A Novel Directional Lighting Algorithm for Concrete Crack Pixel-level Segmentation

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ABSTRACT

External lighting is required for autonomous inspections of concrete structures in low-light environments; however, previous studies have only considered uniformly diffused lighting to illuminate images. This study proposes a novel algorithm that utilises angled and directional lighting to obtain pixel-level segmentation of concrete cracks. The method applies a concrete crack detection algorithm to separate images, each illuminated with lighting from a different direction. Using a bitwise OR operation, the findings from all images are combined; the resulting image highlights the extremities of any present cracks in all lighting directions. When tested on a dataset of cracks ranging in widths from 0.07 mm to 0.3 mm, the algorithm obtained recall, precision and F1 score results of 77%, 84% and 92%, respectively. The algorithm was able to correctly segment cracks that were deemed too thin for similar diffused lighting segmentation methods found in literature. The proposed directional lighting algorithm has the potential to improve concrete inspections in low-light environments.

Keywords: Defect detection, Autonomous inspections, Image processing, White-box technique, Bitwise OR operation, Construction Automation, Structural Health Monitoring.

1. INTRODUCTION

One of the preliminary signs of deterioration of a concrete structure is cracking. The early identification of cracks is vital to ensuring the longevity of a concrete structure.[1] Visual inspections are the most common form of non-destructive evaluation (NDE) inspections; however, when manually conducted, they produce inconsistent results and present a risk to human life.[2] These issues have led to the automation of inspections through image capture and image analysis. Automation of image capture (using robots and drones) reduces the danger to human workers; however, manually analysing the data from this method is still exhaustive, and mistake-prone.[3] This resulted in the development of image defect detection techniques, which can broadly be divided into two categories: white-box and black-box. White-box techniques, more commonly known as image processing techniques, are transparent mathematical operations applied to an image, such as edge detectors and thresholding.[4] Black-box methods utilise machine learning and artificial neural networks; their development has recently accelerated due to the increased availability of computer processing power.[5] Studies comparing the two different approaches for crack detection have found that while black-box techniques are excellent for defect classification and localisation, white-box techniques still prove superior for pixel-level segmentation (the process of labelling a pixel as cracked or uncracked).[6]

Previous studies conducting automated defect detection in low-light environments have only considered diffused lighting sources to illuminate image scenes[7].[8] Other studies have used image processing techniques to remove non-uniform lighting as a pre-processing method.[9] However, in a manual visual inspection, a human inspector may use non-uniform lighting to their advantage and vary the angle and direction of lighting to enhance any present defects. This study seeks to map this human-led directional lighting approach to an automated concrete crack detection method.

2. PROPOSED METHOD

Figure 1 illustrates the proposed method. Four images of the concrete surface are captured, each with lighting projected from a different direction. Image processing techniques are separately applied to four different concrete crack images, with the findings from each image then combined using a bitwise OR operation. Detailed explanations of each step of the method are described in sections 2.1 - 2.3.

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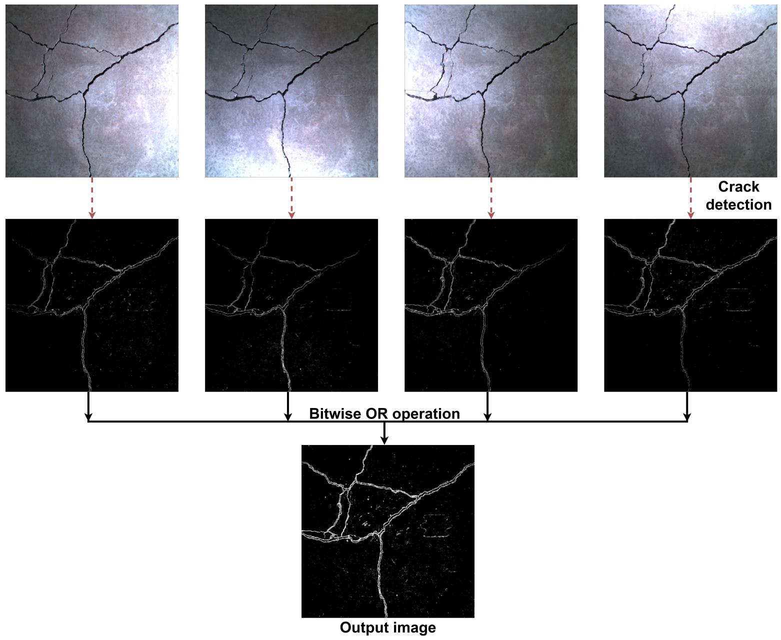


Figure 1. Summary of results of directional lighting method. The individual crack detection results from each lighting direction image are combined using a bitwise OR operation to produce an output image showing the extremities of the crack in all lighting directions.

