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Towards an automated machine learning and image processing supported procedure for crack monitoring

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ABSTRACT

Development of automated and remotely controlled procedures for accurate crack detection and analysis is an advantageous solution when compared to time-consuming and subjective crack examination conducted by operators. Recent studies have demonstrated that Machine Learning (ML) algorithms have sufficient potential for crack measurements. However, training of large amount of data is essential. When working on single sites with permanently installed fixed cameras adoption of ML solutions may be redundant. The purpose of this work is to assess the performance of a procedure for crack detection based on an easy to implement workflow supported by the use of ML and image processing algorithms. The datasets used in this work are composed of temporal sequence of single digital images. The workflow proposed includes three main modules covering acquisition, optimization and crack detection. Each module is automated and basic manual input by an operator is only required to train the classifier. The processing modules are implemented in modular open-source programs (*e.g.*, ImageJ and Ilastik). Results obtained in controlled conditions led to a satisfactory level of detection (about 99% of the crack pattern detected). Experiments conducted on real-sites highlighted variable detection capabilities of the proposed approach (from 12 to 96%). The main limitation of the approach is the production of false-positive detection due to significant variation in illumination conditions. Further work is being conducted to define scalability of the approach and to verify deformation detection capabilities.

I. INTRODUCTION

Aging of the built environment worldwide demands for the adoption of cost-effective structural health monitoring approaches to ensure long-term integrity and adequate levels of safety. Crack patterns initiation and propagation are indicators of the structural integrity and health of a built element. Traditional crack visual inspections are conducted on the site by operators using conventional tools (such as measuring magnifiers, strain gauges, crack rulers, etc.). This task can produce subjective judgment on the state of the crack and introduces gross errors in the measurement.

Recent technological advances in software and sensors offer the unprecedented opportunity to acquire considerable amount of high-quality optical data and process them in real-time with less subjective methods (Nex *et al.*, 2019). For example, adoption of image processing (IP) techniques has been employed in the past for a range of monitoring applications (*e.g.*, Deshmukh and Mane, 2020; Garrido *et al.*, 2019; Guidi *et al.*, 2014). Many researchers have proposed valid IP-based solutions for accurate segmentation of the crack from digital images (Mohan and Poobal, 2018). However, the main limitation of detecting a set of cracks though IP algorithms lies in the little scalability of the approach that is usually only tailored for a certain application or for a limited dataset. When exporting the approach to real-world sites a range of challenges (*e.g.*, light variations, shadows, stains, scratching, camera position, etc.) can severally reduce the efficiency of the detection approach.

Machine learning (ML) algorithms have been extensively applied to buildings research for the past decades. ML-based solutions allow to minimize human involvement and overcome some limitations encountered by solutions based solely on IP methods. Recent studies have demonstrated that sub-branch of ML (such as Convolutional Neural Networks, CNN) algorithms have sufficient potential for crack measurements (Teng *et al.*, 2021). When consistent amount of data is available, ML algorithms can automatically digest intrinsic knowledge of the data (such as hidden structures or relationships) and automatically perform difficult tasks such as localization and classification of different damages (*e.g.*, cracks, spalling, corrosion, etc.). Detailed reviews of research papers focusing on crack detection through ML algorithms are presented by Azimi *et al.* (2020) and Hsieh and Tsai (2020).

Working with ML algorithms certainly represent a suitable solution to the binary classification problems that include distinguishing 'crack' and 'non-crack' regions or pixels. A prerequisite to obtain an accurate and robust crack detection solution based on ML algorithms is the availability of large datasets for training. Training can require a considerably long time. Also, skills and experience in computer vision and machine learning is required to set up proper crack detection solution. Furthermore, when working on single sites with permanently installed fixed cameras the need for training of large datasets may be unnecessary.

Another interesting point is that most of the past research works in the field of crack monitoring implemented solutions in controlled laboratory environments (Mohan and Poobal, 2018). Only recently research efforts are being addressed to develop solutions for real-world applications.

