

Concrete Structure Analysis and Classification using Image Processing

Rashmi R.A¹, A.D Mane², S.L Tade³

Abstract

There is increasing awareness of the need to inspect concrete structures, such as old buildings and other concrete structures, because they may be affected by aging, natural disasters or shoddy workmanship. To maintain and manage these concrete structures properly, it is necessary to inspect and diagnose the state of their deterioration accurately, to detect cracks on their surfaces at an early stage, and to repair detected defects or apply reinforcement. Contact-less remote-sensing crack detection and quantification methodologies are described in this paper. The systems and methodologies include depth perception for detecting the cracks and also quantify the cracks. Proposed method includes the crack detection, strength calculation, inspection and monitoring of the structure and classification using neural network. In addition, in the field of product manufacturing, it is extremely important to maintain high quality control by inspecting products for defects accurately, thereby raising productivity. This is why increasing attention is being drawn to technology for non-destructive testing of concrete structures, which enables unskilled operators to inspect and diagnose aging structures or defective products quickly and accurately without damaging them at all.

Keywords

Crack Detection, neural, Gaussian filter (GF), Red to green (RGB), Concrete surface, Photogrammetry.

1. Introduction

A crack is the separation of an object or material into two, or more, pieces under the action of stress. Depending on the substance which is cracked, the crack reduces the strength of the materials in most cases, e.g. building walls, roads, etc. At the beginning cracks are used to be detected manually. However, detecting a crack manually is a very intricate and time consuming process. With the advance of science and technology, automated systems were used to detect cracks instead of humans. By using the automated systems, less time is consumed and the cost for detecting the cracks reduced.

The stability of structure is an important factor for the construction phase and in the maintenance phase. The importance of safety is increased as the construction of high-rise buildings, super long span bridges, and asymmetric buildings became popular. For this reason, construction safety management system is actively under development these days [1]. In addition, the interest in the automation of the construction management system has been increased, because the civil infrastructure under the management is large in scale, the regular evaluations are needed to guarantee the continuity in service, running cost is very expensive, and the safety of workers should be ensured. Development of an automated and effective infrastructure life-cycle management system, it is possible to secure the stability of the facility, and also reduce the efforts of the inspectors, inspection, time, and maintenance cost. Moreover, we can judge the condition of the structural health objectively by acquiring and processing the data.

Relevance

In these concrete structures, the one of the ways in judging the structural health is to examine a crack on the surface of the structure using multispectral or digital camera in the field of digital image processing. Since the condition of a concrete structure can be easily and directly identified by inspecting the surface crack, the crack assessment should be done on a regular basis to ensure durability and safety within its life-cycle. Automation in structural health monitoring has generated a lot of interest in recent years, especially with the introduction of cheap digital cameras. Concrete is one of the most popular building materials, it is important to know its basic properties and behavior. The performance and stability of the concrete structure will be reducing due to the effect of many factors like environmental effects or incorrect mixture of material during the concrete's age. Continuous structural health monitoring provides the data from the inside of a structure to better understand its structural performance and to predict its durability and remaining life time.



Figure 1: (Left) Crack on road (Right) Crack on building wall

The behavior of a concrete construction gets affected because of the environmental issues and incorrect mixture of materials. Strain and cracks are the external visible indications of the behavior of a loaded construction, so that the analysis of these deformations allows an interpretation.

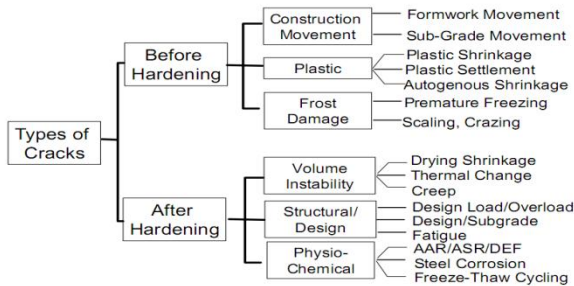


Figure 2: Common causes for cracking in concrete structure [2]

Above figure provides listing of some of the common types of crack and distinguishes this cracks based upon when they appear in concrete [2], before hardening or after hardening.

2. Literature Review

In Europe, many structures originate from the late 40ies or 50ies of the last century replacing structures destroyed during the Second World War.

Methodology

Photogrammetric Measurement

The photogrammetric measurement [3] is the coordinates of targets that are known at each load step. Photogrammetric measurement describes the different methods for the analysis of crack detection. Photogrammetry is a method to reconstruct an object using photos. The hardware of the measurement system is composed of three high resolution digital cameras (Kodak DCS Pro 14n) which take photos from different directions of a grid of targets on a concrete specimen (Figure 1 left). Before testing the cameras are orientated by exposures of a well-known calibration element (Figure 1 right). The

interior orientation (projection properties of the cameras) and the exterior orientation (position in space) are computed with a bundle adjustment. While testing the system measures periodically. In the next step the targets on the concrete construction are calculated by forward intersection. As evaluation software PHIDIAS integrated in the CAD-Software Micro Station is used (Benning, 1997). The results of the photogrammetric calculation are the coordinates of the targets at different load steps of the test.

