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Performance of Image-Based Crack Detection Systems in Concrete Structures

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ABSTRACT

The traditional methods for calculating the width of the cracks in concrete structures are mainly based on the manual and non-systematic collection of information, and also depend on personal justifications and judgment. Due to the fact that these approaches are time-consuming and always there are some human errors inevitably, in recent years more attention is paid to the new methods for detection and monitoring of cracks. One of the most important new approaches is the application of image-based techniques. These schemes use field images and photos provided by the camera to determine specific parameters, such as damage occurrence, location, severity, length of cracks, width and depth of cracks. Moreover, tracking the crack propagation over time using a set of timed photos is among the design purposes of these methods. Image processing, and targeting are two common methods which have their own pros and cons. Results showed that the image processing approach detects some surface noises as cracks which is most challenging error in this method. On the other hand, targeting approach has shown weakness in determining the exact location of cracks. These limitations have pushed researchers to innovate more modern techniques such as Digital Image Correlation (DIC) and mathematical tools like Wavelet transform (WT) to eliminate these errors.

1. Introduction

Concrete is always prone to cracking during the construction and service period due to its natural weakness in tension. Cracking is one of the leading causes of erosion and deformation, and finally, the collapse of concrete structures. Cracks are also a source of moisture and material infiltration and are very dangerous for vibrating structures. Fortunately, it is possible to prevent many financial losses and casualties by early detection of cracks and to prevent their growth and development.

Although the traditional methods of calculating width of cracks have shown acceptable performance in the past projects, but these methods are based on the manual and non-systematic collection of information and personal judgment and justification of specialists, therefore they are time-consuming and always associated with some human error. Furthermore, due to rapid growth in construction and use of concrete structures in recent years, the number of available experts in this field is by no means comparable with the growing needs [1,2].

Automatic detection of cracks on different levels based on digital images is one of the active research fields. Most research in this area includes image processing and decision making based on the threshold. Also targeting and matching methods have been considered in various studies. In recent years, researchers have also utilized mathematical tools, algorithms and optimization tools such as neural network, genetic algorithm, and fuzzy logic to find optimal answers among in this area.

Tsao et al. [3] and Wang et al. [4] used image processing to identify asphalt imperfections. Kaseko et al. [5] used a neural network model to categorize asphalt cracks. Sun and Chang [6] studied the productivity of Wavelet transform (WT) and found that this mathematical tool perform better than traditional Fourier transform in analyzing nonstationary signals but the resolution is poor in the high-frequency region and as crack detection is a local problem captured most likely by high frequency modes, poor resolution of wavelet transform can affect the performance of this technique in damage assessment process.

Chae et al. [7] presented a neuro-fuzzy approach to determining the health of the sewerage pipes. Neural Networks were fed with pre-processed images in this model, and networks recognized the existence of different features such as cracks, connections, and so on. The images and properties obtained from them were eventually combined with the fuzzy logic model to determine the overall health and conditions of the tubes.

Khanfar et al. [8] suggest a non-destructive test using wavelet for detecting cracks using the changes in the reflection coefficient of a surface. A fuzzy logic model was also used to estimate the width and depth of the crack using reflection coefficient, repetition of operation, and scaling of distances.

Byoung Jik Lee and David Lee[9] proposed a method for categorization the cracks based on the crack tiles. They offered three neural networks based images, based on histogram and according to proximity, and compared these three networks with each other.

A neuro-fuzzy categorization was proposed by Sinha et al. [10]. First, they transformed all the available data in an image into the fuzzy space and then fed them into a neural network. Properties that have been used include range, length of the largest axis, length of the smallest axis, and the number of items in an attempt.

Moon and Kim [11] proposed neural network with five hidden layers, which detects the presence of cracks by inserting, the range and the ratio of the largest to smallest axes of all items in an image at a given time as network inputs.

