Automated Detection of Cracks based on Statistical Analysis of Image Histograms

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Abstract: Damage detection on technical components, such as crack detection on concrete surfaces, is an important task in the life cycle of structures. Currently, this is mainly done manually by the human operator, which is time-consuming and cost-intensive as well as error-prone. Automating the process therefore promises considerable advantages. The documentation of damage by means of photographs represents an established procedure, so that these can provide a valuable basis for greater automation in damage evaluation. A major challenge in the automated detection of damage in images, however, is the diversity of damage, but also of surfaces itself. Thus, due to their generalization capability, machine learning methods are increasingly being used in this context. However, these have the crucial disadvantage that they require a considerable amount of training data. In particular, supervised machine learning requires additional annotations (labels) to the image data for the training process, which are often very elaborate to create. In this paper, we present an approach for automated damage detection using traditional image analysis methods like histogram analysis. Thus, compared to machine learning, this method has the significant advantage of being rule-based and therefore does not require training data. The first results on a reference dataset show a classification accuracy of around 99%, which is very promising.

Keywords: Crack detection, Histogram analysis, Image processing, Gaussian Mixture Model

1 Introduction

Cracks are among the most common types of damage occuring in concrete structures, as a variety of factors can promote their formation. From the initial installation throughout the entire life cycle of a concrete structure, a wide variety of weather conditions influence its strength behavior. While cracking is desirable in the composite material reinforced concrete so that the reinforcement can absorb the tensile stresses in the concrete, the formation of cracks itself carries the risk of corrosion by allowing chlorides and other contaminants from the surroundings to penetrate through them into the structural component. In the case of exposed concrete, the formation of cracks is additionally unfavorable for aesthetic reasons.

For these reasons, it is crucial to detect damage to concrete components at an early stage in order to be able to take appropriate remedial measures. In practice, the detection, analysis and documentation of cracks are usually still mainly done manually. Commonly used methods are, for example, crack width gauges, strain gauges or ultrasonic measuring methods. An overview of numerous manual methods is given by Lange and Benning in [1]. These manual procedures, however, suffer from several issues. They are prone to errors, time-consuming and consequently cost-intensive, especially in the case of larger structures, and are generally subject to subjective assessment or evaluation. In addition, humans can only detect cracks up to a certain size with the naked eye, but the finest microcracks can also lead to major damage.

Since damages are usually documented by photographs during periodical inspections, these can serve as a data basis for automating the detection and assessment of damages. In the context of automation, methods of machine learning are often used, however, these have the major flaw of requiring large amounts of training data with annotated labels.

In this paper, we propose a rule-based method based on statistical analysis of the image histograms. The objective is the classification of images into two classes, specifically intact concrete surfaces and concrete surfaces containing cracks. Our study is further based on the assumption that the frequency distribution of the grayscale values of both object types, concrete surfaces and cracks, is normal distributed. The classification is performed considering different decision criteria of the estimated parameters of the distributions.

2 Related Work

There is a vast number of approaches for detecting damage in concrete, which can basically be divided into methods based on machine learning, as well as methods based on traditional image analysis. In this regard, a comprehensive review of 50 research papers is provided by Mohan [2].

A holistic approach for the detection of pavement damages using machine learning has been presented by Sesselmann et al. [3]. They use the mobile mapping system I.R.I.S., which contains a multi-sensor integrated navigation system and captures the roads during the journey by a 3D laser scanner and a surrounding camera. For georeferencing, the 3D measurements obtained by the laser scanner are fused with the images captured by the camera. They exploit a sliding-window approach in combination with a Convolutional Neural Network (CNN) developed for multi-target classification to detect different classes in the images, such as cracks, potholes, patches, road markings and intact asphalt. For large-area damage classes, such as patches, they could not achieve satisfactory results. For rather linear shaped classes, such as cracks or road markings, on the other hand, their model delivered moderate to good results.

In the field of damage detection using traditional image analysis methods, a wide variety of image processing methods come into use. An example is the digital image correlation, which enables the detection of the crack behavior of concrete components by means of a camera-based deformation measurement [4]. This method can also be extended by other measurement techniques such as acoustic emission technique [5] to determine other crack parameters. In common, most of the methods based on image processing have a similar procedure. First of all, the images are pre-processed, for example converted to grayscale or processed by image filtering, in order to subsequently apply the crack detection mechanism. Ultimately, determination of further features of the detected cracks, such as dimensions or density, can be performed [6].

3 Histogram-based Detection of Cracks

3.1 Dataset

The examinations in this paper are based on the open-source dataset of Özgenel et al. [7]. This dataset consists of 458 images taken on the same day and under similar lighting conditions from buildings on the Middle East Technical University (METU) campus in Ankara. From these images, 40,000 patches of uniform size (227 x 227 pixels) were created, visually inspected for cracks, and accordingly classified into intact ("negatives") and cracked ("positives") surfaces. Apart from this classification, the images have not been subjected to any further processing.

