Defects detection in X-ray images and photos

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Abstract: - A new approach for defects detection in low contrast digital images (X-ray or photos) and images with uneven background illumination is presented in this paper. The algorithm comprises two main stages: image pre-processing (noise suppression and correction of the uneven illumination) and adaptive defects segmentation. This approach permits the successful detection of different kinds of defects and irregularities and ensures high accuracy. It is suitable for the analysis of X-ray images of welds, or photos of pipes, plates, etc. The experimental results obtained with the software implementation of the described algorithms prove their efficiency. The paper also points up the advantages of the presented algorithm in comparison with some well-known methods for non-destructive control.

Key-Words: - Image processing, image segmentation, noise filtration, background equalization, defects detection.

1 Introduction

Nondestructive testing is a wide group of analysis techniques used in science and industry to evaluate the properties of materials without causing damage. The corresponding methods usually are based on analysis of visual documents, obtained using electromagnetic radiation, sound, and inherent properties of materials to perform the testing. The inside of a sample can be examined with penetrating electromagnetic radiation, such as X-rays or 3D X-rays for volumetric inspection. Significant part of the investigated problems concerns quality of welds. In general, the welding may encounter various defects, which in result of loads and fatigue during product lifetime can cause failures if not detected in time. The typical welding defects (lack of fusion of the weld to the base metal, cracks or porosity inside the weld, and variations in weld density) could cause a structure to break or a pipeline to rupture. Significant number of algorithms aimed at weld defects detection had already been developed and used [1-3]. The most renowned are described in the brief below:

• A method for automatic recognition of welding defects [4], which is performed in two steps: in the first one, the defects are searched for in the high-frequency areas of the image. For this purpose, the processed image is divided into sub-blocks of 32 × 32 pixels; then, for each sub-block the discrete Fourier spectrum is calculated. In the second step, the likely defects are compared consecutively with a set of typical defects, stored in a pattern library. The main disadvantages of the method are the high computational complexity because of the discrete Fourier spectrum calculation and the dependency on the pre-prepared library.

• A method for intelligent segmentation of industrial radiographic images [5] in which the processing starts with image segmentation based on adaptive threshold detection and the so obtained binary image is processed with neural networks back-propagating the error. The main disadvantages of the method are: high computational complexity, because the uneven background requires the threshold to be calculated as locally-adaptive for every pixel; and the need of time-consuming neural networks training.

• A method for defects recognition, using texture features based on co-occurrence matrix and 2D Gabor functions [6], i.e., Gauss-shaped band
pass filters with dyadic treatment of the radial spatial frequency range and multiple orientations. The main disadvantage is the use of a co-occurrence matrix which requires significant computational power;

- A background subtraction method for weld inspection [7], in which every column of the digital image is approximated with a polynomial function, which is subtracted from the original. The resulting image is processed with fuzzy k-nearest neighbor and multi-layer neural networks; the classification of the defect type is performed by a fuzzy expert system. The basic disadvantage is the high computational complexity: the calculation of the polynomial approximating function is too complicated because of the size of the processed images;

- A method for defects detection using image data fusion [8] based on edge extraction, wave profile analyses, segmentation with dynamic threshold and weld district extraction. The method insufficiency is its dependency on the image contrast (usually very low in the X-ray photos).

In this paper is presented one new approach for defects detection in digital X-ray or photo images, based on the following sequence of operations: Preprocessing of the digital image aimed at the image filtration and correction of the uneven image background; Image segmentation; Individual analysis of the detected likely defects, used to determine their geometrical and brightness parameters; Classification of the detected defects on the basis of the extracted features. The operations “individual analysis” and “classifications” of the detected defects are usually set in accordance with the application and are not included in this paper.

The paper is arranged as follows: section 2 presents the algorithm used for the adaptive noise filtration; section 3 is devoted to the correction of the uneven illumination in the image background; section 4 gives the main idea of the image segmentation based on the “Triangle” algorithm, modified for this application; in section 5 are given some experimental results and Section 6 is the Conclusion.

2 Image preprocessing
The preprocessing of the X-ray images starts with noise filtration. As it is known, these images have relatively low contrast and the existing noise is mainly of the kind Additive Gaussian noise. The most suitable methods used for the noise suppression are based on the locally-adaptive filtration [9]. Specific for the performance of the locally adaptive filters is that they change the processed pixel brightness in dependence of the pixel belonging to the noise or not, which is determined by filter conditions. The likely defects are not affected because their basic characteristics (dimensions, area, shape, contrast, etc.) differ significantly from these of the noise. The approach offered here for the processing of X-ray images is based on the use of the two-dimensional adaptive fuzzy filter (2DAFF), developed by the authors [10].

