Comparison of Methods for Processing of X-ray images of Defects in Reinforced Concrete Product

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Abstract. The problem of automatic determination of the location of defect projections on radiographs of metal and reinforced concrete products is considered. The main research method is a computational experiment. A three-dimensional phantom has been developed that simulates a fragment of a concrete slab reinforced with iron bars with defects inside. Its X-ray image is modeled on the basis of the Bouguer law. Distortion represents uncorrelated noise with a normal distribution in each pixel. A binary Bayesian classifier is used to search for defects. It has been shown to be quite effective as long as the noise SDV does not exceed 1.5% of the average image brightness. At a higher noise level, the classifier does not give stable results. The use of simple low-frequency filtering methods (averaging and median in a sliding window) for noise suppression did not lead to improvement. However, the use of the entropy filter has shown that it can improve the quality of classification. Special image point detectors, in particular the Harris-Stephans detector, were also used to search for defects. The results obtained suggest that this approach may be promising.

1. Introduction

X-ray radiation, due to its high penetrating power, is an effective means of studying the internal structure of objects of various nature. The simplest measurement scheme is an X-ray source and a flat detector, which are located on different sides of the test object. Let's introduce a coordinate system with the origin at the source location, and a coordinate system \( \vec{U} \vec{s} \vec{V} \) on the detector, see Figure 1. Denote by \( I(u, \nu) \) the distribution of the intensity of passed through the object radiation registered by detector. As a rule, when interpreting the measurement results, the following relationship is assumed between the function \( I(u, \nu) \) and the characteristics of the object being tested, see, for example, [1]:

\[
I(u, \nu) = I_0 \exp \left( - \int_S \mu(x(I), y(I), z(I)) \, dl \right)
\]  \hspace{1cm} (1)

Equation (1) is a generalization of the Bouguer law. Here \( I_0 \) is the intensity of the source; \( \mu(x, y, z) \) is the three-dimensional distribution of the X-ray attenuation coefficient in the studied volume. Integration is performed along the segment connecting the source location point \( S \) and the point \( A \) lying on the detector surface.
The X-ray sensing technique is used to check metal and reinforced concrete structures for potentially dangerous internal defects [2–4]. In this case, by the feature of the function \( I(u,v) \), a conclusion about the possibility of further use of the tested nodes is made. According to equation (1), for a ray that crosses a crack, the intensity registered at the associated detector point will be slightly higher than for neighboring rays that do not cross it, since the attenuation coefficient is much lower in a cavity filled with a mixture of gases than in the surrounding material.

In all modern recording systems, the distribution \( I(u,v) \) is represented as a digital grayscale image. The latter consists of pixels, each of which has a brightness \( f(i,j) \), where \( i \) and \( j \) are indexes that number the pixel. The transition from intensity to brightness is performed according to a certain rule. For the sake of certainty, we will assume that pixels associated with rays passing through cracks or places where there is no material are darker. (Note that, according to (1), the radiation intensity is higher for them, but in X-ray flaw detection, they prefer to deal with negative images.) The main task is to identify these pixels. The problem in this case is that the effect caused by the presence of a crack is very weak. It is often comparable in size to the standard deviation of noise, which is inevitably present in the measurement results.

The development of control and monitoring technologies requires that the division (classification) of pixels into that belonging and not belonging to defects projections be automated. The simplest binary classification is that a threshold value \( f_{th} \) is set and pixels are separated by comparing their brightness with it. The success of this procedure depends not only on how well the \( f_{th} \) value is selected, but also on the properties of the image itself, in particular, on the noise level. The authors also consider a classification method based on the assumption that the projections of narrow cracks are special points of X-ray images, so appropriate detectors can be used to search for them. In this paper, these two approaches are compared during a computational experiment. It also studies the procedures of the preliminary image processing aimed to improve the efficiency of classification.

2. Materials and Methods

2.1. The division by the brightness threshold

Bayesian classifiers based on maximization of a posteriori probability are widely used among binary classifiers [5–8]. Let's assume that there are two sets of image pixels with the original brightness values \( f_1 \) and \( f_2 (f_2 > f_1) \), which should be separated. For this problem, the dividing threshold for a Bayesian classifier is generally expressed as follows:

\[
 f_{th} = \frac{\sigma^2}{f_2-f_1} \ln(\eta) + \frac{M}{2} \left( f_2 + f_1 \right)
\]  

(2)

where \( \sigma^2 \) is the variance of noise in the image; \( M \) is the number of pixels that make up the classified fragment. The likelihood ratio criterion \( \eta \) is equal to

\[
 \eta = \frac{p_2 \left( l_{2,1} l_{2,2} \right)}{p_1 \left( l_{1,2} l_{1,1} \right)}
\]  

