Robotic concrete inspection with illumination-enhancement

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ABSTRACT

Existing automated concrete inspection methods are intractable: capturing images under ambient conditions which can vary substantially. Furthermore, an opportunity may have been overlooked: utilizing illumination techniques to enhance defect contrast during imaging which may improve automatic defect detection accuracy. In this work, we present a robotic-mountable lighting apparatus that implements contrast enhancing illumination techniques in an automated package in order to improve crack detection and classification in concrete. Geometrical lighting techniques; directional and angled, were tested on three cracked concrete slab samples. Results from blind/referenceless image spatial quality evaluation (BRISQUE) show that both directional and varied angled lighting influence the quality in different associated regions in an image. Furthermore, the region-based crack detection algorithm Faster R-CNN attained a higher accuracy when images were enhanced with directional lighting during all samples tested. The direction of highest accuracy was not consistent over samples, and is likely dependant on features such as crack location, width, orientation etc. This emphasises the importance of adaptive lighting: illuminating the surface with the most suitable conditions based on an initial observation of the feature or defect. This system represents the initial step in a fully-automated and optimised concrete inspection system capable of defect capture, classification, localization and segmentation.

Keywords: Automated inspections, concrete, illumination techniques, improve crack detection, BRISQUE, Faster R-CNN

1. INTRODUCTION

Conventionally, concrete structures are monitored via assessments carried out by trained inspectors. These assessments can be intermittent, costly, unrepeatable and hazardous.[1] Consequentially, vast research efforts are ongoing to solve these issues, such as: remote sensing,[2,3] self- healing concrete[4] or automated inspections.[5] In the latter, the human inspector is replaced by a robot or drone to perform the physical data collection. The main disadvantage of this method over human-based inspection is the lack of adaptability and flexibility to the type of defect to ensure adequate data collection. Following data collection, the data can be analysed remotely by the inspector or using automatic analysis techniques. Such techniques include white-box image processing and black-box neural networks.[6]

Commercially available automated inspection devices include ground, aerial and subsurface image capturing machines.[7] All of which capture images under ambient conditions, or require additional external lighting during dark environments. The opportunity to utilize known illumination techniques to enhance the image collection phase and, therefore, the final analysis, has been overlooked. Many industries utilize illumination techniques to enhance image capture methods.[8–10] Furthermore, it is commonplace for a human inspector to vary illumination (likely using a flashlight) during concrete inspections, but has not been extensively explored in automated inspections.

In this work, we explore the use of a novel adaptive lighting platform, integrated with robotics, to demonstrate the potential of illumination methods for improving automated inspections and concrete crack detection. This paper is structured as follows: an initial review of state-of-the-art in contrast enhancing illumination techniques and reported examples of illumination in automated inspections is given in Section 2. The illumination platform hardware and the analysis methods used will be described in Section 3. Results from image quality analysis and automatic crack detection on images captured with the illumination methods vs. ambient lighting will be discussed in Section 4. The work will be concluded and planned future work will be discussed in Section 5.

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This is a peer-reviewed, accepted manuscript of the following paper: McAlorum, J., Perry, M., Dow, H., & Pennada, S. (2023). Robotic concrete inspection with illumination-enhancement. In Z. Su, B. Glisic, & M. P. Limongelli (Eds.), Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2023 Article 124860L (Proceedings of SPIE - The International Society for Optical Engineering; Vol. 12486). SPIE. https://doi.org/10.1117/12.2655938

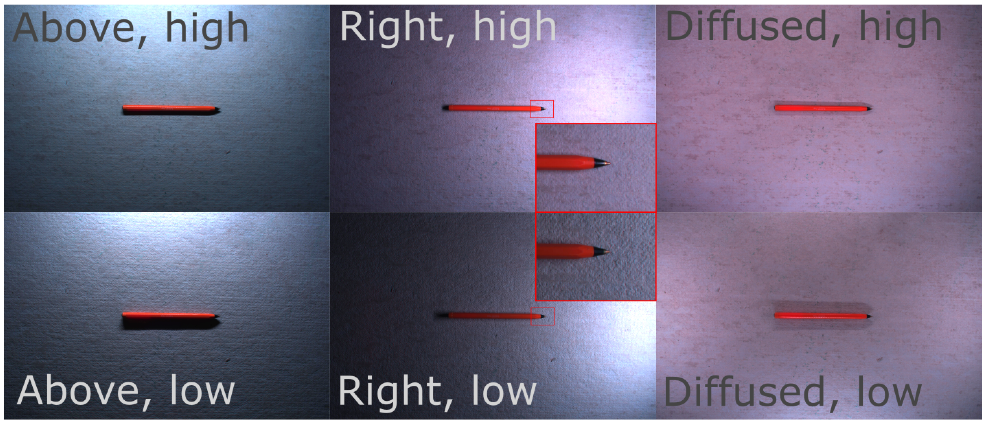

Figure 1. Geometrical illumination techniques to enhance contrast of depth and orientation in an image. Inset: zoomed portion showcasing enhanced surface roughness.

