2nd Conference on Sustainability in Civil Engineering (CSCE'20)
Department of Civil Engineering
Capital University of Science and Technology, Islamabad Pakistan

MACHINE VISION BASED CRACK DETECTION FOR STRUCTURAL HEALTH MONITORING USING HARALICK FEATURES

[a] Arif Zafar, [b] Junaid Mir, [c] Vagelis Plevris, [d] Afaq Ahmad

a: Department of Electrical Engineering, University of Engineering and Technology Taxila, Pakistan, arifzafar966@gmail.com
b: Department of Electrical Engineering, University of Engineering and Technology Taxila, Pakistan, junaid.mir@uettaxila.edu.pk
c: Department of Civil Engineering and Energy Technology, OsloMet- Oslo Metropolitan University, Norway, vageli@oslomet.no
d: Department of Civil Engineering, University of Engineering and Technology Taxila, Pakistan, afaq.ahmad@uettaxila.edu.pk

Abstract- Crack detection in structural elements is pivotal for structural health monitoring. In this paper, an automatic machine vision-based crack detection method is proposed, which is efficient, computationally simple, and fast in contrast to the time-consuming and highly subjective traditional visual inspection approach. Textural analysis of the concrete surface image is performed using Haralick features for crack detection. First, a combination of 8 suitable Haralick features in 4 different directions are extracted from the SDNET2018 image dataset. Then, different SVM classifiers are trained on the extracted features and tested using a 5-fold cross-validation scheme to distinguish between cracked and non-cracked images. The resulting best-trained classifier achieves an overall classification accuracy of 88%. Furthermore, the high classification accuracy for individual image categories indicates that the proposed method can effectively detect cracks in the images. Finally, crack orientation is localized based on the extracted feature values.

Keywords- Crack detection, Haralick features, structural health monitoring, machine learning

1 INTRODUCTION

Concrete cracks are generally unavoidable and very common due to expansion, shrinkage, overloading, settlement, or premature drying, which are common causes of cracks in the concrete surface. While concrete cracks are not always associated with high risk, they are nevertheless the first indicators of compromised structural durability and health. Therefore, the detection and assessment of crack properties, such as width, orientation, and its precise location in the structure, is crucial for structural health monitoring (SHM). Visual inspection by a trained inspector is the conventional method for crack detection which is highly subjective of the person's experience and knowledge. More importantly, visual inspection is a particularly time-consuming and labor-intensive approach. Therefore, several reliable and cost-effective machine vision (MV) based automatic crack detection and assessment techniques have been proposed in the literature as a substitute for the traditional human visual inspection approach for SHM [1].

MV-based SHM techniques mostly rely on the camera image for concrete crack detection. As the crack in a 2D image is characterized by an edge, these methods generally employ edge detection and segmentation algorithms for the detection of cracks in the concrete surface image. In [2], probabilistic relaxation with adaptive thresholding is proposed for crack detection. A pavement crack detection method: CrackTree [3], detected cracks from the crack probability map constructed through the tensor voting scheme after the correction of illumination using the geodesic shadow removal technique. A phase symmetry-based enhancement filter coupled with morphological operations and thresholding is proposed in [4] for concrete crack detection. In [5], cracks are detected by using the Sobel edge detector and OTSU thresholding scheme. This method was further extended in [6], where the connected component analysis was performed in HSV colorspace to detect cracks. In [7], the Sobel edge detector, morphological operations, and particle filter are employed for crack detection. A bottom-hat morphological operation is used in [8] for the detection of crack and surface degradation. A machine learning (ML) centered method is proposed in [9] where a classifier trained on the histogram of oriented gradient features is used for crack detection. A similar approach is presented in [10], where a trained classifier on speeded-up robust descriptors is utilized for the classification of images into cracked and non-cracked images. In [11], crack detection using small drones is proposed by using a deep learning (DL) neural network approach. AlexNet convolutional neural network (CNN) is trained using a transfer learning approach to classify acquired camera images from the drone into cracked and non-cracked images. A method in [12] is also based on the AlexNet CNN, where an exhaustive search with a sliding window is utilized to detect cracks using a smartphone application. In [13], a semantic segmentation is performed to accurately detect crack pixels using a visual geometry group network (VCGNet) based CNN.

