of this paper includes retrieval of surface crack properties such as length and width using binary image-processing such as filtering, dilation and erosion, image complement and skeletonization. The length has been determined from calculating the area of single pixel skeleton region of the image and width through maximum and minimum difference calculations of the crack image. Also, the work involves depth estimation of potholes in pavement surfaces using stereo three dimensional vision processing consisting of disparity calculation through un-calibrated rectification.

The whole paper is divided in to sections: Section 1: Methodology for surface crack length and width. Section 2: Stereo processing for pothole depth estimation. Section 3: Results and discussions. Section 4: Conclusion.

### Section 1: Methodology

Image-processing steps performed in the Fig.1 are as follows:-



**Fig.1. Flowchart of Image processing steps**

### Image Acquisition

A 2-D image of a crack has been acquired in real-time using Minoru Webcam. The size of the image acquired is of 480\*360 in dimensions and it has been reduced to 250\*187 in dimensions and the RGB (Red, Green, and Blue) image has been converted to its gray-scale for analysis of higher accuracy. Fig. 2 shows an RGB image consisting of a cracked region and Fig. 3 shows its conversion to gray-scale.



**Fig. 2. An RGB image of a crack**



**Fig. 3. Converted gray scale image**

### Image Enhancement

The gray scale image is further changed to its binary form such that the crack region can be separated from its background pixels. A 3\*3 neighborhood size median filter is used to filter out portions other than the crack region keeping the padding options as symmetric. Fig.4 and Fig. 5 representing the conversion of gray scale image to binary and its filtered form respectively.



**Fig.4. Conversion of gray scale to binary image**



Fig. 5. A Median filtered image

### Dilation and Erosion

There exists unclear crack region with noise points at the background. To enhance the image, dilation helps in replacing each pixel in the image with the maximum intensity value and erosion process to be continued. During the process of erosion, the image pixels lose its continuity thereby removing the noise points. Further, smoothing has been carried out using median filter of neighborhood size  $7 \times 7$ . Fig.6 and Fig.7 represents subsequent operations like dilation, erosion and filtration respectively.



Fig.6. Dilated image



Fig.7. Eroded and Median filtered image

### Image Complement and Thinning

Since background pixels appear binary-1 and foreground to be of binary-0, image complement has been applied to interchange pixels for user-convenience. Skeletonization process has been performed in the crack region making it to arrive at single pixel width region to find its length through connected components by labeling it. Fig. 8 and Fig. 9 depicting complement form of image and subsequent thinning process.



Fig.8. Complemented image of eroded and filtered image

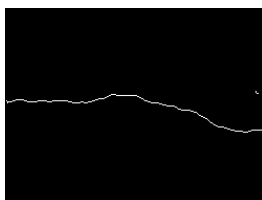
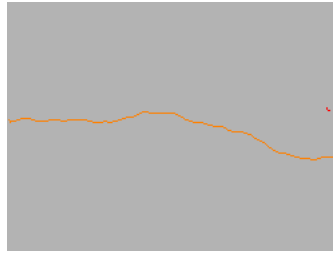


Fig.9. Thinned image with single pixel line

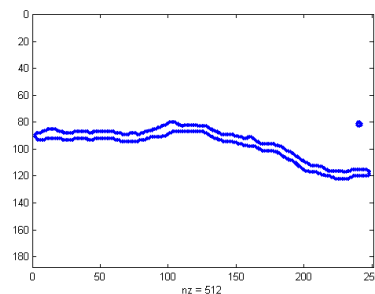
After labeling by using prism color map shown in Fig.10, connected components image is,



**Fig.10. Connected component image**

The length in terms of pixels has been obtained using the area of the colored thinned regions.

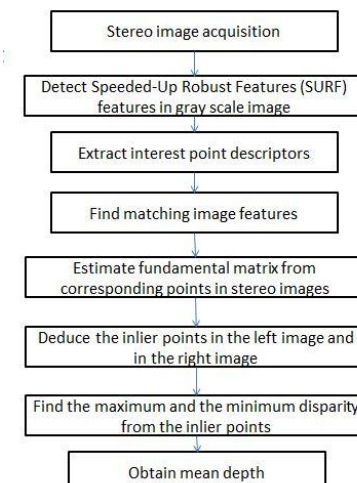
Width has to be calculated for the image which has not been thinned. Edge-detection technique has been used followed by finding non-zero elements in the image row and column wise. Furthermore, a sparsity pattern shown in figure (k) has been created. Depending on the maximum and minimum row or column indices difference, width in terms of pixels can be obtained.