In this context, this paper presents the methodology and initial results of our recent research that is addressed at implementing an automated, cost-effective and user-friendly procedure to monitor cracks over time. The purpose is to implement and test the efficiency of a crack detection solution based on modern open-source image processing and ML software. A cost-effective commercial solution for data collection and transmission with a single digital camera is presented also. The overall system, based on the combination of the data collection solution with the crack detection solution, is intended for a diffuse exploitation among technicians in the AEC (Architecture Engineering Construction) market.

II. Methodology

The proposed algorithm for automatic crack detection (summarized in Figure 1) consists of three main modules including photo acquisition (PAM), photo optimization (POM) and crack detection (CDM).

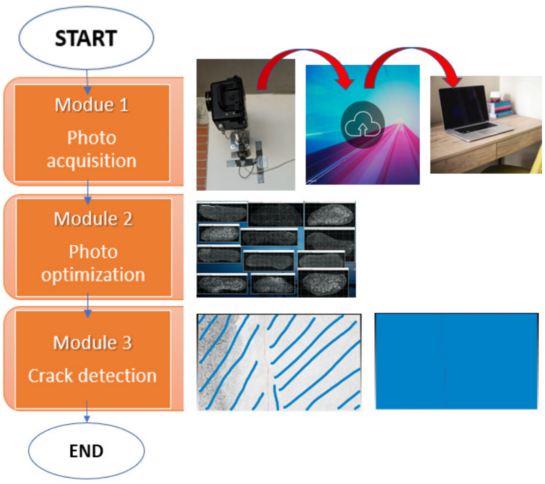


Figure 1. A summarization of the three modules proposed in this study that include image acquisition and transferring, image pre-processing and crack detection.

The PAM kit includes a single digital single-lens reflex (DSLR) camera, an intervalometer and a protective case (Figure 2). Specifically, a Canon 2000D (~24 megapixels, sensor APS-C CMOS and equipped with 18–55 mm lenses) was mounted in a protective case and installed in a fixed location with the camera axis perpendicular to the photographed crack. Acquired images can be transferred using an FTP server or saved on a cloud storage service in just a few seconds for a near real-time data processing. The whole PAM kit used in this study was provided by the company Bixion (www.bixion.com).

Figure 2. The acquisition kit provided by the company Bixion.

After acquisition, the POM conducts a radiometric optimization that is implemented using an open-source image-processing software, namely ImageJ (2021). Initial tests showed the presence of illumination-dependent deformation. Adoption of pre-processing steps (such as radiometric optimization) improves the repeatability of the implemented crack analysis workflow avoiding the estimation of false deformations. The output generated after the POM steps is a corrective image with a smoother distribution of pixel intensity that presents a decreased level of noise while maintaining information related to the crack patterns. The optimized image is passed to the CDM, which classifies the image pixels in classes. This module runs a semantic segmentation via an active learning system (Kan, 2017) and is completely implemented in Ilastik (2021), an open-source software that allows even unexperienced operators to adopt ML-based algorithms to classify image regions in different classes. More detailed information about the software is provided in Berg *et al.* (2019). For this work an innovative single-acquisition machine learning-based training method is proposed. With this method, user work is only required to train the model based on the first acquisition. The operator uses a mouse interface to label two classes on the image (namely “crack” and “background”). The software, based on the user-based selected classes, assigns labels to each pixel interactively based on a Random Forest non-linear classifier. The work by Geurts *et al.* (2009) is suggested for more technical information about this classifier. With such an approach, training is only required once on the first image. Images acquired subsequently are classified in batch mode by the trained classifier allowing for automatic crack detection.

The proposed modules were tested on three different sites to investigate the crack detection capabilities in a range of conditions including controlled (namely 'Test1') and real-world sites (namely 'Test2' and 'Test3') conditions.

Test1 was carried indoor with stable light condition and the camera fixed at 4 m from the object during acquisition. Camera focal length was fixed at 27 mm. A simulated cracked wall was used to reduce challenges in the detection phase. A drawing representing a total of seven multi-scale and multi-orientation cracks was generated in AutoCAD, printed and attached on the photographed wall (Figure 3). Cracks width varies from a maximum of 1.75 to 0.05 cm. A total of three images (three epochs) are considered.