The existing MV-based crack detection techniques are generally conditional variant due to pixel-based detection of cracks. Therefore, their performance is seriously compromised due to different light conditions, blemishes and concrete spalls. On the other hand, accuracy of DL-based crack detection methods is largely dependent on the quality and quantity of the utilized training dataset. In the present paper, a MV-based method for the automatic detection of cracks from the camera images is presented, which relies on the concrete surface texture analysis as a suitable measure for crack detection. For ameliorating this, Haralick features are initially extracted from the diverse database of the cracked and non-cracked concrete surface images. Then, the ML-based classifiers are trained and tested on the extracted features for crack detection. The trained classifier on the extracted features achieves high classification accuracy for crack detection. In contrast to existing techniques, the proposed method is based on the global robust features, and therefore, the performance of the proposed method is invariant to image translation, rotation, scale, and illumination.

The remainder of the paper is organized into four sections. In Section 2, the materials and methods utilized in the proposed technique are presented. The proposed methodology is detailed in Section 3. Results are discussed in Section 4, and the conclusions and future work is presented in Section 5.

2 MATERIALS AND METHODS

2.1 Materials

The required material for this study is the concrete images of different civil structures annotated as cracked or non-cracked. For this purpose, SDNET 2018 is utilized, which is a publicly available comprehensive dataset of more than 56,000 camera images of concrete walls, pavements, and bridges [14]. The images in the dataset (as detailed in Table 1) are labeled and categorized into two image classes: cracked and non-cracked. SDNET2018 is a challenging and diverse dataset as it includes images with different illumination conditions and obstructions. Further, it includes images of different crack widths ranging from 0.06 mm to 25 mm. Figure 1 shows some of the SDNET2018 images of different conditions and cracks widths. For our method, we have pre-selected images (as detailed in Table 1) for each class (cracked and non-cracked) from each category. The selection was primarily done to balance the classes and more importantly, to remove images having barely visible cracks or cracks within tolerable crack width as per guidelines of American concrete institute (ACI) [15].

(a) (b) (c) (d) (e)

Figure 1: SDNET2018 image dataset: Non-cracked (a) and cracked (b-e) sample images with different crack widths and lighting conditions of walls (top row), pavements (middle row), and bridge decks (bottom row).

Table 1- Details of original SDNET2018 and Utilized image dataset.

Category	SDNET2018			Utilized dataset (Selected Images)		
	Cracked images	Non-cracked images	Total	Cracked images	Non-cracked images	Total
Bridge deck	2025	11,595	13,620	960	960	1920
Pavement	2608	21,726	24,334	964	964	1928
Wall	3851	14,287	18,138	960	960	1920
Total	8484	47,608	56,092	2884	2884	5768

2.2 Haralick Features

Haralick features are extracted from the gray-level co-occurrence matrix (GLCM) [16]. GLCM matrix is the statistical method of examining texture based on the spatial relationship of the pixels. The normalized and symmetric GLCM matrix is computed by calculating how often a pixel with a grayscale value i occurs with a specific pixel offset and direction to a pixel with the grayscale value j. For our proposed method, we have selected 8 Haralick features out of 14. The selected features are: *Contrast*, *Angular second moment (ASM)*, *Energy*, *Dissimilarity*, *Homogeneity*, *Entropy*, *Correlation*, and *Variance*, which were the most suitable ones for the texture analysis of the concrete crack surface. The mathematical expressions for these features are presented in Table 2, where $I(i,j)$ is the GLCM matrix of size $N \times M$ with i and j index values, μ is the mean value and σ_x and σ_y are the standard deviation in the x and y directions, respectively.

Table 2- Selected Haralick features.

Feature	Expression	Feature value in presence of Crack
Contrast	$\sum_{i,j}^{N-1} (i-j)^2 * I(i,j)$	Higher value
ASM	$\sum_{i,j}^{N-1} [I(i,j)]^2$	Lower value
Energy	$\sqrt{ASM}$	Lower value
Dissimilarity	$\sum_{i,j}^{N-1} \lvert i-j \rvert * I(i,j)$	Higher value
Homogeneity	$\sum_{i,j} \frac{I(i,j)}{1+\lvert i-j \rvert}$	Lower value
Correlation	$\sum_{i,j}^{N-1} \frac{(i,j) * I(i,j) - \mu_x * \mu_y}{\sigma_x * \sigma_y}$	Lower value
Entropy	$-\sum_{i,j}^{N-1} I(i,j) * \log I(i,j)$	Higher value
Variance	$\sum_{i,j}^{N-1} (i-\mu)^2 * I(i,j)$	Higher value

3 PROPOSED METHODOLOGY

The block diagram of the proposed MV-based crack detection method from the concrete surface images is depicted in Figure 2 with the details presented below. The processes involved in the proposed methodology were implemented and executed using MATLAB and Python computer programming languages.