Recently, some methods of crack detection have been suggested based on the concept of image inspection [12–14]. Abdel-Qader et al. [15] presented a comparison of the effect of using wavelet transform, Fourier transform, Sobel filter, and Canny filters to determine cracks on images from the surface of a bridge. They concluded that the wavelet transformation provides more reliable results than other methods. Hutchinson et al [16]. used a Canny filter and wavelet transformation for crack identification and estimated the parameters used in analyzing the receiver operating characteristics (ROC). Hashimoto et al. [17] also proposed an automated image inspection system using photographs taken by a digital camera. This system can detect and analyze concrete surface cracks by combining various image processing techniques, including wavelet transform, shading correction, and binarization. Kawamura et al. [18] presented a method for precise crack identification using a genetic algorithm for semi-automated optimization of image processing parameters. However, these methods do not address some crucial characteristics of cracks, such as their connection. They also use global image processing techniques, such as wavelet transforms to increase the quality of accuracy of images.

The Wavelet, Curvelets and Contourlets and are three kinds of new transforms which can capture the intrinsic geometrical structure of data and are remotely sensed image denoising based on multiresolution analysis. These methods basically have been innovated to decrease the amount of noise on high resolution multispectral images [19]. Ansari et al. [19] performed some simulation analysis on the performance of these three transforms and found out that the Curvelet transform performs better than the Wavelet and Contourlet transform in terms of the Peak Signal to Noise Ration (PSNR) and denoised images resulted from Curvelet transform appear more pleasant. Their experimental results also verified that the Curvelet transform is more effective in denosing than two other multiscale methods and it is more applicable to high resolution images as low and medium resolution images are less prone to sensor noise.

On the other hand, some approaches use local image processing techniques to identify the crack [20,21]. In the local image processing techniques, it is necessary to extract some specific features of the cracks, such as the direction and the way they are connected. Some researchers have paid attention to this issue in their work. This study basically reviews the different image processing methods and recent development for defect detection specially in concrete structures.

The new and innovative damage assessment methods always have been a concern in terms of long term durability of structures and can decrease the subjectivity of inspection results of different structures and infrastructures like bridge, dam tall buildings and so on. Recent studies on long term performance of bridge decks has shown that the accurate estimation of service life of decks requires precise image processing tools instead of personal inspection [22].

These study exclusively focuses on two main crack evaluation approaches include image processing approach and targeting approach which basically have been used for assessing dimension, location and patterns of cracks. A brief comparison between these approaches and pros and cons of each process is illustrated and need of new methods to address drawbacks is also explained. New innovative methods like Wavelet, Curvelets and Contourlets transforms which know as digital image correlation techniques have addressed the image processing deficiencies in two primary damage assessment methods and are considered as new generation of image processing.

2. Image-Based Systems for Crack Monitoring

Image-based systems have several benefits for monitoring the crack propagation in different structural material. Initially, when these systems were used to measurement of cracks, more attention was paid to features of objects and repeatability [23]. Also, the use of remote sensing techniques allows the measurement of cracks without the need for access to the validated elements, and also provides stable image storage for each observation in any period. These systems are helpful for those who are involved in the design of structures or those who are responsible for maintaining the infrastructure systems when analyzing the relationship between loading and damage locations.

Currently, it is aimed to utilize imaging systems for identifying cracks in images and determine certain parameters (such as length of cracks) on the one hand, and, on the other, it is desired to track how cracks are propagated over time using a set of sequential photographs. For the second purpose, generally, two approaches (or a combination of them) is used to implement systems. The first method, which has the largest share in the published works, is an approach based on image processing algorithms and developed over time using optimization algorithms. The second approach is based on a targeting method that is enriched by a combination with the comparison method. In the following sections, these two methods will be introduced with more details.

2.1. Image processing algorithms

Since the cracks are much darker than their background material, they appear as edges in the image space. Therefore, edge identification algorithms such as Sobel, Prewitt, Roberts, Laplacian of Gaussian, or other algorithms may be used. However, usually, many types of edges are detected, so detection of cracks among all these edges will be complicated [13,14].