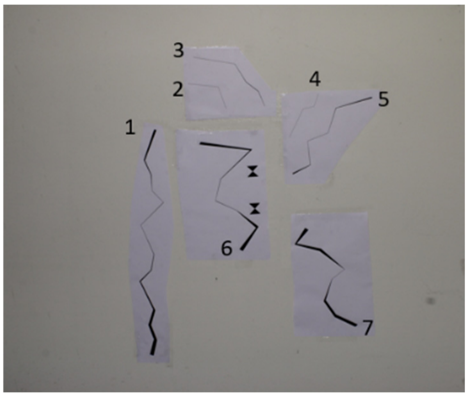


Figure 3. The seven artificial cracks used in Test1.

For Test2 a small portion of an indoor wall of a residential building was selected. The wall is characterized by the presence of multiple cracks with width <0.5 mm and two areas of plaster removed (Figure 4). During acquisition the camera with focal length fixed at 37 mm was installed perpendicular to the cracked wall at about 4 m. For Test2 the proposed approach was tested on a total of six epochs.

Figure 4. Test2: the acquisition kit and the area of interest (red box).

Test3 was conducted outdoor acquiring drone-based images (Figure 5). The considered site was a residential wall presenting a minor crack with width <0.5mm. The drone used for Test3 is a DJI mini 2 that incorporates a camera with a 1/2.3" 12 Megapixel CMOS image sensor. The camera has an 83° FOV, 24 mm equivalent, fixed aperture F2.8 lens. A total of 4 images were acquired (Figure 5). Specifically, the first flight (epoch0) conducted on a sunny day at 11am, allowed to capture two images (epoch 0_A and 0_B) from slightly different positions but with the same illumination conditions (images were acquired within only a few seconds difference). The second flight (epoch1) was conducted on the same day at 3 pm. A further image (epoch2) was acquired the next morning at 9 am on a cloudy day. All images were acquired with the drone flying manually at about 1.5 m from the crack pattern.

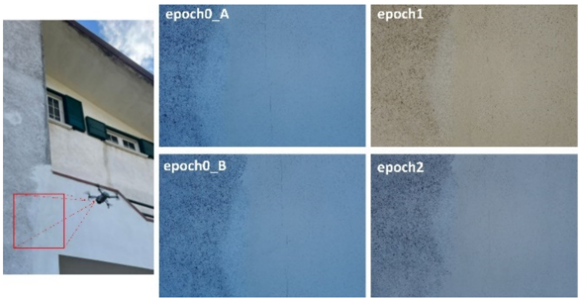


Figure 5. The four images acquired for Test3 with the drone-based approach. The red box is the area of interest.

A summarization of the three tests carried out in this work is presented in Table 1. For all tests the CDM and POM were carried out on a laptop Windows 10 Pro with an Intel Core i7-10750H Processor, operating a 2.60 GHz CPU and using 16 GB of RAM.

To validate the efficiency of the proposed crack detection both qualitative and quantitative assessment were carried out. Specifically, the assessment was conducted through a visual assessment of the multi-epoch segmentation and by comparing the automatic segmentation to a ground-truth. The ground-truth was obtained by manually determining all pixels appertaining to the cracked surface. Thus, the quantitative analysis was carried out by counting the total number of automatically detected crack-pixels and estimating their percentage against the crack-pixels identified from the ground-truth.

III. Results and Discussion

For each test described in this paper the training of the classifier was carried out in less than one hour while the subsequent processing in batch mode led to classification and segmentation of the defined classes (namely 'crack' and 'background') in only a few seconds.

Pixel-level crack segmentation outputs returned by the CDM for the Test1 are shown in Figure 6. Results demonstrate that the proposed approach correctly detected all cracks. Noise effects, false detection or poorly segmented cracks were not observed. Test1 results show that detection is not influenced by the crack orientation or size when using the proposed approach in controlled conditions.