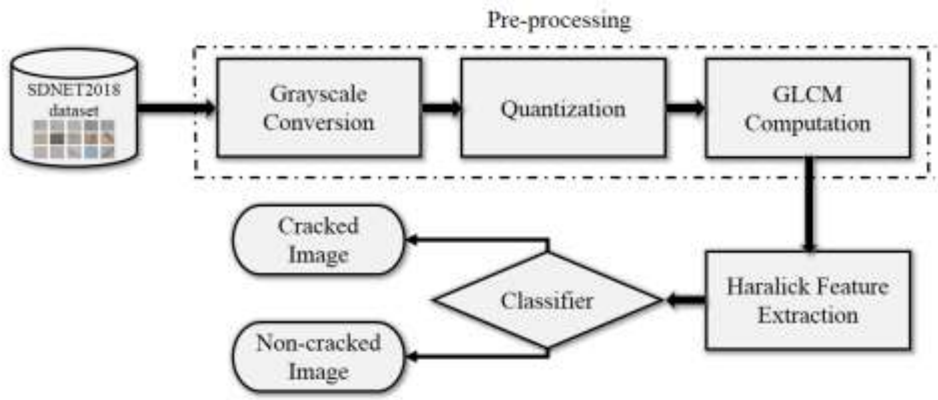

Figure 2: Block diagram of the proposed method.

3.1 Pre-processing

The color concrete surface image is first converted to grayscale format using a linear transformation. Then, the image is quantized to 12 grey levels which were found enough for retaining the cracks with sufficient detail. The resulting quantized grayscale image was an accurate approximation of the original 256 grey level image. The quantization was done to facilitate the computation of GLCM as it is computationally very expensive to calculate GLCM for all 256 grey levels. After the quantization, GLCM is computed with a pixel offset of 1 for four angles (0˚, 90˚, 45˚ and 135˚), corresponding to four directions: the horizontal, the vertical, and the two diagonals, respectively.

3.2 Haralick Feature Extraction

Selected Haralick features (as detailed in Section 2.2) are extracted from the GLCM. Out of the 8 features, 6 features (except *Entropy* and *Variance*) will have 4 values from 4 different directions. Therefore, the resulting feature vector length is 26. Further, the main orientation of the crack can be observed by analyzing the feature values in four different directions as there is a distinct discrepancy present among GLCMs generated at different angles. Cracks are generally oriented along with local minima or maxima of that individual feature, depending on the behavior of feature in the presence of the crack.

3.3 Classifier

A support vector machine (SVM) is used as a classifier for training and testing the proposed method. SVM is a global classifier suitable for fitting multi-class data distribution. Based on the kernel, it can perform both linear and non-linear fitting for classification. For linear classification, a suitable hyper plane divides each cluster equally by the support vectors. While in non-linear classification, it transforms the initial distribution to a higher dimension where they are separable. The tested kernels included *radial basis function (RBF)*, *Histogram intersection (HI)* and *linear*. For training and testing the SVM kernels, k-folds cross-validation scheme was utilized. The data were randomly partitioned into k equal sets and then the classifier is trained on $k - 1$ sets with remaining 1 set left out for testing. The process is repeated for each set and the final accuracy is collectively calculated for the complete set. The value of k was 5 in our method.

4 RESULTS AND DISCUSSION

To quantify the performance of the trained classifier for crack detection, *Accuracy* (*Acc.*), *Recall* (*R*), *Precision* (*P*) and *F1-score* (*F1*) are computed. Table 3 presents the utilized performance metrics where *TP* is True Positive: a cracked image correctly classified as a cracked image, *TN* is True Negative: a non-cracked image correctly classified as a non-cracked image, *FP* is False Positive: a non-cracked image incorrectly classified as a cracked image, and *FN* is False Negative: a cracked image incorrectly classified as a non-cracked image.