2. BACKGROUND

2.1 Illumination techniques

The purpose of performing variances in illumination is to create contrast in an image between the feature(s) and the background. In our work, the feature of interest is a crack and the background is the concrete. Conventional illumination can be split into 4 categories:[11]

- Geometrical: vary the physical position/vector of the light
- Spectrum: change the colour of the light
- Type: vary the source of light (LED, halogen, natural)
- Filtering: alter the projected light between source and object (polarization, neutral density filters)

In this work, we are focusing on the Geometrical illumination methods, mainly: angle and direction of projected light. These techniques create contrast by causing varied pixel intensities and shadowing which allows a more detailed insight into the depth and orientation differences of features in the scene.[12] Figure 1 shows images of a pen against a surface captured under varying geometrical illumination conditions. This shows the importance of directional lighting, as light projected perpendicularly to the pens length causes more shadowing. When light is projected at a *low* angle, the shadow becomes more elongated. Geometrical methods have been utilized in some works to improve crack detection.[13] However, it is clear that there is more research required.

2.2 Lighting in automated inspections

At the time of writing, there are no commercially available examples of fully automated inspection systems that perform automatic defect detection. However, there are various data collection-based platforms reported in research: Liang et al.[5] created a wall-climbing robot for concrete structure inspection and provided the addition of optional LEDs for compensation when ambient light was insufficient. Loupos et al.[14] showcased a tunnel inspection robot and faced poor lighting conditions, using a large LED panel to provide sufficient illumination to capture images. In these examples, and others, lighting is used simply to provide sufficient illumination for image capture. To our knowledge, there are no reported uses of contrast-enhancing illumination techniques in automated inspection platforms.

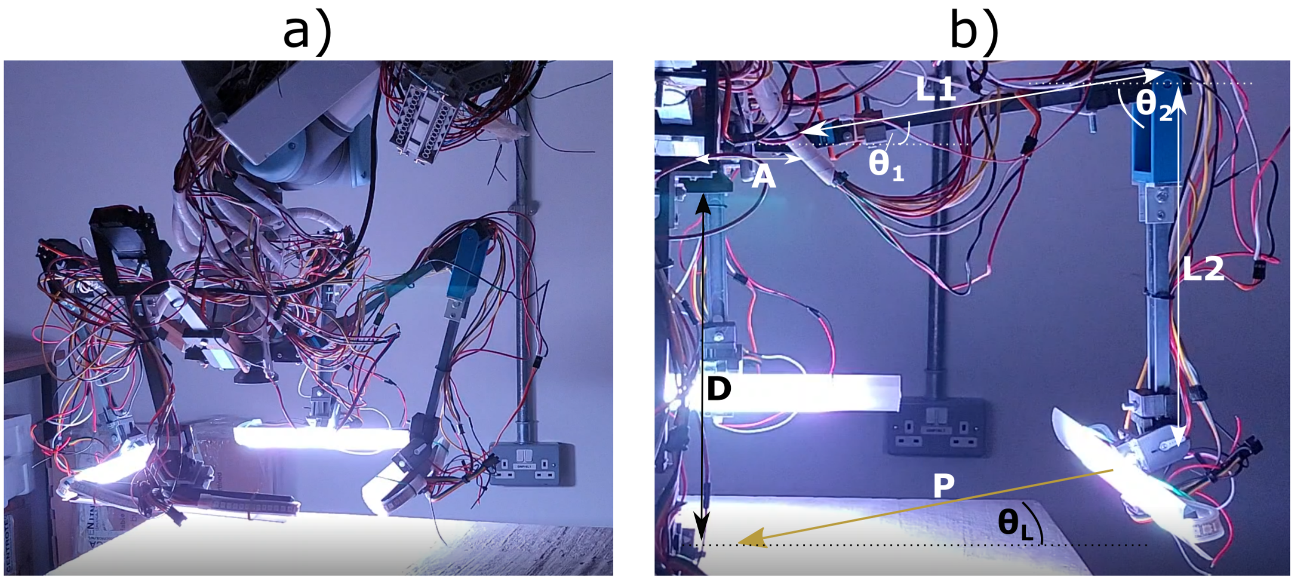

Figure 2. a) Entire set up of robotic illumination with b) single arm annotated.

