Performance Analysis on Surface Crack Detection in Buildings & Bridges Using Image Processing Method

Kosari Krushitha[1],Eeslavath Ganesh [2],Tatikonda Anil Kumar Reddy[3], J.Mohan[4]

[1]B.Tech student, Dept. of ECE, Institute of Aeronautical Engineering, Hyderabad, 500043,India

[2]B.Tech student, Dept. of ECE, Institute of Aeronautical Engineering, Hyderabad, 500043,India

[3]B.Tech student, Dept. of ECE, Institute of Aeronautical Engineering, Hyderabad, 500043,India

[4]Professor, Dept. of ECE, Institute of Aeronautical Engineering, Hyderabad, 500043, India

Emails: krushithakosari08@gmail.com[1], ganeshnayaknair@gmail.com[2], tatikondaanilkumarreddy@gmail.com[3] , J.Mohan@iare.ac.in[4]

Abstract

Surface crack detection in buildings and bridges is critical for ensuring structural integrity and preventing potential failures. It presents a performance analysis of surface crack detection using image processing techniques, offering an efficient and non-invasive solution. Traditional manual inspection methods are labor - intensive, subjective, and prone to human error, making automated systems more desirable. In this study, we utilize digital image processing techniques such as edge detection, thresholding, and morphological operations to identify and quantify surface cracks. Key performance indicators such as detection accuracy, computational efficiency, and robustness to varying environmental conditions are evaluated. The experimental results demonstrate the system's effectiveness in detecting fine cracks with high accuracy and low false positive rates, providing a reliable alternative for infrastructure maintenance. Additionally, the proposed method reduces inspection time and improves decision-making in the assessment of structural health. This study contributes to advancing automated crack detection systems, which are crucial for modernizing maintenance practices.

Keywords: Automated inspection, Edge detection, Structural integrity, Thresholding

1. INTRODUCTION

Infrastructure, such as buildings and bridges, is critical to public safety, and regular maintenance is essential to ensure their structural integrity. One of the most common signs of potential failure is the presence of surface cracks, which, if not detected and repaired in time, can lead to catastrophic consequences. Traditional manual inspection methods, while effective, are time-consuming, labor-intensive, and prone to human error. As a result, automated and accurate crack detection systems have gained significant importance in recent years.

Image processing has emerged as a powerful tool for detecting surface cracks, offering a non-destructive, efficient, and scalable solution to structural monitoring. Among the various techniques, the Otsu method stands out for its simplicity and effectiveness. It is an automatic thresholding technique that separates foreground (cracks) from background (non-cracked regions) based on image intensity levelsIn the context of surface crack detection, the Otsu method is particularly advantageous because it does not require prior knowledge of the crack characteristics or manual intervention to set threshold levels. This makes it ideal for large-scale, real-time monitoring applications where cracks may appear in different shapes, sizes, and lighting conditions. The performance of this method, when applied to buildings and bridges, can be enhanced by integrating it with other image pre- processing techniques such as noise filtering, edge detection, and morphological operations to improve accuracy.

This study focuses on analyzing the performance of the Otsu method in detecting surface cracks on buildings and bridges, assessing factors such as accuracy, detection speed, and reliability under various conditions. By evaluating these parameters, the aim is to understand the strengths and limitations of using the Otsu method for real-time structural health monitoring, ultimately contributing to more robust and automated maintenance strategies for infrastructure.

II. LITERATURE SURVEY

Alam et al. [1] proposed a detection technology combining digital image correlation and acoustic emission. The former method allows for accurate measurement of displacement and hence determination of crack aperture and crack spacing. To complete the process and study the damage, acoustic emissions caused by internal damage are also analyzed. A clustering method (similar to the Kmeans method) was used to identify different sound emission power units from three different beams. They use three different types of lines in their approach to maximize results.