The dataset is characterized by a variety of surfaces and by clear visibility and different sizes and patterns of the cracks. In Figure 1, a selection of images is presented with their corresponding histograms:

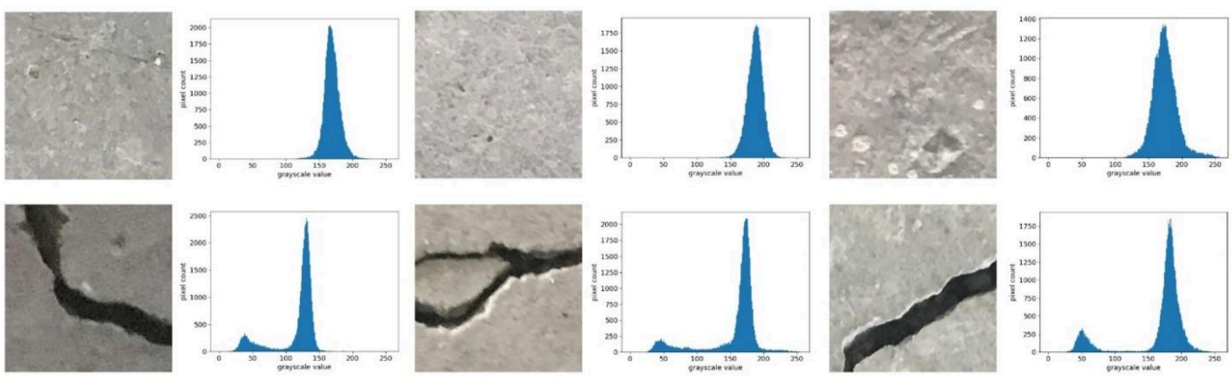

Figure 1: Examples of intact (top) and cracked surfaces (bottom) with associated histograms.

3.2 Parameter estimation of a Gaussian distribution

Following the assumption that the frequency of grayscale values of intact concrete surfaces behaves normally distributed, the corresponding parameters can be estimated from the image histograms. For our study, we consider the first two moments of a random variable, which are the expected value μ and variance σ^2. These can be determined by the following well-known expressions:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n}, \quad \sigma = \sqrt{\frac{\sum_{i=1}^{n} (x_i-\mu)^2}{n}}. \tag{1}$$

Given a histogram of an image, these parameters can be approximated by the arithmetical mean $\bar{x}$ and the empirical standard deviation s of the sample. To determine the goodness of fit of the Probability Density Function (PDF) with the estimated parameters μ and σ, the coefficient of determination is used:

$$r^2=1-\frac{\sum_{i=1}^{n}\left(y_i-\hat{y}(x_i)\right)^2}{\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2}. \tag{2}$$

with r^2 the coefficient of determination, y_i the given frequency and $\hat{y}(x_i)$ the estimated frequency of the grayscale value x_i and $\bar{y}$ the sample mean.

3.3 Parameter estimation of a Gaussian Mixture Model using EM algorithm

Due to the presence of multiple object types in a crack image (crack and surface), the grayscale values of the image originate accordingly from different populations. Given the assumption that both populations follow a normal distribution, whose parameters are in general unknown, this is commonly referred to as a Gaussian Mixture Model (GMM). In the histogram of crack images, this fact is usually reflected as a bimodal distribution, caused by a mixture of two Gaussian distributions.

The parameter estimation of a GMM, however, is not as straightforward as in the case of a Gaussian distribution. For the data points (in our case the grayscale values), it is typically unknown from which population they originate. Neither is there any information about the parameters of the underlying distributions in the GMM. A solution for this, however, is the Expectation-Maximization (EM) - algorithm. EM is an iterative algorithm for clustering and parameter estimation of GMM based on two steps. It requires the number of Gaussian distributions and initial guesses for the parameters.

The Expectation-step estimates the probabilities of the data points to originate from the individual distributions based on the given parameters and thus assigns each data point proportionally to the single distributions. Based on these assignments, the Maximization-step recalculates and updates the parameters of the distributions. These two steps are repeated for a predefined number of iterations or until converge is reached. The pseudocode for EM is given in Algorithm 1.