Other image processing approaches are based on one of two methods of analyzing the gray value of a segment or a section. Previous approaches were usually implemented in the following flowchart:

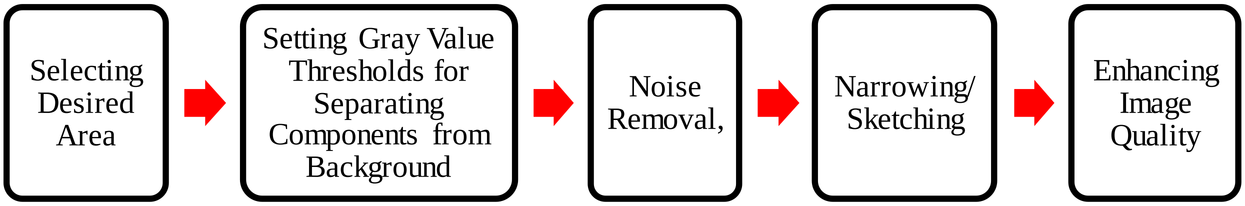

Fig. 1. General Implementation of image processing methods [24].

As a measurement criterion, the result of a narrowed sketch should appear in the center of the cracks [14]. Based on manual selection of the start and endpoints of a crack and then tracking the crack, one of the following two methods can be used [13]:

1. Selection of the pixels with the lowest grey value along the line connecting the start and endpoints (Router algorithm).

2. Selecting of the pixels in the path that has the lowest total gray value, which coincides with the crack path (Fischer Flight Algorithm).

In a review article about the researches carried out in this area, Mohan and Poobal [25] introduced the following structure as the general structure of crack detection methods using image processing (Fig. **2**).

Fig. 2. General structure of crack detection methods using image processing [25].

2.1.1. The Traditional Method of Crack Detection Using Image Processing

In the following one of the most well-known methods for crack detection using image processing, which is proposed by Ito et al. [17] is described:

1. For imaging concrete surface using a CCD camera, usually, a high-quality linear scan is required. Fig. **3** shows a typical real image used as an input of the process. The necessary size of pixels is directly related to the application and the required accuracy. However, Ito et al. [17] claimed that size of 0.33×0.33 mm is appropriate for most applications, but considering that the minimum width to be inspected practical cases is less than 0.1 mm, their suggestion does not seem reasonable and more appropriate size range is required.

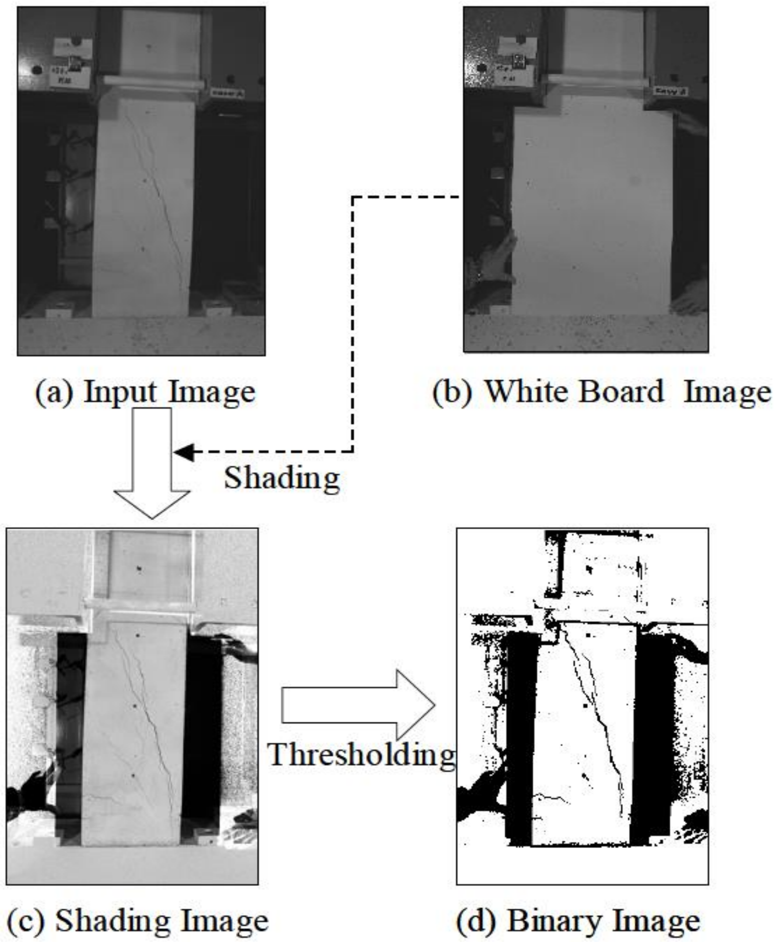

Fig. 3. An example of shading correction and determination of the initial threshold [17].