Table 3- Performance metrics.

Metrics	Mathematical Expressions
Accuracy (%)	$Acc. = \frac{TP+TN}{TP+TN+FP+FN} \times 100$
Recall (%)	$R = \frac{TP}{TP+FN} \times 100$
Precision (%)	$P = \frac{TP}{TP+FP} \times 100$
F1-score (%)	$F1 = \frac{2 \times P \times R}{P+R} \times 100$

Table 4 presents the 5-fold cross-validation results in terms of *Acc.*, *R*, *P*, and *F1* of the tested classifiers for individual categories and all categories combined. It can be observed that the *HI*-based SVM classifier has the maximum performance metric values for individual categories. The proposed method can distinguish between cracked and non-cracked images with an accuracy of 88% for bridge deck surface images, 94% for pavement surface images and 89% for wall surface images. Further, when all categories are combined, the proposed method has a classification accuracy of 88% and the best-trained model is a *Linear*-based SVM classifier.

Table 4- Performance evaluation of the proposed method. 5-fold cross-validation results of SVM kernel-based classifiers trained on each image category and all images combined.

Category		Bridge deck			Pavement			Wall			All		
SVM kernel		*RBF*	*HI*	*Lin*	*RBF*	*HI*	*Lin*	*RBF*	*HI*	*Lin*	*RBF*	*HI*	*Lin*
Metrics	*Acc.* (%)	74	***88***	88	88	***94***	92	66	***89***	88	64	57	***88***
	R (%)	66	***85***	84	84	***93***	91	74	***89***	87	74	59	***86***
	P (%)	77	***91***	91	91	***95***	93	57	***89***	88	59	55	***90***
	F1 (%)	70	***88***	87	87	***94***	92	64	***89***	88	65	56	***88***

After the crack detection by a trained classifier, the extracted Haralick feature values in four directions are assessed to localize the main orientation of the crack in the image. While all extracted Haralick features show a distinctly different value along the direction of the crack orientation in comparison to the other directions, we have found the *contrast* as the most suitable feature for the localizing the main direction of the detected crack in an image. Therefore, the crack's main orientation is ascertained by finding the maximum value of the *contrast* feature. To elaborate on this, Figure 3 shows two sample images with 135˚ and 45˚ crack orientations. The corresponding four *contrast* feature values calculated from GLCMs for these two images are tabulated in Table 5. As GLCMs have distinct discrepancies among themselves in the presence of a crack, this is reflected in the computed feature values. Figure 3(a) has the maximum *contrast* feature value of 2.36215 for GLCM computed at an angle of 135˚. Therefore, the main orientation of the detected crack in the image is the diagonal direction of 135˚. Similarly, the maximum contrast value for Figure 3(b) is 3.80787 for computed GLCM at 45˚angle, which is indeed the main direction of the crack orientation in the image.

(a) (b)

Figure 3: (a) Cracked image with 135˚ crack orientation (b) Cracked image with 45˚ crack orientation.

Table 5- Haralick *Contrast* feature values for sample images in Figure 3.

***Contrast* Values**	**GLCM Angles**			
	0˚	**45˚**	**90˚**	**135˚**
Figure 3 (a)	1.49887	1.74825	0.87333	***2.36215***
Figure 3 (b)	2.67880	***3.80787***	1.10470	2.80471

Finally, the performance comparison of our proposed method is made with a recent study in [17], where six different MV-based algorithms are benchmarked for crack detection in concrete surfaces. Among the tested algorithms, the crack detection in spatial domain using Laplacian of Gaussian (LoG) filter proved to be the best performing technique for concrete crack detection. While the rest of the evaluated algorithms had a classification accuracy of below 85% [17], the LoG-based algorithm yielded a similar performance with 92% accuracy with 88% precision, which is comparable with our proposed method. However, the performance of the algorithm is reported on an image dataset size of 100 images of concrete panels only.

5 CONCLUSION

The following conclusions can be drawn from the conducted study:

- An automatic crack detection from concrete surface images of different civil structures can be made using advanced machine vision techniques.
- Crack detection can be done through textural analysis of the concrete surface image using a combination of appropriate Haralick features.
- Crack orientation can be determined by assessing the extracted features in different directions.