3. METHODOLOGY

3.1 Robotic Illumination platform

The objectives of the hardware designed in this research are: i) capture multiple images of a concrete surface at various working distances, ii) illuminate the surface with multi-direction, multi-angled light and iii) move to various positions and repeat. This entire process must be performed autonomously. The overall final design of the hardware is shown in Figure 2 a). Firstly, a machine-vision camera is attached to a six-axis robot. Illumination is achieved via four triple-jointed servo-motorized arms with RGB LED strips on the ends. A single arm is annotated in Figure 2 b) for clarity. Using the three joints, the arms can project light on to the surface at any angle between 5 and 50° and at any proximity. This is done by solving the following vector equations:

$$A + L_1 \cos\theta_1 = L_2 \cos\theta_2 + P \cos\theta_L \tag{1}$$

$$D = L_1 \sin\theta_1 + L_2 \sin\theta_2 + P \sin\theta_L \tag{2}$$

where $A = 80$ mm is the distance from the camera centre to the “shoulder” joint, $L_1 = 260$ mm and $L_2 = 270$ mm are the arm lengths, P is the proximity of LED to concrete surface, D is the camera working distance, $-90^\circ \leq \theta_1 \leq 90^\circ$ and $0^\circ \leq \theta_2 \leq 180^\circ$ are the angles of the arms relative to the horizontal and θ_L is the incident angle of LED to concrete surface. The above can be solved by a least-squares minimization for selected P, D and θ_L, an example of which is shown in Table 1.

The hardware is used to capture images with directional lighting (**L**eft, **R**ight, **U**p, **D**own) and **A**mbient lighting (diffused: high angle, all directions), at various angles of projected light ($\theta_L = 10, 20, ...50\,^\circ$).

3.2 Analysis

The analysis in this research will attempt to assess the improvement, if any, of geometrical illumination techniques compared to regular ambient lighting. This will be done in two stages by assessing i) overall image quality and ii) automatic crack detection accuracy. Metrics to estimate both were chosen as: i) Blind/Referenceless Image Spatial Quality Evaluation (BRISQUE)[15] and ii) Faster Regional-Convolutional Neural Network (R-CNN).[16]

Table 1. Example angle calculation by minimization.

	Variable	Value
Desired condition	D	300 mm
	P	300 mm
	θ_L	20°
Required angles	θ_1	-15°
	θ_2	80°
	θ_3	20°

3.2.1 BRISQUE

BRISQUE, unlike other methods, estimates the quality of an image without a high quality reference of the same scene. This is done through the use of a support vector regression model trained on a large database of images with set subjective numerical quality scores.[15] The model then analyses features of an input image (such as pixel intensity distributions) and predicts a score of 1 to 100 where a lower scores represents a better quality image.

BRISQUE scores are usually calculated for an image as a whole. However, due to the nature of directional lighting, certain areas will have better BRISQUE scores than the overall image since areas not lit will be dark and of poor quality. For this reason, we crop the image into blocks of 224 × 224 pixels and observe the BRISQUE score of individual blocks during each lighting condition. This will allow us to examine which lighting condition is best for each block.

3.2.2 Faster R-CNN

R-CNN is a single tool in a large toolbox of object detection algorithms that exist today. Object detection can be described as using machine learning to both locate and classify one or more objects in a scene. The research in this paper does not aim to develop a new, or improve an old, object detection model. Instead, we will utilize an available model to determine if the result it provides can be improved by using images enhanced by the described illumination techniques. As described before, we capture images from the following directions: (**L**eft, **R**ight, **U**p, **D**own) and **A**mbient lighting. In this work, prior to R-CNN predictions, we enhance the images by multiplying each direction (L, R, U, D) by the ambient baseline (A), and then apply Laplacian sharpening (to the new images, and the ambient baseline).[17] This provides a fair comparison of ambient vs. ambient × directional to determine if enhancing the image with directional will improve accuracy of crack detection.