2. At this step, non-uniform light that occurs during the shooting process is deleted. One method for this step is to inspect a white screen with the same dimensions of the concrete section, and performing the shading correction process by comparing the pixel information of the main image with this white page image.

3. The initial threshold is determined by using a constant threshold to obtain an approximate binary image of the surface. The threshold k is determined based on statistical analyses of the images as follows:

$$k = \frac{Ave+Min}{1.25} \tag{1}$$

In this relation, Ave and Min stand for the average and minimum brightness in the whole image, respectively.

4. If there is a certain number of black pixels in the 9×9 pixels around a black pixel in the image for which the initial threshold is set, then there may be an unidentified crack in this range. Threshold increasing in such areas is performed using the discrimination analysis method. This approach determines the local threshold for the maximum distance in the area. Fig 4 shows a threshold increasing setting.

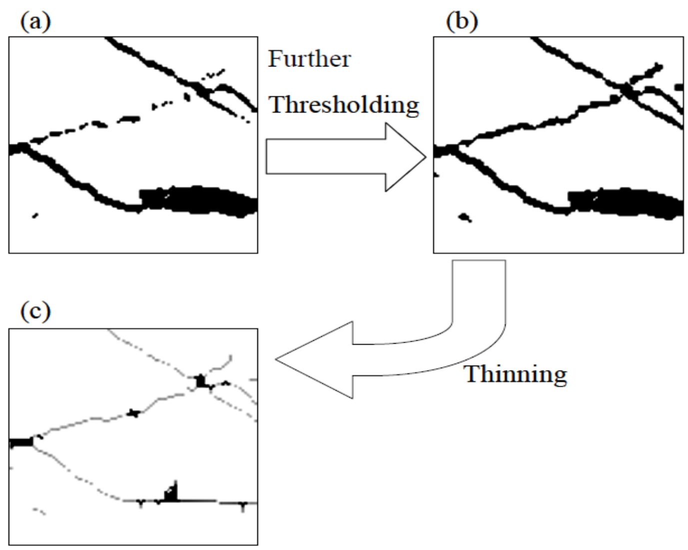

Fig 4. An example of a threshold increase and a slimming process [17].

5. For extracting the geometric structure or direction of a crack, a thinning process is performed to reduce the crack width, as shown in Fig 4.

6. Identification and marking of a crack starting from a starting point, for example, the crack tip or the crack breakpoint, to an endpoint (the point located at other tip or the other extension point). An example of how to mark the dimension of the crack is shown in Fig. **5**.

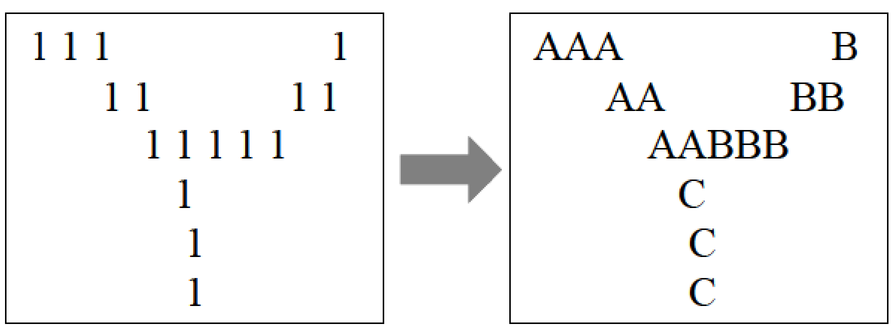

Fig. 5. An example of the marking process [17].

7. Using the data obtained in the previous steps, the direction and scope of each crack are marked and determined. Then the length, thickness, and direction of the cracks are calculated.