The proposed method shows a good classification accuracy for cracked and non-cracked images which motivates us to explore other Haralick features in future works. The proposed method can be integrated with unmanned aerial vehicles (drones) for autonomous concrete crack detection. Also, more robust pre-processing steps can be examined to enhance the region of interest to improve the crack detection and thereby, further improve the classification accuracy.

ACKNOWLEDGMENT

The careful review and constructive suggestions by the anonymous reviewers are gratefully acknowledged.

REFERENCES

[1] Arun Mohan and Sumathi Poobal. Crack detection using image processing: A critical review and analysis. *Alexandria Engineering Journal*, 57(2):787–798, 2018.

[2] Yusuke Fujita and Yoshihiko Hamamoto. A robust automatic crack detection method from noisy concrete surfaces. *Machine Vision and Applications*, 22(2):245–254, 2011.

[3] Qin Zou, Yu Cao, Qingquan Li, Qingzhou Mao, and Song Wang. CrackTree: Automatic crack detection from pavement images. *Pattern Recognition Letters*, 33(3):227–238, 2012.

[4] Hoang-Nam Nguyen, Tai-Yan Kam, and Pi-Ying Cheng. An automatic approach for accurate edge detection of concrete crack utilizing 2D geometric features of crack. *Journal of Signal Processing Systems*, 77(3):221–240, 2014.

[5] Ahmed Mahgoub Ahmed Talab, Zhangcan Huang, Fan Xi, and Liu HaiMing. Detection crack in image using Otsu method and multiple filtering in image processing techniques. *Optik*, 127(3):1030–1033, 2016.

[6] Sattar Dorafshan, Marc Maguire, and Xiaojun Qi. Automatic surface crack detection in concrete structures using OTSU thresholding and morphological operations. 2016.

[7] F´abio Celestino Pereira and Carlos Eduardo Pereira. Embedded image processing systems for automatic recognition of cracks using UAVs. *IFAC-PapersOnLine*, 48(10):16–21, 2015.

[8] S Sankarasrinivasan, E Balasubramanian, K Karthik, U Chandrasekar, and Rishi Gupta. Health monitoring of civil structures with integrated UAV and image processing system. *Procedia Computer Science*, 54:508–515, 2015.

[9] Baoxian Wang, Weigang Zhao, Po Gao, Yufeng Zhang, and Zhe Wang. Crack damage detection method via multiple visual features and efficient multi-task learning model. *Sensors*, 18(6):1796, 2018.

[10] Hyunjun Kim, Eunjong Ahn, Myoungsu Shin, and Sung-Han Sim. Crack and noncrack classification from concrete surface images using machine learning. *Structural Health Monitoring*, 18(3):725–738, 2019.

[11] Sattar Dorafshan, Robert J Thomas, Calvin Coopmans, and Marc Maguire. Deep learning neural networks for suas-assisted structural inspections: Feasibility and application. In *2018 International Conference on Unmanned Aircraft Systems (ICUAS)*, pages 874–882. IEEE, 2018.

[12] Shengyuan Li and Xuefeng Zhao. Image-based concrete crack detection using convolutional neural network and exhaustive search technique. *Advances in Civil Engineering*, 2019.

[13] MM Islam and Jong-Myon Kim. Vision-based autonomous crack detection of concrete structures using a fully convolutional encoder–decoder network. *Sensors*, 19(19):4251, 2019.

[14] Sattar Dorafshan, Robert J Thomas, and Marc Maguire. Sdnet2018: An annotated image dataset for non-contact concrete crack detection using deep convolutional neural networks. *Data in brief*, 21:1664–1668, 2018.

[15] Mohamed Abou-Zeid, David W Fowler, Edward G Nawy, John H Allen, Grant T Halvorsen, Randall W Poston, James P Barlow, Will Hansen, Royce J Rhoads, Merle E Brander, et al. Control of cracking in concrete structures. *Report, ACI Committee*, 224:12–16, 2001.

[16] Robert M Haralick, Karthikeyan Shanmugam, and Its' Hak Dinstein. Textural features for image classification. *IEEE Transactions on systems, man, and cybernetics*, (6):610–621, 1973.

[17] Sattar Dorafshan, Robert J Thomas, and Marc Maguire. Benchmarking image processing algorithms for unmanned aerial system-assisted crack detection in concrete structures. *Infrastructures*, 4(2):19, 2019.