2.1 Image acquisition

Four directional lighting images are captured, each with a single lighting source projected from the Above (A), Below (B), Right (R) and Left (L) directions relative to the image scene. A representative sample of the captured images for our proposed method are displayed in Figure 1. A diffused lighting image (D) is also captured.

The directional lighting images are captured using our inspection apparatus. The device consists of a camera surrounded by four angle-adjustable arms, each fitted with an LED lighting strip. As shown in Figure 2, the lighting arms are set to an angle of 50-degrees incident to the concrete surface. This enhances the shadows cast in the cracks, increasing their visual contrast from the surface. Images are captured under dark conditions to remove any ambient light and to test solely directional lighting.

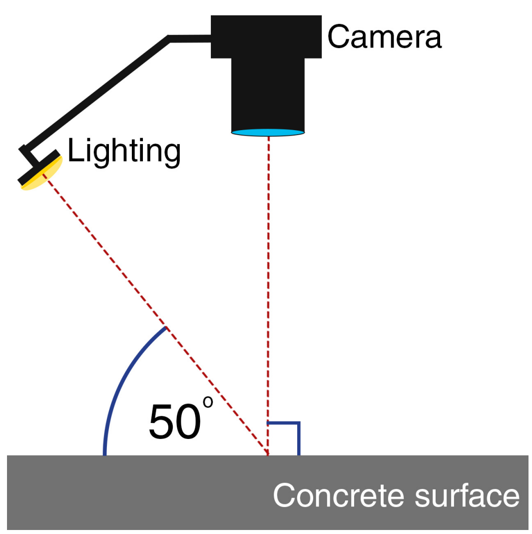
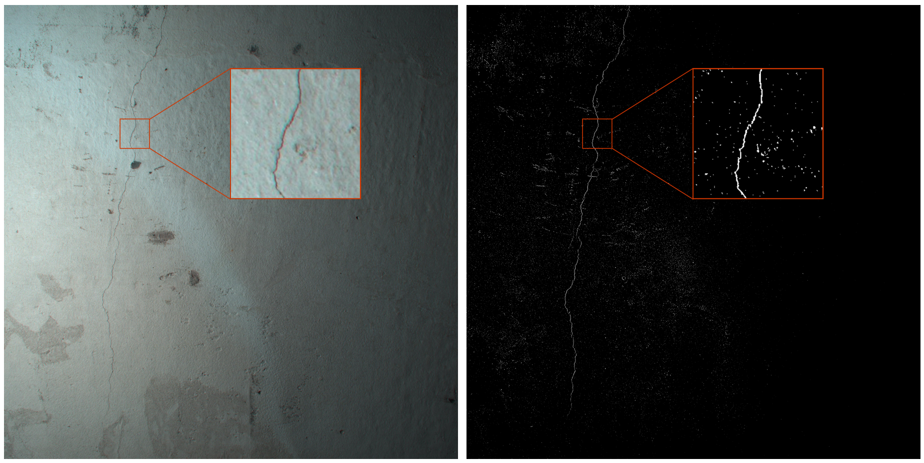


Figure 2. Custom inspection hardware used to project lighting at 50-degree angle of incidence.

2.2 Crack detection

Our crack detection method is applied to each image with directional lighting. Using the diffused lighting image, contrast enhancements are applied before converting the image to greyscale. Similar to Andrushia et al.,[10] the image is smoothed to remove noise using anisotropic diffusion. Following this, a 3×3 Laplacian kernel is applied to extract the edges (cracks) in the image. The edge enhancements from the Laplacian of Gaussian (LoG) method described by Dorafshan et al.[6] are applied to further enhance the crack. The resulting binary image shows pixels labelled as cracked (white), or uncracked (black).



(a) (b)

Figure 3. Crack detection algorithm with 224×224 inset on part of the crack element. (a) algorithm input image, (b) algorithm output image.

2.3 Image combination

The resulting binary images for each lighting direction are combined into a single image using a bitwise OR operation; as shown in Figure 1, this creates an image where a pixel x,y is positive if x,y is positive in any of the input images. The output image of the bitwise OR operation highlights the extremities of cracks in the image in every lighting direction.

2.4 Noise removal

Noise removal is applied to the resulting bitwise OR image to remove false positive pixels. In this study, an unpublished algorithm was used; however, any noise removal method, such as an area threshold, would be suitable.[6]

3. METHODOLOGY

Analysis of the proposed method requires:

- formation of a directionally illuminated concrete crack dataset;
- dataset ground truth definition; and,
- description of benchmarking methodology.