2.1.2. Crack Detection Using Percolation Model

Yamaguchi and Hashimoto proposed an image processing technique based on the percolation model [24,26,27] , which considers the neighboring relationship to identify the cracks. This method is a scalable limited processing method that takes into account the connection between the brightness of the adjacent pixels. It is shown that this method has higher accuracy than previous techniques. However, when the contrast of the crack region is not clear, this method cannot accurately detect cracks because it is only based on light information during the percolation process. Accuracy in crack detection is crucial in inspection because the inspection is done on the basis of detected cracks.

In the following of them, Yamaguchi and Hashimoto proposed new methods, which improved shortcomings of this approach. Of course, the use of the percolation model has always been an integral part of their research. The percolation is a physical model based on the natural phenomenon of liquid percolation. This model is very effective in describing various phenomena, such as the spread of contagious diseases, fires in fields, ferromagnetism, and irregular electric networks. The process of percolation process is as follows:

1. Initially, the size of the initial window is fixed on, for example, the size N × N, and the maximum window size, for example, is the value of M × M. The pixel located in the center of the window is defined as the initial ps pixel for percolation and is part of the percolated area D_p. Besides, the percolation threshold, T, is the brightness value of the initial pixel I(ps).

2. The threshold T is updated as follows[27]:

$$T = \max\left(\max_{p \in D_p}\left(I(p)\right), T\right) + w \tag{2}$$

Where w is used as an intensification factor to intensify the percolation.

3. The eight neighboring regions of D_p are defined as the candidate regions, D_c. In Dc, the pixels which their brightness level are less than the threshold T are identified and added to D_p. If there is no such pixel, the darkest pixel in D_c is selected and added to D_p.

4. When the D_p reaches the boundary of the window N×N, the percolation process is followed in step 5, and the value of N is increased to N + 2. Otherwise, the process returns to step 2.

5. The threshold T is updated as described in step 2.

6. In the neighborhood of Dc from D_p, the pixels which their brightness is less than T are added to D_p. If there are no such pixels, the percolation process is over. Otherwise, N will be increased to N+2.

7. If N is greater than the maximum window size, M, the process is terminated; otherwise, the process returns to step 5.

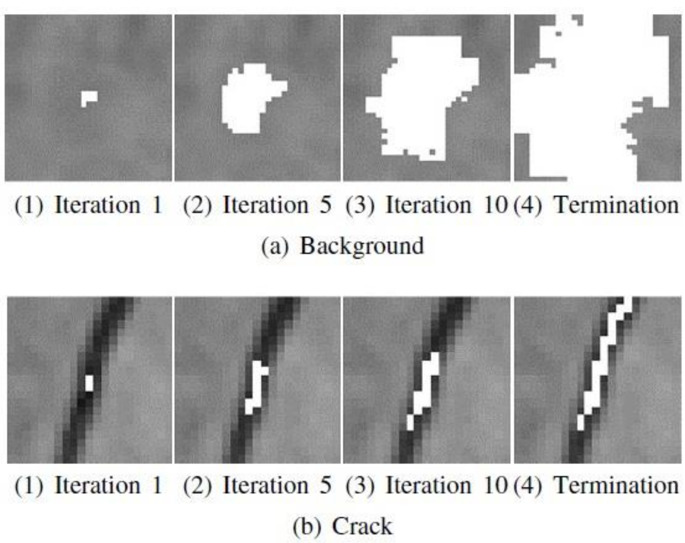

Fig. 6. Examples of the percolation process [27].

Indeed, the final D_p is obtained as the resultant area of the percolation process, as shown in Fig. **6**. Then, it is possible to specify whether the central pixel belongs to a crack or not, by drawing D_p. F_c, as a characteristic of D_p, can be derived from the following equation [27]:

$$F_c = \frac{4C_{count}}{\pi C_{\max}^2} \quad (3)$$

In this relation, C_{count} is the number of pixels within D_p and C_{max} is the maximum length of it. F_c is a defined criteria based on D_p to depict the general pattern of cracks and varies between 0 and 1. For example, when the shape of Dp is close to a circle (Fig. **6**), the F_c value is close to 1. On the other hand, when the shape of D_p as a crack is linear and completely different from a circle (Fig. **6**), the F_c value is close to zero.

Finally, the brightness of the central pixel is correlated with the F_c component in the output image by using the value of Fc×255. The percolation process is performed for each pixel in the input image. By using the value of F_c×255 it is determined that whether pixels are parts of a crack or not.