Algorithm 1: EM algorithm

```
p ← Data points
N ← Number of distributions, here: N = 2
α ← Proportion of distribution to total distribution
μ ← Expected values of the probability functions
σ^2 ← Covariances of the probability functions

Input: p, N
Random estimates of μ,σ^2,α
for t=1:T with T: maximum number of iterations
    //Expectation-step
    for k=1:K with K: number of data points
        for n=1:N
            P(x_kn) = α_n K(p_k|μ_n, σ_n^2) / (Σ_{i=1}^{n} α_i K(p_k|μ_i, σ_i^2))
        end
    end
    //Maximization-step
    for n=1:N
        μ_n = Σ_{k=1}^{K} P(x_kn) p_k / Σ_{k=1}^{K} P(x_kn)
        σ_n^2 = Σ_{k=1}^{K} P(x_kn)(p_k-μ_n)(p_k-μ_n)^T / Σ_{k=1}^{K} P(x_kn)
        α_n = (1/K) Σ_{k=1}^{K} P(x_kn)
    end
end
Output: Expected values μ, covariances σ^2 und proportions α
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The algorithm finally provides an output of estimates for the parameters of the underlying normal distributions, such as the expected values μ_i and covariances σ_i^2, as well as the proportions of the individual distributions α_i in the overall distribution. Furthermore, the assignment of the data points to the distributions are associated with probabilities, which is why the method is also referred to as soft-clustering. Figure 2 shows an example of a crack image with estimated parameters.

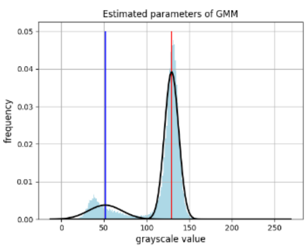

Figure 2: Example of an image containing a crack with estimated parameters of a GMM

3.4 Decision Criteria for Classification

For a robust classification of the concrete images, we formulated multiple decision criteria based on parameter estimations of Gaussian distributions (section 3.2) and of the GMM (section 3.3).

The first criterion is based on the coefficient of determination r^2 of the estimated Gaussian distribution. In case of the coefficient approaching 1, it can be concluded that the estimated Gaussian PDF is fitting the underlying sampling distribution very accurately and thus it can be assumed that there is only one significant texture present in the image, which can only be the surface itself. We found a threshold of 0.975 to be suitable for the coefficient. Thus, images with a lower coefficient of determination undergo the following two criteria whilst the others are excluded since it is assumed there are no cracks in these images.

As second criterion, the estimated expected values μ_1, μ_2 of the GMM are used. Cracks are generally significantly darker in the images than the rest of the surface, leading to the expected values μ_1, μ_2 to differ as correspondingly strong. Therefore, we adopt a threshold of 20 grayscale values for the difference between the two expected values (based on the observation of the current dataset). If the difference of the expected values is smaller than the threshold, the respective image is also considered as "intact" and the remaining images are subjected to the next criterion.

The third criterion involves the proportions of the two mixed Gaussian distributions in the GMM. Cracks in the image usually constitute a smaller part than the intact surface itself, which is also reflected in the proportions of the distributions accordingly. As ratio between the proportions, we found that 0.7 represents a suitable threshold value. Therefore, if the proportion of the distribution with the lower expected value is lower than 0.3, the image is considered to include a cracked surface.

Only if all three criteria are fullfilled, we classify the respective image as a cracked surface (Fig. 3). In all other cases, the image is considered to be of an intact concrete surface.

Figure 3: Criteria for classification of concrete images into intact and cracked surfaces

4 Results

Testing the entire dataset of 40,000 images based on the introduced decision criteria shows a good classification accuracy especially for images containing cracks. For intact surfaces, the number of images classified incorrectly as images containing cracks is slightly higher than the number of images containing cracks classified incorrectly as intact. For crack images, this gives us a rate of 99.995%, while for images of intact surfaces it is 97.58%. The overall classification accuracy is therefore about 98.79%. Figure 4 shows the results in a confusion matrix.

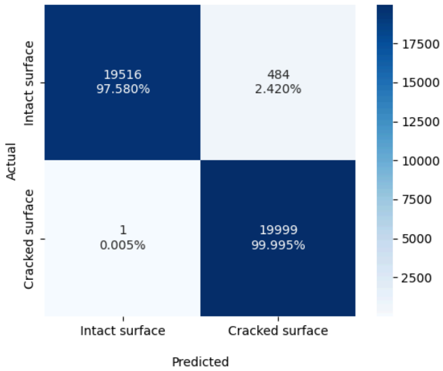

Figure 4: Results obtained for the reference dataset

5 Discussion

The presented method shows an appropriate classification performance on the dataset used. However, it has to be taken into account that the methodology was developed and tested using only this dataset and is therefore only representative to a certain extent.

It is noticeable that intact surfaces are classified generally worse than ones with cracks. A reason for this might be the diversity of the surfaces and the presence of blobs and spots in the surfaces, which lead to the formation of two peaks, similar to the cracked surfaces, which in turn leads to a bimodal distribution. In practice, however, this constellation is less critical, since it would be much riskier to classify a cracked image as intact than the other way around.

Contrary to other algorithms like k-means clustering, the EM algorithm performs a soft-clustering of data points by assigning probabilities to the points for belonging to the individual populations. These probabilities in turn could be further considered in classification process.

The grayscale values of both surfaces and cracks were assumed to be normally distributed and independent. However, these are actually based on visual assessment and must first be verified.

Up to now, we only considered two moments of a random variable, specifically the expected values and variances. However, the frequency distributions of the grayscale values could also involve other significant moments, such as skewness or kurtosis, which should be taken into account.

6 Conclusion

In this paper, we presented a method for binary classification of images to intact and cracked surfaces based on three decision criteria. The results on the reference dataset used show an appropriate classification accuracy. The presented methodology thus forms a baseline approach to serve a basis for further research.

The proposed method could be extended for image segmentation by adapting a sliding-window approach, as presented by Sesselmann [3]. This in turn could be used to measure the crack width.

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