Iyer et al. [2] developed a three step method to detect cracks in similar images. This method uses curvature measurements and mathematical morphology techniques to identify cracklike patterns in noisy environments. It relies on mathematical morphology and curvature measurements to identify the fractured structure as in noisy environments. In their work, segmentation is based on precise geometric patterns that identify the structure as fractured. Linear filtering is performed after cross curvature analysis to distinguish background samples. They identified irregularities in the cross section by analyzing the fracture characteristics based on geometry.Yang et al. [3] have proposed an image analysis method to capture thin cracks and minimize the requirement for pen marking in reinforced concrete structural tests. They have used the studies like crack depth prediction [54], change in detection without image registration [54], crack pattern recognition based on artificial neural networks [55], applications to micro-cracks of rocks [56], and efficient subpixel width measurement [57]. Stereo triangulation method was the adopted technique based on cylinder formula approximation and image rectification. Once they have the rectified output, the surface of the observed regions can be unfolded and presented in a plane image for following displacement and deformation analysis. From which the crack detection was analyzed.

Hamrat et al. [4] conducted an experimental study on the behavior of three types of concrete: normal strength concrete (NSC), high strength concrete (HSC) and high strength fiber concrete (HSFC), using digital imaging to measure and filter the product including crack detection, crack development, crack width. They use classical measurement techniques (strain gauges, LVDT sensors) and DIC technology to identify strains. The common understanding between the two measurements shows that DIC is an effective measurement tool to obtain changes. Routine systems generally do not measure weights and changes at or near failure due to personnel safety and risk of equipment damage. They reduce the distance between cracks and the crack width in millimeters from 35% to 70% (estimated error).

Talab et al [5] -A new imaging method for detecting cracks in rock formations has been proposed. The process here consists of three steps: first, use the edge image to convert the image to a gray image and then use the Sobel method to render the image using the Sobel filter to reveal the cracks. The binary image is divided into foreground image and background image using appropriate pixel threshold. When the image is decomposed, Sobel filtering is used to remove noise. After extensive filtering of the images, cracks are detected using the Otsu method. In some cases, they replaced the sobriety filter with a more neutral filter.

Wang et al [6] -An image-based detection system is proposed and cracks are characterized based on its results. They divided the existing image-based search into four groups. They are algorithms, morphological methods, access and input methods. Shadow correction is done by a combination algorithm. Analysis of uncertainty estimation using filtering techniques. Crack detection is the detection of micro cracks using morphological methods with high performance techniques.

Mustafaraba et al [7] -A crack detection with high spatial imaging resolution and excellent ability to measure 3D space by laser scanning is proposed. The design has more potential due to the combination of data acquisition and data collection. Search and drawing are performed in three steps: shadow correction, crack detection and crack mapping. They identify cracks in pixel coordinate system. Once identified, the fractures are reverse engineered to remap a joint. This is achieved by a hybrid concept of a terrestrial laser scanner point cloud and the associated camera, i.e., by switching from a pixel coordinate system to a terrestrial laser scanner or spherical coordinates. Experimental results showed that the average distance between the ground laser scan and the total location in the x, y and z directions is approximately 30.5, 16.4 and 14.3 mm, respectively.

III. PROPOSED METHOD

The method we are proposing is the otsu method. Here the process how it works:

1. Histogram Analysis:

The Otsu method begins by analyzing the histogram of the grayscale image. The histogram represents the frequency of pixel intensity values (ranging from 0 to 255 for an 8-bit image). In a typical scenario, the histogram may show two peaks, one for the background and another for the foreground, with a valley in between.

2. Threshold Initialization:

The algorithm evaluates every possible threshold value (ranging from 0 to 255) that could separate the two classes of pixels: the foreground (e.g., cracks) and the background (e.g., concrete or metal surface).

3. Class Probability Calculation:

For each possible threshold, the image is divided into two classes: Class 1 (C1) consists of pixel intensities below the threshold. Class 2 (C2) consists of pixel intensities above the threshold. The algorithm calculates the probability of each class by determining the relative number of pixels in C1 and C2.

4. Class Mean Calculation:

The mean intensity values for both classes, C1 and C2, are computed. These means represent the average pixel intensities of the two regions (foreground and background).