2.2. Targeting / Comparison Algorithms

Targeting algorithms are developed based on the idea that if the distance between the two target or the two groups of targets increases, it is an indication that a crack is appearing or expanding [28]. Here the main point is where the targets should be located. When the cracks already exist, the goals can be set to precisely on both sides of the crack, and the algorithm is quite successful when used to calculate the crack thickness [29]. However, if there are no apparent cracks at the beginning, the entire specimen surface should be sampled by targets, which can be considered as an overwhelming task. It is also possible that new cracks appear on the surface after targeting. This method has been developed to prevent implementing predetermined targets and to use image comparison, instead. For instance, by matching the images produced at different times, the extent of the displacement between given pixels can be calculated, and accordingly, the cracks are identified as discontinuities in displacements.

This system operates with the installation of distinct targets whose three-dimensional coordinates are precisely determined (Fig. **7**), and then the cracks will be determined by increasing the distance between the adjacent targets. In fact, the occurrence of a crack will change the initial coordinates of the targets. In a 100×100 mm square sample, this technique is able to provide micrometric resolution. Using well-equipped imaging systems, one can efficiently and accurately measure with high reliability. However, further technical efforts are required to make the sampling rods bolder.

Accordingly, the quality of the results of this approach depends on several factors, such as the accuracy of the initial measurement and the quality of the provided images. Also, in some cases, the displacement of the camera from its original location may cause a disruption or at least a challenge in the measurement process for finding cracks. Obviously, targets should be well-grounded in their original position so that their unwanted displacement during the process does not distort the system.

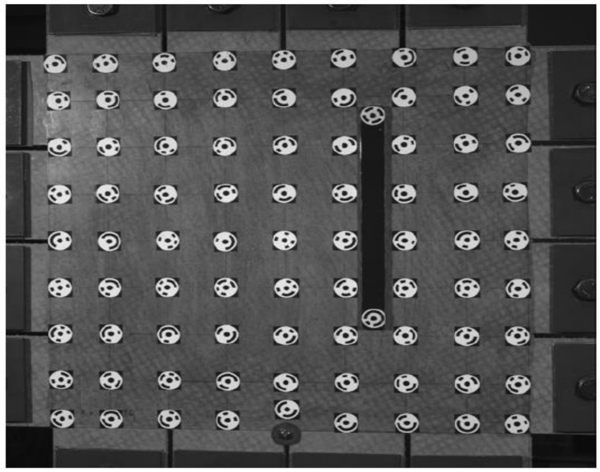

Fig. 7. Concrete specimen with distinct targets [28].

An example of using this method for measuring the crack width of a concrete sample is provided by Benning et al.[30]. They targeted a 30×30 cm square concrete plate with 3481 (59×59) at a distance of 5 mm. The coordinates of the targets were determined with a precision of 3 μm.

Barazzetti and Scaioni, [24] also used targeting to measure the width of cracks. However, their approach was limited to determining the location of only one cracks in a sample area. Another system for targeting is provided by Robbins et al.[31].

The accuracy and precision of a targeting technique can be improved by applying image matching techniques that scan the natural or synthetic surface of the sample to find similar points in successive images from a series of images. These comparative and adaptive techniques create a displacement vector on a regular graph grid. By setting the lengths of this grid as much as the entire length of the image and using edge detection techniques, cracks can be identified and traced. For example, Fig. **8** illustrates a hypothetical grid, on which the displacement vectors are drawn. By connecting these vectors, a broken line has resulted. The analysis of this diagram, as depicted in the Fig. **8**, shows that the protraction of each unusual vertical line on the horizontal axis determines the crack location (C_p) and the length of this vertical line indicates the width of the crack (C_w).