(3)

\[ \]
P₁ and P₂ are the probabilities that the taken fragment consists entirely of pixels of the first and second sets, respectively. The second relation in (3) characterizes the loss of the classifier. The values of the coefficients Lₖ₁ are found based on specific conditions, often with the use of training. Since it is difficult to calculate the likelihood ratio criterion in practice, it was proposed in [9, 10] to determine the value of f₀ using the minimality condition of the weighted sum of the probabilities of errors of the first and second kind: Pterr₁+αPterr₂. Here, the non-negative coefficient α characterizes the relative significance of errors of the second kind. Assuming that the noise at each point has a normal distribution for a fragment consisting of a single pixel, the following expression was obtained there

\[ f₀ = \frac{\sigma^2}{f_2-f_1} \ln \left( \frac{a(1-P₁)}{P₁} \right) + \frac{1}{2} (f₂+f₁) \]  

(4)

that coincides with (2), where the relation \((L₂₁-L₂₂)/(L₁₂-L₁₁)\) equals the α, which is the set weight of errors of the second kind.

Let's return to the problem under consideration. Let the index “1” denote the pixels that make up the crack image. Generally speaking, even in the absence of noise, the X-ray image is not binary, since the lengths of the intersections of the rays with the object are different. Therefore, one should find reasonable estimates for \(f₁\) and \(f₂\). Following [11], \(f₂\) can be estimated as the average over a sufficiently large region that does not include crack projections. Moreover, this can be done without referring to the image itself, but using equation (1). In particular, if we study an object made of a homogeneous material with an attenuation coefficient \(μ₀\), then \(I(u,v)=I₀ \exp(-μ₀IY)\), where \(I(u,v)\) is the length of the intersection of the corresponding ray with the area occupied by the material.

Based on the Bouguer law, one can also estimate the brightness of the crack image. Let's assume that the radiation source is located on the Y-axis, and the crack passes in a plane perpendicular to it. Denote by \(ΔI_Y\) the average size of the cracks in the Y direction, i.e. its width. For an estimate of the value \(f₁\), we take the brightness corresponding to the intensity \(I₁=I₀ \exp(-μ₀(IY-ΔI_Y))\), where \(ΔI_Y\) is the average length of the intersection of the object with the rays parallel to the Y-axis. The probability that an arbitrary image pixel belongs to the defect projections (probability \(P₁\)) should be determined based on the specific conditions of the problem. At the same time, it is possible to attract results obtained by other research methods.

### 2.2. Detectors of singular points

Methods for searching for special points, including angles, are divided into three groups. The first one is based on intensity differences between close pixels. The second utilizes the contours extracted from the image. Detectors from the last group use intensity distribution models. The paper considers the Harris-Stephens method, which belongs to the first group. This choice is explained by the fact that contour selection is an independent complex problem that requires separate study. At the same time, the methods of the third group are essentially reduced to the choice of the model that is most appropriate for images of a certain type.

The Harris-Stephens method, as well as similar algorithms, analyzes the properties of the function \(S(u,v)\) obtained by summing, possibly with weights, the squares of pixel intensity differences belonging to shifted regions [12]. The earliest implementation of this approach belongs to Moravec. He suggested calculating the following values for a square window \(W\):

\[ S_{a,b}(u,v)=\sum_{u',v'\in W} \left( f(u'+a, v'+b)-f(u', v') \right)^2 \]  

(5)

In this case, the shift vector \((a, b)\) takes the values \((-1, -1), (-1, 0), (0, -1), (-1, 1), (1, 1), (0, 1), (1, 0), (1, 1)\). Thus, the window is shifted by one pixel in eight directions. Then \(S(u,v)=\min_{a,b} S_{a,b}(u,v)\), is assumed, and the local maxima of the function \(S(u,v)\) greater than a certain threshold value are considered special points. Harris and Stephens modified the Moravec detector by adding weights and resolving non-square windows. Expression (5) was converted by them into the form

\[ S_{a,b}(u,v)=\sum_{u',v'\in W} \left( f(u'+a, v'+b)-f(u', v') \right)^2 \]  

(5)
\[ S(u,v) \approx \sum_{u',v' \in W} w(u',v') \left( uf_{u'}(u',v') - vf_{v'}(u',v') \right)^2 \approx (u,v) A_{u,v} \left( \frac{u}{v} \right) \]  

Here \( f_u \) and \( f_v \) are partial derivatives of the intensity, the matrix \( A_{u,v} \) is defined as

\[ A_{u,v} = \sum_{u',v' \in W} w(u',v') \begin{bmatrix} f^2_u(u'+u,v'+v) & f_u(u'+u,v'+v) f_v(u'+u,v'+v) \\ f_u(u'+u,v'+v) f_v(u'+u,v'+v) & f^2_v(u'+u,v'+v) \end{bmatrix} \]  

Special points are considered local maxima of the function \( R(u,v) = \det(A_{u,v}) \cdot \lambda \left( \text{trace}(A_{u,v}) \right)^2 \), where \( \lambda \) is a configurable sensitivity parameter. The recommended range of its values is from 0.04 to 0.15.