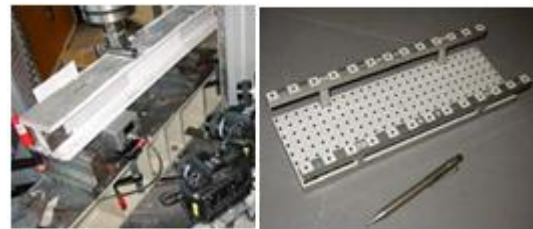


Figure 3:(left) photogrammetric experimental setup (Right) calibration element for orientation of the cameras [3]

Pre-processing

The input digital image is subjected to a set of pre-processing steps so that the image gets transformed suitably for the further processing. Here we employ two step preprocessing procedure in which first the input image is passed through a Gaussian filter. Passing the image through the Gaussian filter enhances the image quality. In the second step of preprocessing, we convert the image from the RGB model to Grey-scale Image. This makes the image more fit to be segmented into cracked or non-cracked images.

Gaussian Low-pass Filter

Smoothing the images is the most important characteristic of Gaussian low pass filter. This filter is used to connect the small gap of the crack line. It can also adjust the distortion of the crack shape. In this process, spatial filter can be classified into linear and nonlinear spatial filtering.

Here **one dimensional thresholding** is used in Gaussian low-pass filters. Transfer function of Gaussian low pass filter is defined as:

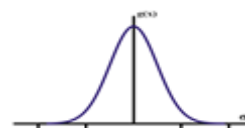


Figure 4: Gaussian Low-pass Filter

In theory, the Gaussian function at every point on the image will be non-zero. In practice, when computing a discrete approximation of the Gaussian function, pixels at a distance of more than 3σ are small enough to be considered effectively zero. Thus contributions from pixels outside that range can be ignored.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \dots\dots\dots (1).$$

Where x is the distance from the origin in the horizontal axis and σ is the standard deviation of the Gaussian distribution. Here in the preprocessing step, the input image is passed through a Gaussian filter which results in reduction of the noise in the input image and also results in obtaining an image fit for further processing.

Block Diagram

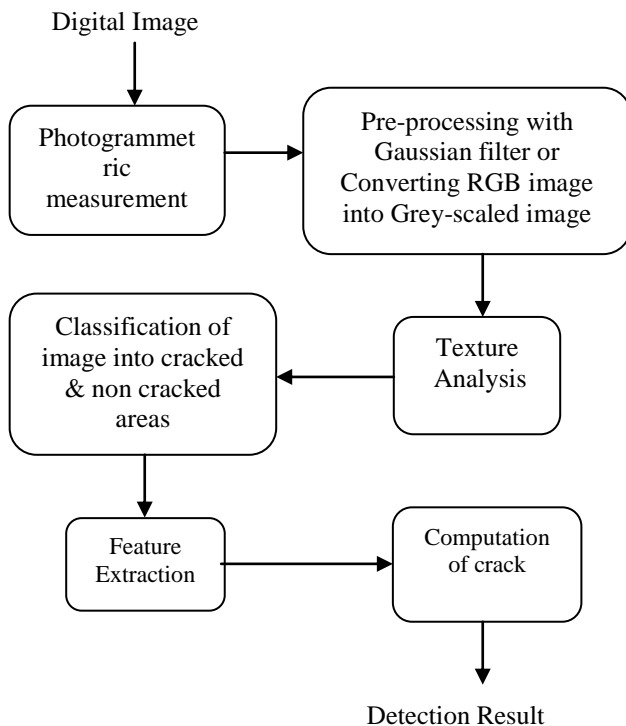


Figure 5: Block Diagram of Concrete structure analysis

Converting RGB image into Grey-scaled image

This step converts the true-color image RGB to the gray-level intensity image by eliminating the hue and saturation information while retaining the luminance. In this process, the amount of image data decreases. To generate the monochrome or brightness signal that represents the luminance of the scene, the three camera output is added through a resistance matrix in

the proportion of **0.3, 0.59 and 0.11 of R, G and B** resp. This is because with white light contains the three primary colors in the above ration, the camera output were adjusted to give equal voltages.

$$Y = 0.3R + 0.59G + 0.11B \dots\dots\dots (2)$$

Y is the signal voltage that develops across the common resistance R_c represents the brightness of the image.