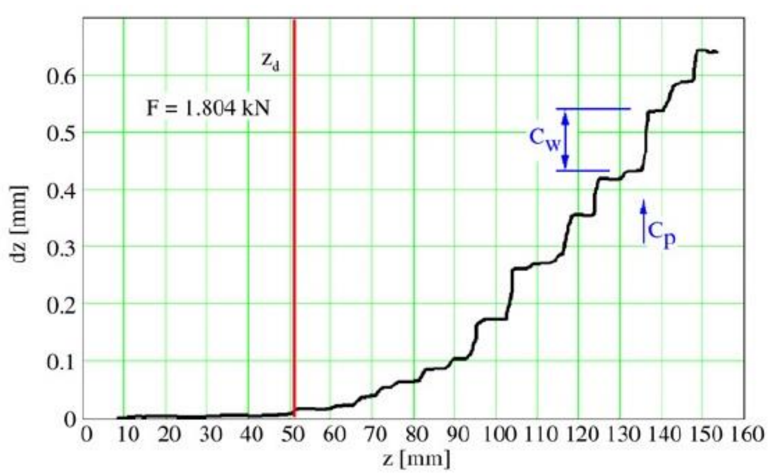

Fig. 8. An example of a matching diagram [28].

3. Conclusion and Presentation of the Findings

This paper presents a review of the research into the use of image-based systems for the crack identification of concrete surfaces. It is possible to categorize the previous studies in two main approaches. The first approach, which has an older background, is the image processing method. In recent years, the ability of this approach in identifying the location and size of cracks have been improved by using new models such as the percolation model. The second approach, known as the targeting method, although less widely used, has the potential to measure the size of the cracks accurately. However, these approaches also have shortcomings, which are mentioned in the following.

The actual concrete surface images, as shown in Figure 8, in rectangular frames, have some noise, such as air bubbles, stains, and shades of different sizes. It's challenging to distinguish cracks, from noise images, by conditional methods that do not take into account the characteristics of cracks. Also, since the length and width of the cracks differ in real concrete surfaces, methods that fix the size of the window (the same dimensions of the photo being investigated) are not applicable for accurate detection of cracks. For this reason, the mentioned conditional methods cannot be considered as proper methods because they also consider noises as cracks. This error is the most significant challenge in applying image processing approaches.

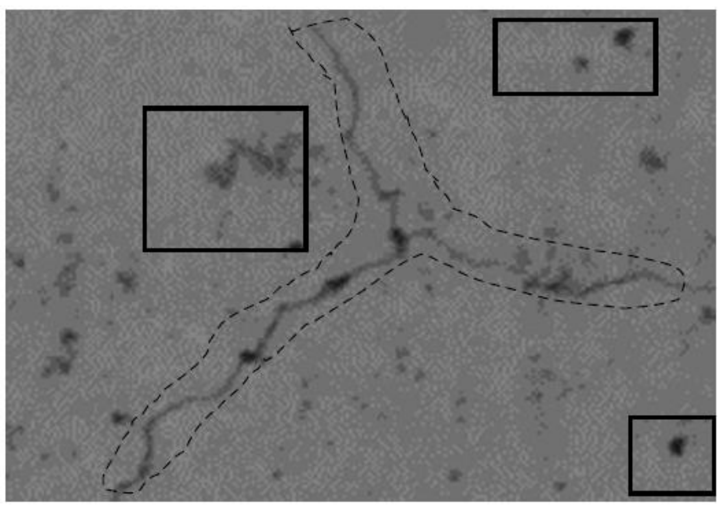

Fig. 9. Cracks and similar noises [27].

On the other hand, the most important weakness of a targeting approach is the fact that this method is very general in the detection of crack location. Where the crack width can be determined with a resolution of 1/50 pixels, the location of a crack is not exactly known. The pattern of the targets' location only shows there are cracks between certain targets, but their exact locations are not known. Moreover, this technique only represents the total width of the cracks when there are several cracks in a range. Also, when a crack is extended among various targets, this approach results faces difficulties in crack identification.

Though these methods face challenges and weaknesses, they are rapidly becoming widespread due to their potential ability to identify the cracks automatically. Recently, optimization algorithms have improved the speed and accuracy of these approaches. New innovative Digital Image Correlation (DIC) techniques like Wavelet, Curvelets and Contourlets transforms combine information from multiple images of the same scene to get a composite image that has more quality and addressed the potential drawbacks in primarily methods like image processing and targeting approach. Finally, it is suggested that the use of new image-based technology and, in particular, augmented reality technology in further research be considered and still there is room to improve the damage assessment and image processing.

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