2.3. Pre-processing

The improvement of the efficiency of classification can be achieved by the images pre-processing. Here it is advisable to apply two types of procedures: noise suppression and contrast enhancement. The first of them are well studied [13–15] and will not be considered here. Averaging in a sliding window is used in numerical simulation carried out. On the one hand, it is simply implemented and does not require non-trivial a priori information; on the other hand, it successfully suppresses broadband noise. In the method of increasing contrast in images one can distinguish two approaches: transforming the histogram and high frequency filtering. From the analysis of the most well-known histogram transformations [16, 17], it follows that to solve the problem on this basis, you actually need to know the threshold \( f_{th} \). However, its calculation is one of the goals of the work. Therefore, the second approach was chosen. Filtering by means of differential operators, in particular the gradient [18], is widely used here. In [11], the Laplace operator was also used. Practice shows that such processing significantly increases high-frequency noise, which in this case is highly undesirable. In this regard, the entropy filter was used in this paper. In general it can be written as follows

\[ \tilde{f}(i,j) = G \left( f(k,l) \cdot f(k,l) \cdot \ln(f(k,l)) \right) \]  

To the left in equation (8) is the brightness of the filtered image in pixel \((i,j)\); \( G \) denotes the function that performs the conversion. The indices \( i \) and \( j \) enumerate the pixels in the filter window. For example, if the image discretization is \( N \times N \), the filter window is \( n \times n \), where \( n \) is odd, and the indexes \( i \) and \( j \) take values from \( 1+(n-1)/2 \) to \( n-(n-1)/2 \). Then there is \( i \in (1+(n-1)/2 \leq i \leq i+(n-1)/2 \) and \( j \in (1+(n-1)/2 \leq j \leq j+(n-1)/2 \). Implementations of the general formula (8) are presented in [19, 20]. In [11], the authors developed the following filter to increase the contrast of crack projections on radiographs:

\[ \tilde{f}(i,j) = \frac{1}{n \cdot n} \sum_{k=i-(n-1)/2}^{i+(n-1)/2} \sum_{l=j-(n-1)/2}^{j+(n-1)/2} \frac{f(k,l)}{f(i,j)} \]  

where \( \tilde{f}(i,j) \) is the average brightness value in the \( n \times n \) window:

\[ \tilde{f}(i,j) = \frac{1}{n \cdot n} \sum_{k=i-(n-1)/2}^{i+(n-1)/2} \sum_{l=j-(n-1)/2}^{j+(n-1)/2} f(k,l) \]  

It was also shown in [11] that filtering (8) allows increasing the jumps in the distribution \( f(i,j) \), thereby emphasizing the boundaries of objects in the image, while increasing the noise level is regulated by changing the size of the window.

3. The results of numerical simulations

The methods described in the previous section were compared in the computational experiments. A three-dimensional mathematical phantom was developed that simulates a fragment of a concrete slab reinforced with iron. The fragment is oriented perpendicular to the \( Y \)-axis. It also contains an X-ray source. The resulting X-ray image (projection) is shown in Figure 2, a. The resolution is 640 × 490
pixels. Figure 2, b shows the same image that the noise was superimposed on. To model the noise, a normally distributed centered random variable with the variance $\sigma^2 = \xi^2 \bar{f}^2$ was added to the function $f(u,v)$ at each point, where $\xi$ is a positive number and $\bar{f}$ is the average value of the projection data in the absence of noise. For Figure 2, b, the noise level corresponds to the value $\xi = 0.01$, i.e. the standard deviation of noise is only 1% of the average brightness of the image.

The simulated defects are located in the areas whose borders are marked in Figure 2, a by dotted lines. In areas $1$ and $2$ there are cracks in the rebar, and in area $3$ there is cavity in the concrete. In order to quantify the quality of images of these defects after various processing procedures, a normalized root-mean-square error was calculated for each of the areas:

$$\Delta_m = \frac{1}{n_m} \left( \sum_{(i,j) \in D_m} (f(i,j) - f^0(i,j))^2 \right)^{1/2}$$  \hspace{1cm} (11)

Here, the index $m$ numbers the areas; $n_m$ denotes the number of pixels in them; $f^0$ is the original image, see Figure 2, a. In particular, for Figure 2, b $\Delta_1 = 0.016$, $\Delta_2 = 0.013$ and $\Delta_3 = 0.012$.