Table 1. Summarization of the 3 tests main features

Conditions	Test1	Test2	Test3
LocationI	Indoor	Indoor	Outdoor
Illumination	Stable	Variable	Variable
Object	Only cracks	Cracks and noise	Cracks and noise
Camera	Canon 2000D	Canon 2000D	Built-in DJI Mini 2
Acquisition set-up	Ground-based fixed station; Distance: 4m	Ground-based fixed station; Distance: 4m	Aerial variable station; Average distance 1.5m

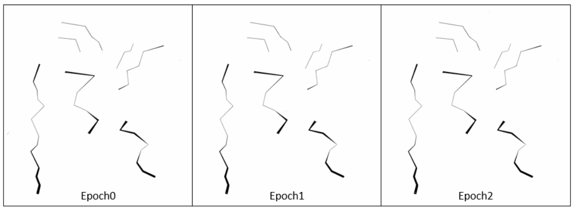
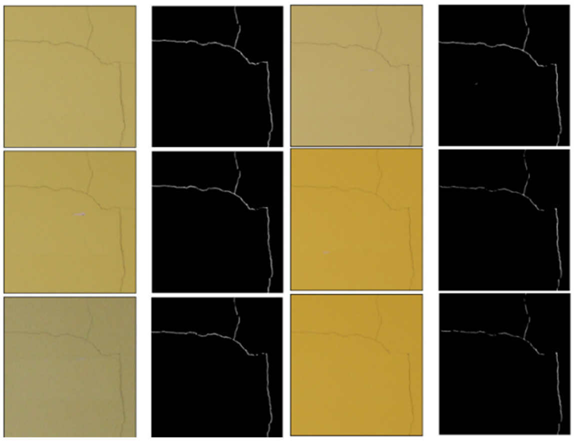


Figure 6. Detection outputs obtained in Test1.

Regarding Test2, the proposed crack detection method produced again acceptable results. Outputs of the CDM, plotted in Figure 7, are satisfactory considering that most of the cracks were correctly identified. Noise or other extraneous features were correctly classified as background while most of the crack patterns are detected. As illustrated in Table 2, for most epochs, a good level of completeness of automatically detected cracks is achieved (above 90%). On the other hand, with respect to the last two epochs the performance of the automatic detection was lower. In fact, only approximately between 65 and 69% of the crack pixels were correctly detected when compared to the ground-truth.



a) b) c) d)

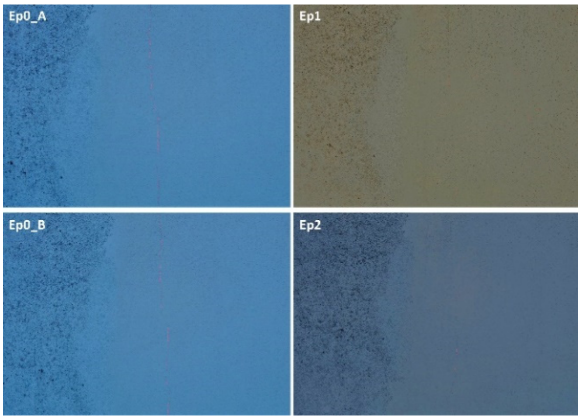
Figure 7. Test2: a) and c) RGB acquisition; b) and d) Detection results generated with the proposed approach.

According to results shown in Table 2 the proposed approach produced poor detection with images acquired for Test3. In fact, for this test, in epoch1 and epoch2 only <16% of the total crack-pixels were correctly identified. Figure 8 shows evidence of a moderate detection result when images are acquired with the same illumination condition (epoch0_A and epoch0_B). However, zooming in on the crack pattern

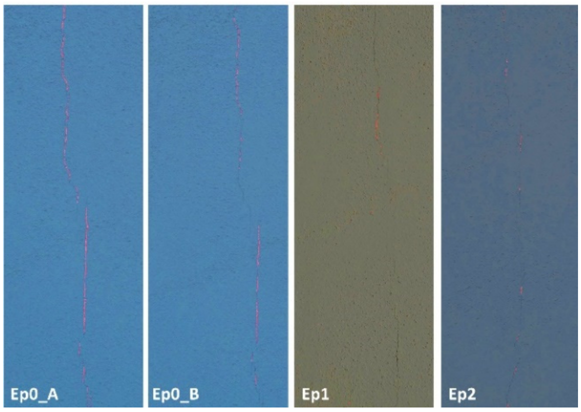
Figure 8b indicates that epoch1 and epoch2 are not suited to the proposed detection approach.