R-CNN is formed from two networks: i) region proposal network (RPN) which initially detects regions of interest before feeding into a ii) CNN classifier network which will classify any objects in the regions of interest.[18]

To determine the effect of illumination techniques on the accuracy of an R-CNN model, we can use the "Area under the curve" (AUC) of the Precision-Recall plot. AUC is used as a substitute for accuracy in object detection as, unlike image classification, there is no way to compute true negatives. AUC is calculated as:

$$AUC = \int_0^1 P(R)dR \tag{3}$$

were $P = \frac{TP}{TP+FP}$ is the Precision and $R = \frac{TP}{TP+FN}$ is the Recall for the accumulative True Positives, TP, False Positives, FP and False Negatives, FN. A higher AUC corresponds to a more accurate model.

4. RESULTS AND DISCUSSION

Four 400 × 400 mm concrete samples with 0.1 - 0.5 mm wide cracks distributed randomly were captured during both ambient and geometrical illumination using the lighting apparatus. Every image was cropped into 224 × 224 pixel blocks and the BRISQUE score for each block under each lighting condition was calculated. Figure

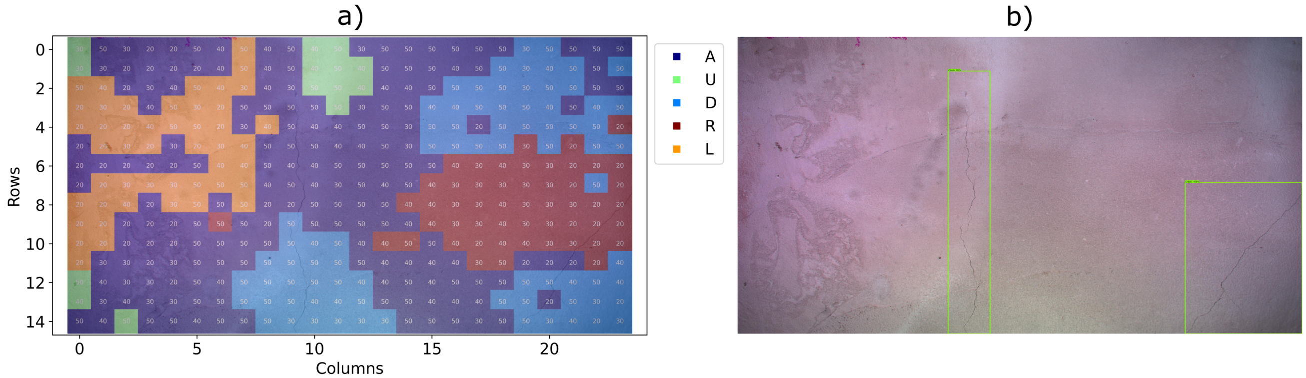

Figure 3. Results for a single sample area: a) Colour contour illustrating the lighting condition with lowest BRISQUE score for each block and b) the output of the R-CNN.

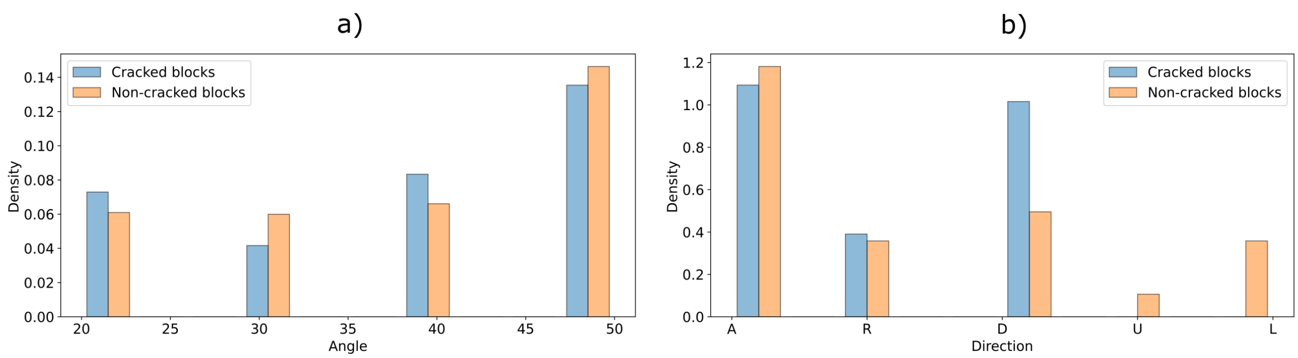

Figure 4. Density of a) angle and b) direction with lowest BRISQUE score for "Cracked" and "Non-cracked" blocks.