![Figure 2](image.png)

**Figure 2.** Model image: no noise (a); SDV of noise is equal to 1% of the average brightness of the image (b).

The results of processing a noisy projection by a moving average filter with a $5 \times 5$ window and an entropy filter with an $11 \times 11$ window are shown in Figure 3, a and b, respectively. For Figure 3, a $\Delta_1 = 0.009$, $\Delta_2 = 0.007$ and $\Delta_3 = 0.008$. The images in Figure 2, a and Figure 3, b are incomparable in amplitude. Therefore, errors (11) were not calculated for the latter.

![Figure 3](image.png)

**Figure 3.** Results of processing of image in Figure 2, b: Averaging, window $5 \times 5$ (a); entropy filter, window $11 \times 11$ (b).
Figure 4, a and Figure 5,a show the results for the Harris-Stephans singular point detector. The value of the sensitivity parameter \( \lambda \) is 0.1. For a more visual representation, the points found by the detector are assigned an amplitude of 1.2 from the maximum of the image on which they were searched. The values at the other points are not changed. Figure 4,a is obtained from Figure 3,a, i.e. from the smoothed image. The errors for Figure 4,a are \( \Delta_1 = 0.009, \Delta_2 = 0.008 \) and \( \Delta_3 = 0.009 \). When calculating them, the image at special points, on the contrary, equated to the minimum of what is shown in Figure 3, a. Figure 5,a is obtained from a noisy image processed by an entropy filter, see Figure 3,b. The results obtained by the classifier (4) for the same images are shown in Figure 4, b, Figure 5,b, respectively. The values \( f_1 \) and \( f_2 \) are the minimum and maximum values of images that the classifier was run on. The probability \( P_1 \) was estimated as the ratio of the number of pixels that make up the defect images to their total number, and it turned out to be \( P_1 = 0.0008 \). Just as in the case of singular point detectors, pixels with brightness lower than the threshold in the original image were assigned brightness 1.2 times greater than the maximum, and the remaining pixels did not change.

![Figure 4](image)

**Figure 4.** Results of processing of image in Figure 3,a: Harris-Stephans detector(a); binary classifier (b).

### 4. Discussion

The results of the computational experiments showed that in typical problems of X-ray diagnostics of reinforced concrete products, the images of defects on radiographs have a very low contrast. If there is even a slight noise (in the experiments, the value of its standard deviation was 1% of the average brightness of the image), the defects become almost indistinguishable. The application of simple low-frequency filtering procedures did not bring the desired effect, as can be seen from Figure 3,a, which is the result of applying averaging in a sliding window. Although the noise in the image is largely suppressed, there are no signs of defects. Similar images were obtained for a median filter and a filter with a Gaussian frequency response. The entropy filter proposed in [11] was more effective. In Figure 3,b, all defects are clearly distinguished, including the cavity in the concrete. A detailed study of the entropy filter was conducted in [11].

![Figure 5](image)
**Figure 5.** Results of processing of image in Figure 3, b: Harris-Stephans detector (a); binary classifier (b).

Visual identification of a defect does not mean that it will be detected by the automatic system, but this requirement is currently the most relevant. There are many studies on this topic; however, we cannot say that the task of detecting low-contrast small-size structures is completely solved. In this paper, we consider a relatively simple Bayesian classifier (4). Numerical modeling has shown that it is quite effective in the case of low noise, see Figure 4, b. The main problem when using it is that in practice it is difficult to determine the brightness corresponding to the object and background that are required to calculate the dividing threshold. The difficulty is that even if the object under study is binary, its X-ray image is not binary. However, the correct choice of the threshold value is extremely important in the task of recognizing low-contrast elements. In particular, for Figure 4, b, a change in the threshold value of only half a percent led to the fact that the cracks were no longer visible.

The use of singular point detectors can be useful, because it can find objects with different brightness levels without additional reconfiguration. For example, in Figure 5, the detector found not only pixels belonging to the cavern and cracks, but also inhomogeneities of concrete that were also included in the three-dimensional phantom (two vertical stripes on the right side of the image). The disadvantage of detectors is that they indicate only individual points, and projections of defects are usually simply connected areas. Comparing Figure 4 and Figure 5, it can be concluded that the preliminary application of an entropy filter that emphasizes the boundaries of regions with different brightness, allows increasing the efficiency of classification.

**5. Conclusion**

In this paper, two approaches to solving the problem of automatic detection of defects on X-ray images of reinforced concrete products are compared using a computational experiment. One of them can now be considered as traditional. It is a binary classification. The other, utilizing of singular point detectors, occurs in this context for the first time, as far as the authors are aware. Numerical modeling has shown that both approaches can be used. At the same time, they provide solutions to various aspects of the problem. By means of binary classification, with the correct choice of the dividing threshold value, it is possible to determine the shape of the projections of defects, including thin cracks, quite accurately. Special point detectors can find pixels that belong to images of defects that are almost not identified by other methods. It was also shown that preliminary increasing of the image contrast (in this work, an entropy filter was used for this purpose) in many cases increases the efficiency of automatic X-ray image analysis.

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