5. Intra-class Variance Calculation:

The intra-class variance (or within-class variance) is the measure of how dispersed the pixel intensities are within each class. For each threshold, the intra-class variance for both C1 and C2 is calculated. The aim is to minimize this variance, which corresponds to finding a threshold that best separates the two classes.

6. Optimal Threshold Selection:

The Otsu method searches for the threshold value that minimizes the total intra-class variance (within both C1 and C2). Alternatively, this is equivalent to maximizing the interclass variance, which ensures that the two groups (foreground and background) are as distinct as possible in terms of pixel intensity.

7. Binary Image Creation:

Once the optimal threshold is determined, the image is binarized by assigning all pixels below the threshold to the foreground (usually represented as black or white pixels) and those above it to the background.

IV. FLOWCHART

Image Acquisition

Digital Cameras: High-resolution images can be captured using standard cameras, Drones: For large structures, drones equipped with cameras offer aerial views, Thermal Imaging: Used to identify cracks not visible to the naked eye. Considerations Lighting Conditions: Ensure optimal lighting to avoid shadows and reflections, Camera Calibration: Necessary for accurate measurements and to reduce distortion.

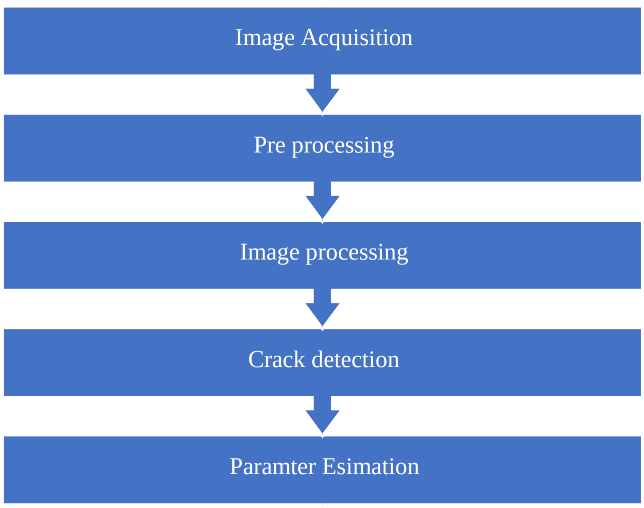


Figure 1. Flowchart implementation of the method

Preprocessing

Enhance image quality, Reduce noise, Prepare images for effective crack detection. Techniques: Grayscale Conversion: Simplifies the image by reducing color complexity, Noise Reduction: Filters like Gaussian or median filters can be applied to minimize background noise, Contrast Enhancement: Techniques such as histogram equalization improve visibility of cracks.

Image Processing

Techniques for Crack Detection- Edge Detection: Algorithms like Canny and Sobel detect edges which often correspond to cracks, Morphological Operations: Operations such as dilation and erosion help in highlighting crack structures, Segmentation: Techniques like thresholding or region-based segmentation isolate cracks from the background. Machine Learning Approaches- Deep Learning: Convolutional Neural Networks (CNNs) can be trained on labeled datasets for automated crack detection, Feature Extraction: Extracting features like length, width, and orientation for further analysis.

Crack Detection

Detection Metrics- Accuracy: Proportion of true positives in relation to the total number of detections, Precision: Ratio of true positives to the sum of true and false positives.

Parameter Estimation

Length and Width: Essential for assessing the severity of the cracks, Depth Estimation: Can be inferred through advanced imaging techniques like 3D reconstruction, Orientation and Pattern: Analyzing the geometric characteristics provides insights into potential causes.

V. IMPLEMENTATION

The process begins by loading the target image using the imread function, which imports the image from a specified file path. If the image is in color (having three channels), it is then converted to grayscale using rgb2gray to simplify subsequent analysis. This grayscale image serves as the foundation for detecting cracks.

Next, we apply Otsu's thresholding method to distinguish cracks from the background. This involves calculating an optimal threshold value that effectively separates the pixel values representing cracks from those representing noncrack areas. The resulting binary image, created using imbinarize, highlights the detected cracks, turning them into prominent features for further examination.