Table 2. Detection quality results for Test2 and Test3

Test	Epoch	Total crack-pixels	%
2	Ground-truth	6972	100
	1	6693	96
	2	6321	90.7
	3	6365	91.3
	4	4796	68.8
	5	4528	64.9
3	Ground-truth	4501	100
	0_B	3152	70
	1	712	15.8
	2	547	12.1



a)



b)

Figure 8. Test3: a) Detection results overlaying the original RGB image; b) Zoom-in on the crack. In red the detected crack.

Overall, the proposed method proved its efficiency in generating noise-free segmentation, avoiding the need for manual operations and further post-processing that can affect the quality of the crack detection (Fujita and Hamamoto, 2011). This was possible thanks to the operator-based identification of not relevant features that is carried out on the first image of the dataset.

It is suggested that when a uniform illumination on the site is guaranteed during the whole acquisition period, it can certainly favor the results in terms of segmentation (see for example Test1). When dealing with a set of images acquired with minor variation in illumination conditions, adopting radiometric corrections shows its potential to diminish the probability to generate inaccurate crack-pixel identification. However, for some epochs of Test2, erroneous classification of pixels leading mainly to false negative outputs was still observed. In fact, for the last two epochs (see Figure 7) the proposed approach tends to fail crack detection. Specifically, small regions of the cracks are classified as non-crack, resulting in loss of the connectivity of the crack pattern. This is a common issue with image processing and machine learning-based detection algorithms (Weidner *et al.*, 2019) that is usually faced with the adoption of morphological operators (Galantucci and Fatiguso, 2019). Such solutions were not initially considered for the current study but must be carefully implemented to achieve a reliable crack monitoring system.

A different behavior was observed for results generated from Test3. For outdoor sites, images acquired on different days and times can present significant variation in illumination conditions (Figure 5). Furthermore, acquiring from similar positions flying the drone manually is a difficult task. As a consequence, drone-based acquisitions of this study were carried out with slightly different distances from the object affecting size of the field of view. Adoption of more stable and RTK-GNSS drones (Stott *et al.*, 2020) and the use of distance sensors (Park *et al.*, 2020) can support the operator in this task. Also, the proposed detection approach can potentially benefit from acquisition with a higher resolution camera. Previous suggested improvements can potentially lead to achieve a better level of detection even when dealing with highly variable light conditions.

Processing of the last two epochs of the drone-based test (Test3) highlighted a very poor ability of the proposed approach to detect crack. It is suggested that variation in illumination is the main limitation of the approach. The limited size of the studied crack in Test3 has potentially influenced the inadequate detection results also.

In summary, the presented single-acquisition machine learning-based training is better suited for applications where the set of crack site is well defined and not affected by significant illumination variation (typical of outdoor sites). Thus, the presented procedure may be successfully applied in those cases requiring a multi-temporal crack detection in indoor scenarios allowing for a fixed installation of the equipment typical of several monitoring applications of the built environment. For different scenarios (*e.g.*, multiple set of cracks with undefined locations, outdoor sites, etc.) other solutions based for example on CNN techniques may be more adequate.

IV. Conclusion

Current technological advancement offers the tools for the development of a simple near-real time long-term monitoring approach based on a monoscopic system able to detect and analyse cracks with little operator intervention. This paper described an approach based on the combination of two open-source software (ImageJ and Ilastik) and a smart data acquisition and transferring kit (Bixion). The proposed method can greatly reduce the crack inspection time and has the potential to achieve higher measurement accuracy for long-term monitoring when compared to traditional and subjective approaches. The study highlighted that in presence of significant variation in illumination conditions alternative crack detection approaches must be considered. For more information about Test1 and Test2, including an assessment of the accuracy and precision of the proposed method, the reader can refer to Parente *et al.* (2022).

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