For example, $R=8$ bit; $G=8$ bit; $B=8$ bit; so Put each value in eq. (1)

$$R + G + B = 8 + 8 + 8 = 24 \text{ bit.}$$

$$Y = 0.3(8) + 0.59(8) + 0.11(8) = 8 \text{ bit.}$$

The RGB color pixel having a depth of 24 bit ($2^8 \wedge 3 = 16,777,216$ color) is converted into 8 bit gray-level ($2^8 = 256$ level).

Texture analyses

Existing detection software in the market cannot detect the target object accurately because they often recognize interfering objects as edges, and thus produce many incorrect detection results so the proposed method include texture analysis. In image processing, texture means a pattern on the surface of an object.

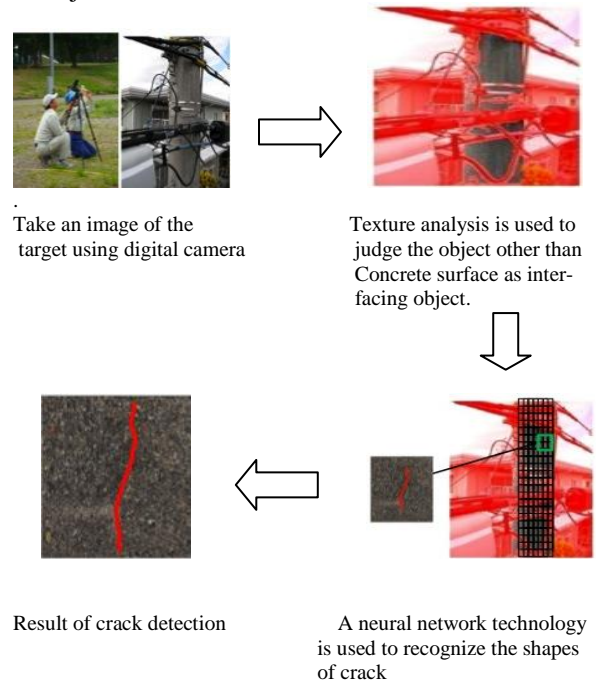


Figure 6: Crack detection technology using Texture analysis [4]

The pattern is characterized by the formation, direction, regularity, luminance, etc. of minute shapes that make up a texture [4]. This technology analyzes color and texture in an image of a concrete structure, taken using a digital camera, and automatically excludes interfering objects from the image.

Texture analysis is used to judge the object other than the concrete surface as interfering object and to exclude them.

There are four major issues in texture analysis [5]:

- 1) **Feature extraction:** to compute a characteristic of a digital image able to numerically describe its texture properties;
- 2) **Texture discrimination:** to partition a textured image into regions, each corresponding to a perceptually homogeneous texture (leads to image segmentation);
- 3) **Texture classification:** to determine to which of a finite number of physically defined classes (such as normal and abnormal tissue) a homogeneous texture region belongs;
- 4) **Shape from texture:** to reconstruct 3D surface geometry from texture information.

Classification of image into cracked & non cracked areas

Once pre-processing is finished with Gaussian filter or converting RGB image into grey-scale image classification of image is performed. Classification of image is done into cracked image and non-cracked image.

The non-crack feature vectors were extracted from actual scenes. The performance of several SVM and NN classifiers was evaluated. A nearest similar classifier was used to evaluate the performance of the above classifiers. Performances of these classifiers were analyzed, with the analysis showing that the SVM and NN approaches have very close performances, which were better than a nearest-neighbor classifier.

Difference between the SVM and NN is that the SVM method is a discrete classifier, whereas the NN approaches typically needs a threshold to act as a discrete classifier. In an implemented embodiment, if the value of the crack output neuron was found to be greater than the value of the non-crack neuron, the pattern was classified as a crack, otherwise, as a non-crack.

Feature Extractions

After segmenting the patterns of interest, they can be assigned a set of finite values representing quantitative attributes or properties called features. To determine discriminative features useful for classification purposes, the inventors initially defined and analyzed twenty nine features. These features were selected as potentially appropriate features for further analysis. Using the LDA approach, the following five features were found to be discriminatively appropriate (i.e., preserving 99.4% of the cumulative feature ranking criteria) for classification: **(1)eccentricity** (a scalar that specifies the eccentricity of the ellipse that has the same second-moments as the segmented object), **(2)area of the segmented object** divided by the area of the above ellipse, **(3)solidity** (a scalar specifying the proportion of pixels in the convex hull that also belong to the segmented object), **(4)absolute value of the correlation coefficient** (here, correlation is defined as the relationship between the horizontal and vertical pixel coordinates), and **(5)compactness** (the ratio between the square root of the extracted area and its perimeter). The convex hull for a segmented object can be defined as the smallest convex polygon that can contain the object. The above features were computed for each segmented pattern under examination.