**Fig.11. Edge detected sparsity image**

## Section 2: Stereo processing for pothole depth estimation

Stereo vision processing involving Un-calibrated rectification i.e. finding the depth without the disparity map shown in Fig.12 has been implemented here as follows:-



**Fig.12 Stereo vision Un-calibrated rectification Process**

### Stereo Image Capture

Stereo images of pothole has been taken form the database shown in Fig.13 and Fig.14 and converted to gray scale images. The size of images has been reduced for easier analysis and to avoid software conflicts.



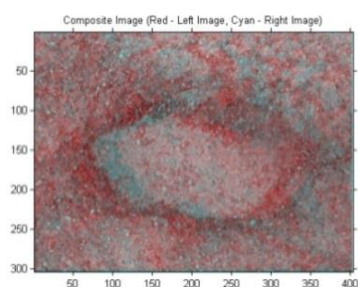
**Fig.13. Left image of Pothole**



**Fig.14. Right image of Pothole**

### Color-composite image

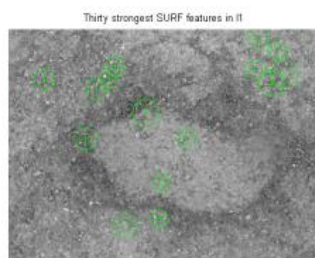
To know about the pixel-wise differences between the stereo images, a composite image of two different color separations represented in Fig.15 has been introduced.



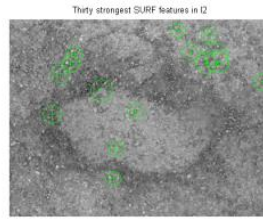
**Fig.15 Composite image of left and right images**

### Collect interest feature points from each image

Since, there is certain amount of offset involved between the images a much necessary step of rectification has been performed. The rectification process includes finding a set of corresponding matching points, aligning them to calculate disparity. Here, SURF feature algorithm has been used which is shown in Fig.16 and Fig.17 respectively. SURF chooses region of interest as blobs from the rectilinear scale-space, and forms local features constructed on the gradient dissemination of the image. Speeded up Robust Features algorithm is based on summation of 2D Haar wavelet responses. It uses integral images.



**Fig.16 SURF feature extraction of left image**



**Fig.17 SURF feature extraction of right image**

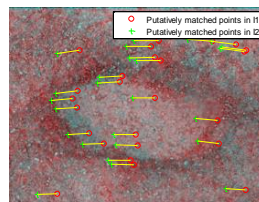
### Finding putative point correspondences

Extracting features and matching features for each blob has to be computed. Sum of absolute differences (SAD) has been used to find and calculate matching indices and matching points' location. The SAD algorithm is one of the modest algorithms measuring the dissimilarity of the left and right stereo pictures analogous with four-sided window. Intensity dissimilarities for each epicenter pixel (x, y) in a window W (i, j) is computed as follows:

$$SAD(i, j, d) = \sum_{(x,y) \in W(i,j)} |I_{left}(x, y) - I_{right}(x - d, y)| \dots (A)$$

Where  $I_{left}$  and  $I_{right}$  are functions of pixel intensities of the left and right stereo images individually. The disparity calculation has been repetitive through the x-direction encompass in the row section of the image of the investigated 3D image. The smallest distinction value over that frame specifies the best corresponding pixel, and its location.

Note that the image correspondences consist of some outliers shown in Fig.18.



**Fig.18 Putatively matched correspondences**

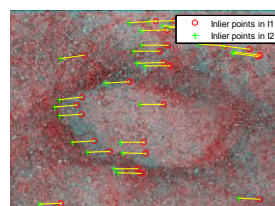
### Removal of outliers

The appropriately matched points must fulfill epipolar constraints. The Fundamental matrix denoted as F is a 3x3 network which relates comparing focuses in stereo images. In epipolar theory, with identical picture directions, X and X', of comparing focuses in a stereo image pair, FX depicts an epipolar line on which the relating point X' on the other image must lie. That means, for all pairs of corresponding points holds

$$X'FX = 0 \dots (B)$$

RANSAC: Random Sample Consensus can be contemplated as a web crawler. It chooses again an indiscriminate sample of correspondences and calculates the inliers acumen the fundamental matrix.