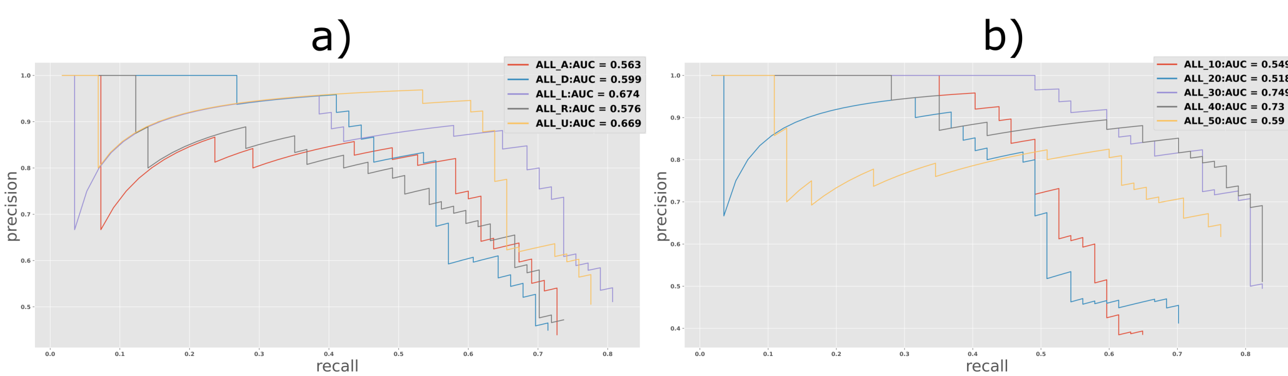

Figure 5. Precision-Recall from R-CNN predictions for all four samples during varied a) direction and b) angle illumination.

3 a) shows a colour contour of the lowest BRISQUE scores and associated lighting condition for each block in the image of a single sample. The colour represents the direction, whereas the associated angle is written on the block. Following this, each block was manually labelled either "Cracked" or "Non-cracked".

Figure 4 shows the density of each a) angle and b) direction in both the "Cracked" and "Non-Cracked" blocks. These results show firstly that the lighting direction has a large influence on the image quality. Generally, the regions closest to the direction of light projection have better quality when compared to ambient lighting, as shown in Figure 3 a). Interestingly, there are two cracks in this sample, indicated by R-CNN detection in Figure 3 b), located in i) bottom center and ii) bottom right of the image. Consequently, when we analyse these "Cracked" blocks, the directions with best BRISQUE scores correspond to the location of the cracks: i.e. the best direction for the crack in the bottom right was found to be light from the **D**own and **R**ight lighting conditions. In terms of the angle of light incident on the surface, there doesn't seem to be any correlation between the best angle and "Cracked" regions. This could be due to the fact the cracks being analysed are of hairline widths, and so a lower angle change has no real benefit in terms of casting a shadow.

Figure 5 shows the Precision-Recall plot for all four samples combined during variations of a) direction and b) angle of illumination. The AUC value for each curve is calculated and given in the legend. In a) the worst value for AUC is given by the ambient lighting on it's own (ALL_A), and the best is found when directional left is combined with ambient (ALL_L). This shows that enhancing the ambient lighting with directional does indeed improve the AUC of the R-CNN P-R plot, suggesting a more accurate crack detection. In b) it is clear that angle of light incident on the surface also impacts the AUC values. Angles 30 ° and 40 ° showcase the highest AUC, whereas all other angles are much worse.

Overall, these results show great potential in utilizing illumination to gain improved image quality and crack detection accuracy. The "best" lighting conditions seem to vary depending on factors such as crack location, orientation, width etc. An adaptive system would, therefore, be preferable, to vary the lighting conditions to best fit the feature in the scene.

5. CONCLUSION

Illumination techniques have been under utilized in automatic crack detection methods. Research in this paper has demonstrated an adaptive, robot mounted lighting platform that is capable of capturing concrete surfaces under geometrical illumination (varied direction and angle). Results show that both direction and angle of light incident on a concrete surface impact both i) the quality of the image, specifically in certain regions and ii) the accuracy of an R-CNN-based crack detection algorithm. The lighting condition with best quality and highest R-CNN accuracy varied between samples, showcasing dependence on the feature itself. This suggests an adaptive system, that varies illumination in real-time, would be required to ensure the most suitable lighting condition is used.

ACKNOWLEDGMENTS

The research in this paper was supported by the Scottish Funding Council (BE-ST, CENSIS) and the University of Strathclyde's Advanced Nuclear Research Centre (ANRC-33).

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