Computation of cracks

In this study, we assume that the cracks are divided in the following two characteristics: (i) their shape is thinner than those of other textural patterns and (ii) their brightness is lower than that of the background. Cracks with dark colours can be easily detected, while cracks with bright colours are difficult to detect since their brightness is similar to that of the background [6]. Shape information is extremely effective for detecting the unclear cracks. Once the features are extracted the result is classified into various parameters like area, width, length, depth and performance of crack.

Calculation of width of crack:

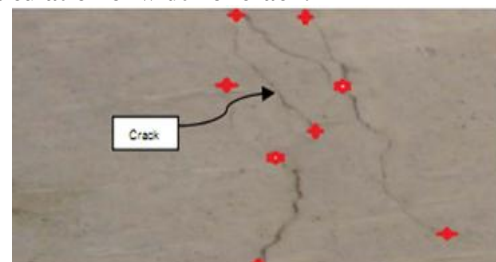


Figure 7: Width of crack

Cracks are shown by 4-corner stars and splitting points are shown by 5-corner stars. Crack widths are calculated in mm. The width is calculated at the ends and the center of each segment. Width of the crack can be calculated as

$$W_k = S_{r.max} (\epsilon_{sm} - \epsilon_{cm}) \quad \dots\dots\dots (1)$$

Where,

W_k = design crack width;

$S_{r.max}$ = maximum crack spacing;

ϵ_{sm} = mean strain in the reinforcement;

ϵ_{cm} = mean strain in concrete between cracks.

Calculation of length of crack:

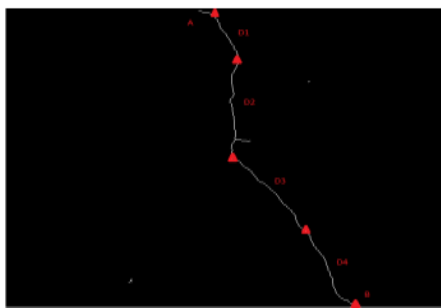


Figure 8: Length of crack

Length of crack is distance between end points or splitting points. A typical crack-skeleton has been subdivided into 5 segments to extract its length and width based on crack definition.

3. Experimental Estimation

In order to evaluate the usability of the proposed algorithm. Images were acquired under the different illumination and background conditions [1]. Image size is 160*120, and it is composed of RGB color. In the step1, total 225 images are processed using the image processing techniques described above and then features such as object size and its ratio of axis are obtained

Table1: The optimal parameters by Taguchi method

Train images		Test images		Accuracy (%)		
Crack	Non-crack	Crack	Non-crack	Crack	Non-crack	Total
1 st	70	35	36	24	92	92
2 nd			36	24	89	92
				90.5	92	90.25

The 105 images are used for training the ANN and the 120 images are used for testing. Among 105 images used in training, the number of cracked image is 70 and that of non-cracked image is 35. After training network once with these images, two experiments were performed with different set of test image. In this training stage, we need to set the reference output whether the corresponding image contains crack or not. In the image processing step, the required parameters are optimally selected by Taguchi method [1], and they are A2B1C1D1F1 in Table 1. The optimal parameters determined by Taguchi method effect on the performance of crack visualization as well as the performance of classification

4. Characteristic Features

Visual inspection will help to maintain the safety of concrete structure. By using the automated systems, the time consumed and the cost for detecting the cracks is reduced and cracks are detect and explained with a detailed description. It also decides the life of concrete. Visual inspection of structures is a highly qualitative method in which inspectors visually assess a structure's condition. It can be used as a tool for post-earthquake damage evaluation purposes. We can judge the condition of the structural health objectively by acquiring and processing the data. This method is useful for non expert or new inspectors. It reduces human efforts & Consumes less time.

5. Conclusion

The review paper provides contact-less remote-sensing crack detection methodologies that are based on three-dimensional (3D) scene reconstruction, image processing, and pattern recognition. These methodologies are used to analyze the images captured from any distance and using any focal length or resolution. The recognition rate of the crack image from the experimental estimation was 90% and non-crack image was 92%. Back-propagation neural network was trained using 105 images of concrete structure, and the trained network was tested for new 120 new images. The recognition rate of the crack image was 90% and non-crack image was 92%.

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Rashmi. R. A received her B.E. degree from P.C.C.O.E, University of Pune in 2012. She is currently pursuing M.E in VLSI and Embedded Systems from P.C.C.O.E, Pune University.



Ashwini D. Mane received her B.E. degree from MIT AOE, University of Pune in 2012. She is currently pursuing M.E in VLSI and Embedded Systems from P.C.C.O.E, Pune University.



Prof. Sunil Tade is an assistant professor of electronics and telecommunication engineering at Pimpri Chinchwad College of Engineering, University of Pune, India. He received his B.E degree from Amravati University and M.E. degree from University of Pune. His research interests include signal and image processing.