3.1 Dataset formation

In our laboratory facilities, two large and thin concrete slabs were cast; cracks were created by applying force at the slab edges while the desired crack location was supported by a thin metal bar. Crack widths on these samples range from 0.07 mm to 0.3 mm. Our directional lighting apparatus was used to capture dataset images of the slabs under directional lighting illumination conditions. For each inspection area, five illumination images are captured, matching the A, B, L, R, and D requirements of the algorithm, as outlined in Section 2.1.

3.2 Ground truth

For each dataset image scene, a ground truth was defined by tracing the crack using image editing software. As the camera position did not move during image acquisition, one ground truth is suitable for all five images of the dataset image scene (A, B, L, R, & D)

3.3 Benchmarking methodology

The directional lighting method was both qualitatively and quantitatively compared to the ground truths. For the quantitative analysis, the algorithm output of each image scene and the respective ground truth were used to calculate the true negatives (TN), false negatives (FN), false positives (FP) and true positives (TP). The resulting TN, FN, FP and TP values of all image scenes were then summed, allowing the performance metrics in Table 1 to be calculated. This was done on the entire dataset and on only positive 224 × 224 blocks.

Table 1. Performance metrics for a classifier.

Name	Description	Equation
True positive rate (recall) (TPR)	The estimated probability that an actual cracked pixel tests cracked.	$TPR = \frac{TP}{TP+FN}$
Positive predictive value (precision) (PPV)	The estimated probability that a cracked prediction is a true positive.	$PPV = \frac{TP}{TP+FP}$
F1 score (F1)	The weighted average of recall and precision.	$F1 = \frac{2 \times TPR \times PPV}{TPR + PPV}$

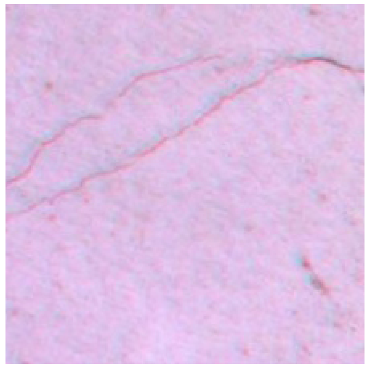
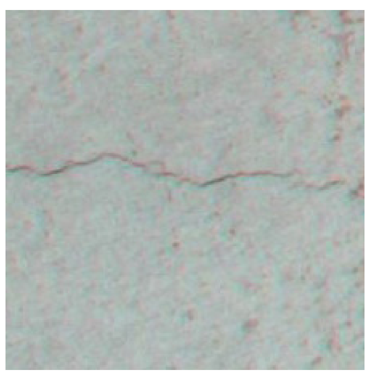
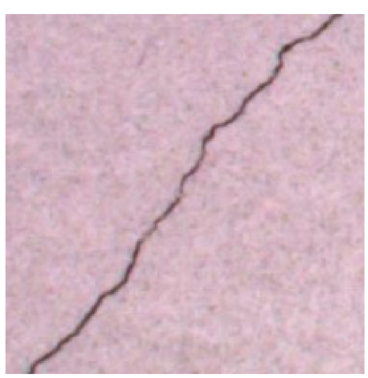
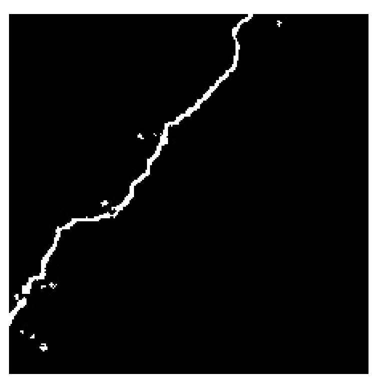
4. RESULTS

4.1 Qualitative Results

Table 2 shows a diffused view of a cracked area of a slab and the corresponding directional lighting algorithm output for that area. The input images for the algorithm are the A, B, L, R and D directional lighting images for that corresponding input area. While the algorithm is applied to the whole image area, these areas are cropped to 224 × 224 pixels to allow user viewing; the red inset in Figure 3 shows this area size in comparison to the full-resolution image.

On thinner cracks (e.g. Sample 1 and Sample 3), the performance of the algorithm is good; however, sections of the crack are disconnected or entirely missing. On thicker cracks (e.g. Sample 2 and Sample 4), the algorithm has performed very well, correctly segmenting the majority of cracked pixels in the image with minimal false positives. The algorithm was also able to successfully detect cracks in vertical, horizontal and traverse directions.

Table 2. 224 × 224 pixel view of diffused cracked area and the corresponding directional lighting algorithm output.

Dataset	Input Area	Algorithm Output
Sample 1		
Sample 2		
Sample 3		
Sample 4		

4.2 Quantitative Results

Table 3 shows the TN, FP, FN, and TP results of the directional lighting algorithm when compared to each ground truth image on the entire and positive datasets. These results were used to calculate the performance metrics shown in Figure 4.