To visually assess the results, both the original grayscale image and the binary image are displayed side by side in a single figure using subplots. This allows for immediate comparison and evaluation of the crack detection effectiveness. For further analysis, the images are converted to double precision format to ensure numerical accuracy in calculations. The binary image is scaled appropriately to match the original image’s pixel intensity range, facilitating precise metric computations.

The next step involves calculating the Signal-to-Noise Ratio (SNR), which measures the ratio of the original image's power to the noise introduced by the cracks. This is achieved by computing the average power of the original image and the noise power (the difference between the original and binary images). The SNR is expressed in decibels, providing a clear indication of image quality. Following SNR, we compute the Peak Signal-to-Noise Ratio (PSNR), which quantifies the quality of the cracked image relative to the original. This calculation involves determining the Mean Squared Error (MSE) between the two images and using it to derive the PSNR value, also in decibels.

To further evaluate the similarity between the original and binary images, we calculate the Structural Similarity Index (SSIM). This metric provides insights into the perceived quality of the images by assessing structural information. Finally, the computed metrics—SNR, PSNR, and SSIM—are printed to the console, offering a comprehensive overview of the image quality and the effectiveness of the crack detection process. This systematic approach ensures clarity and effectiveness in identifying and analyzing cracks in the image.

VI. RESULT

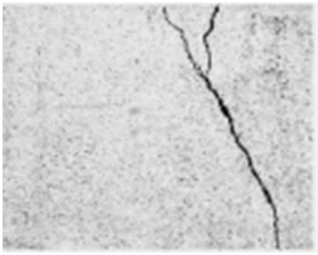


Fig.Wall Crack Image

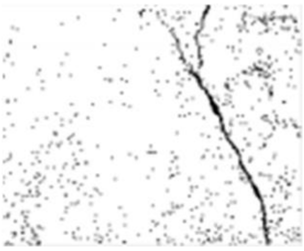


Fig Segmented Image

	observation		
	SNR	PSNR	SSIM
	12.81db	14.37db	0.2154

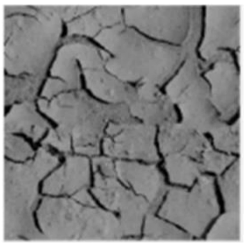
Table 1: Analysis of Results of Wall crack detection

Bridge Crack Image

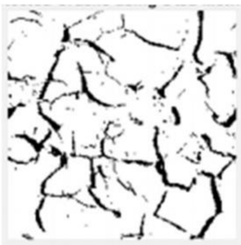
Segmented Image

	observation		
	SNR	PSNR	SSIM
	9.20db	11.97db	0.0355

Table 2.Analysis of Results of bridge crack detection



Crack image

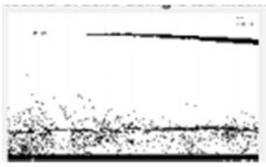


Segmented Image

	Obseravation		
	SNR	PSNR	SSIM
	0.66db	6.74db	0.1368

Table 3: Analysis of Results of Cracks Detection

Road Crack Image



Segmented Image

	observation		
	SNR	PSNR	SSIM
	9.20db	11.73db	0.1256

Table 4: Analysis of Results of Road Crack Detection

 Face Crack Image	 Segmented Image

	observation		
	SNR	PSNR	SSIM
	3.60db	10.52db	0.2058

VII. CONCLUSION

This paper explores the effectiveness of automated crack detection systems in infrastructure maintenance. Traditional manual inspection methods, while effective, are labor intensive, time-consuming, and susceptible to human error. This paper demonstrates the advantages of using image processing techniques such as edge detection, thresholding (with a focus on the Otsu method), and morphological operations for identifying and quantifying surface cracks in buildings and bridges. The automated system provides high detection accuracy, reduces false positives, and is robust under various environmental conditions. By improving detection speed and reliability, it significantly reduces the time needed for inspections and enhances decision-making in the maintenance of structural health. Ultimately, the research highlights how automated crack detection systems offer an efficient, noninvasive, and scalable solution for modernizing infrastructure monitoring and ensuring long-term structural integrity.

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