Fig.19 denotes the formed inliers after RANSAC.



**Fig.19 Inlier points of left and right images**



### Estimation of depth

Set of disparity values have been checked from the obtained inlier points,

$$disparity = \sum_{i=1}^N |I_{nleft}(x, y) - I_{nright}(x, y)| \dots (C)$$

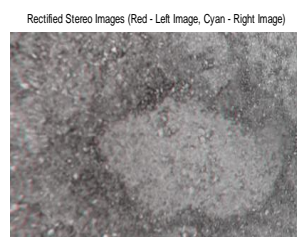
Where,  $I_{nleft}$ ,  $I_{nright}$  are the inlier points in the left and in the right stereo images respectively.

Depth values can be computed from disparity values as,

$$depth = \frac{f \cdot b}{disparity} \dots (D)$$

Where f and b are focal length of the camera in mm and baseline between two optical centers in mm respectively. Disparity can be measured in pixels.

Rectified and cropped image in 3-D shown in Fig.20 as,



**Fig.20 Rectified stereo image**

### Section 3: Results and Discussions

#### Calculation of crack length and width

The determined length and width through connected components area of a single pixel line and sparsity non-zero indices are shown in tables 1, 2 and 3 respectively as,

**Table 1: Connected components**

Field	Value
Connectivity	8
Image Size	[187,250]
Number of Objects	2

**Table 2: Width properties**

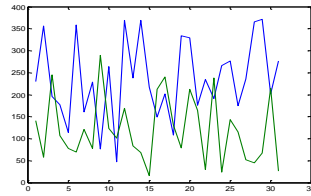
Properties	Estimated value (pixels)
Row indices	Min-80, Max-122
Column indices	Min-2, Max-248
Width	42

**Table 3: Crack properties**

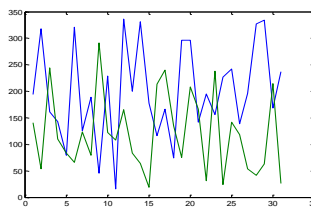
Properties	Estimated value (pixels)
Length	247
Width	42
Orientation	Horizontal

### Depth estimation of Pothole image

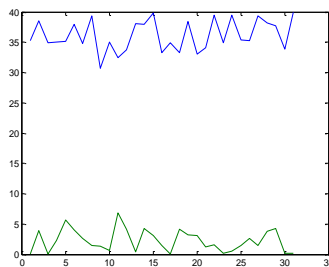
Disparity check defined from the formula (C) gives the x coordinate location difference between the two images. From the values obtained from the inlier points, maximum and minimum disparities of pothole image shown in figures (u), (v), (w) are computed.



**Fig.21 Plot of inlier SURF points of left image**

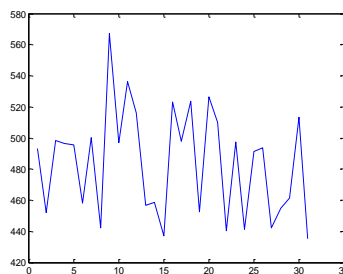


**Fig.22 Plot of inlier SURF points of right image**



**Fig.23 Disparity plot from inlier SURF points**

Taking 0.02 mm/pixel as pixel size, Maximum depth for minimum disparity and minimum depth for maximum disparity is computed.



**Fig.24 Estimated depth plot of pothole image**

**Table 4: Depth estimation of pothole image**

Properties	Estimated Values(mm)
Maximum depth	567.1198
Minimum depth	435.3266
Mean depth	501.2232

### **CONCLUSION**

This paper is aimed at inspecting and retrieving surface crack properties such as length and width in 2D mode and pothole depth extraction in stereo mode of image processing. The results obtained shows that the manual measurement of length deviates four units lesser than the obtained result. Therefore, a reasonably accurate calculation of length and width values has been determined and pothole mean depth values have been estimated through MATLAB environment. The future work can be carried out using calibrated rectification methodology for depth estimation to improve accuracy.

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