Table 3. TN, FP, FN and TP results of each method across the dataset.

Method	TN	FP	FN	TP
Entire dataset	112,693,136	34,736	38,898	129,230
Positive only dataset	22,149,323	10,869	38,898	129,230

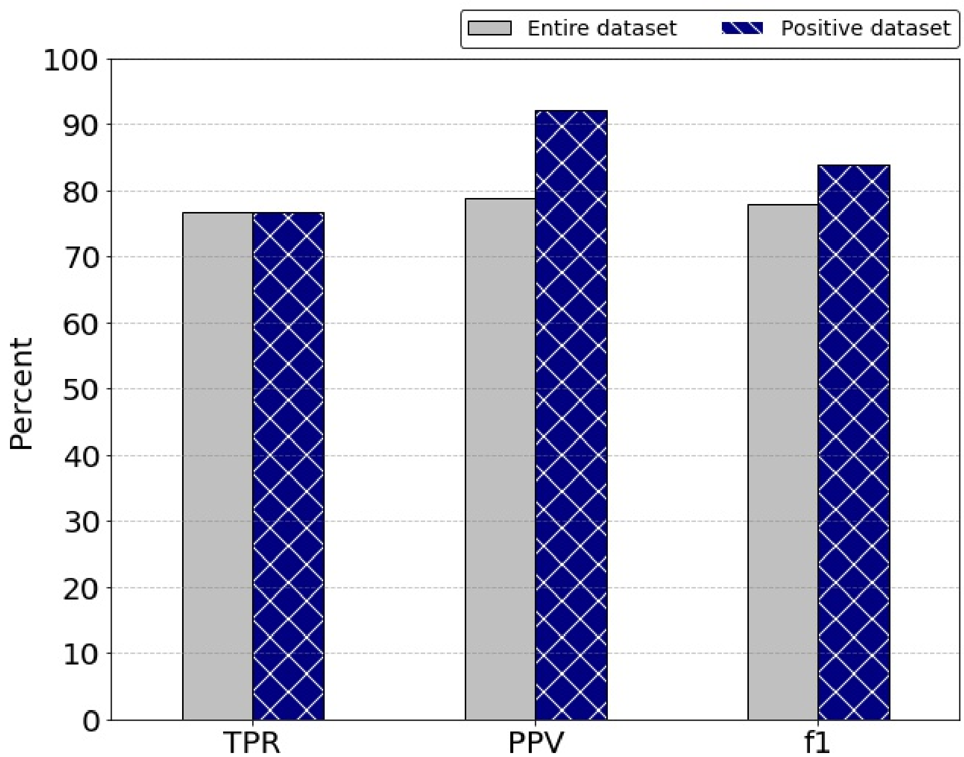


Figure 4. Performance metrics of the proposed method on the entire dataset, and positive only dataset. Abbreviations are described in Table 1.

On the entire dataset, the directional lighting method obtained a recall of 77%, precision of 79%, and F1 score of 78%. Testing on a positive-only dataset emulates a hybrid crack detection method, where a black-box classifier algorithm selects fewer negative (uncracked) portions of an image for subsequent white-box segmentation. The positive block dataset reduced the FP pixel count from 34,736 to 10,869; this resulted in increased precision and F1 scores of 92% and 84%, respectively.

Authors in Ref. 6, tested a similar Laplacian crack segmentation technique that uses a single diffused lighting image. When tested on their entire dataset, the method obtained an F1 score of only 11%. This is 67% lower than our method on our entire dataset. When their algorithm was used in a hybrid method (where the white-box algorithm is only passed through cracked images), they obtained an F1 score of 68%, falling 16% short of our method's results on the positive dataset.

5. CONCLUSION

This paper proposed a novel crack detection algorithm; the method uses multiple images of a concrete surface, each illuminated with lighting from different directions. A series of image processing techniques are then applied to each individual image to segment the cracked pixels. The findings from all individual images are combined using a bitwise OR operation. The resulting image highlights the extremities of any present cracks in all lighting directions. The proposed method was compared to user-defined ground truths; qualitative results showed that the method accurately detected cracks as small as 0.07 mm. Quantitative results showed that on the entire dataset, the method achieved an F1 score of 78%. A hybrid classification was then emulated, where performance metrics were calculated using 224 × 224 block images that contained a crack. This reduced the overall false positive count, leading to an increased F1 score of 84%. These were substantially better than the results from a similar study found in literature that used diffused lighting. This paper has demonstrated that directional lighting can be utilised to conduct automated concrete defect detection and has suggested that the method may be better than other non-directional lighting methods. Although the technique relies on darkness to work, a suitable shroud would enable imaging in ambient lighting. Future studies should quantitatively compare the directional lighting method to diffused lighting methods to conduct a thorough analysis and benchmarking.

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