The basic conditions assumed are:

- The processed image is presented as a matrix of size $M_1 \times M_2$.
- The filter works with a sliding window of size $(2N_1+1) \times (2N_2+1)$ pixels.

The filter performance is defined by the relation:

$$
y(i,j) = \begin{cases} 
\sum_{r=-N_1}^{N_1} \sum_{s=-N_2}^{N_2} b(i+r,j+s)x(i+r,j+s) \\
\frac{1}{MN} \sum_{r=-N_1}^{N_1} \sum_{s=-N_2}^{N_2} x(i+r,j+s) \\
\text{if } \Delta(i+r,j+s) \leq \alpha; \\
\frac{\Delta(i+r,j+s) - \beta}{\alpha - \beta}, \text{if } \alpha \leq \Delta(i+r,j+s) \leq \beta; \\
0, \text{if } \Delta(i+r,j+s) \geq \beta,
\end{cases}$$

where: \(\lfloor \cdot \rfloor\) is a rounding operator; \(T\) is a threshold; and \(x(i,j)\) and \(y(i,j)\) are pixels, belonging respectively to the input and the filtered image;

$$
b[(i+r,j+s)] = \begin{cases} 
1, \text{if } \Delta(i+r,j+s) \leq \alpha; \\
\frac{\Delta(i+r,j+s) - \beta}{\alpha - \beta}, \text{if } \alpha \leq \Delta(i+r,j+s) \leq \beta; \\
0, \text{if } \Delta(i+r,j+s) \geq \beta,
\end{cases}$$

is the membership function with parameters \(\alpha\) and \(\beta\) (\(\beta > \alpha\)), which define the filter fuzziness;

- the argument \(\Delta\) is the module of the difference between the central pixel \(x(i,j)\) in the filter window and the pixel \(x(i+r,j+s)\), which is placed at a distance \((r,s)\):

$$
\Delta(i+r,j+s) = \left| x(i,j) - x(i+r,j+s) \right|
$$

for \(r=-N_1, N_1\) and \(s=-N_2, N_2\).

The values of parameters \(\alpha\) and \(\beta\) are defined in accordance with the image contents and with the kind of the distortions, which should be corrected.
3 Correction of the background uneven illumination

This correction is performed, because it simplifies the next operations – the detection and segmentation of the likely defects. The usual reason for the uneven illumination in the image background is the form of the processed parts.

In this paper is presented a method for correction of the background uneven illumination with 2D linear digital filter of a non-recursive kind [11], whose performance is described by the relation:

\[
    z(i,j) = g[x(i,j) - \frac{1}{A} \sum_{m=-N_1}^{N_1} \sum_{n=-N_2}^{N_2} x(i+m,j+n)] + \mu_x =
    \]

\[
    = g[x(i,j) - \mu_x(i,j)] + \mu_x
    \]

Here: \( x(i,j) \) is the brightness of the element \((i,j)\) from the non-corrected image (before the background correction); \( z(i,j) \) – the brightness of the element \((i,j)\) from the corrected image; \( \mu_x \) - the mean brightness of the non-corrected image; \( \mu_x(i,j) \) - the mean local brightness in the window around the pixel \( x(i,j) \); \( A = (2N_1+1)(2N_2+1) \) - the number of pixels in a rectangular window of size \((2N_1+1)(2N_2+1)\); \( g \) – coefficient, representing the contrast enhancement applied to the small details in the image \((g \geq 1)\). The value of \( \mu_x \) is defined by the relation:

\[
    \mu_x = \frac{1}{2}(x_{\text{max}} - x_{\text{min}}),
    \]

where \( x_{\text{max}} \) and \( x_{\text{min}} \) are respectively the pixels with maximum and minimum brightness value in the processed image.

In order to accelerate the filter performance, presented with Eq. 4 in this work is offered to transform the relation in a recursive form, and to perform it in correspondence with the relations below:

\[
    \mu_x(i,j) = \mu_x(i-1,j) + \mu_x(i,j-1) - \mu_x(i-1,j-1) + \frac{1}{A} \left[ x(i+N_1,j+N_2) - x(i+N_1,j-N_2) - x(i-N_1,j-1) + x(i-N_1,j-N_2-1) \right]
    \]

Then from Eqs. 4 and 6 follows:

\[
    z(i,j) = z(i-1,j) + z(i,j-1) - z(i-1,j-1) + g[x(i,j) - x(i-1,j) - x(i,j-1) + x(i-1,j-1) - \frac{1}{A} \left[ x(i+N_1,j+N_2) - x(i+N_1,j-N_2) - x(i-N_1,j+1) + x(i-N_1,j-N_2-1) \right]}
    \]

The number of components in the last equation is always 11 and does not depend on the filter window size, which in this case is \((2N_1+1)(2N_2+1)\).

In case that \( N_1 > 1 \) and \( N_2 > 1 \), and when Eq. 7 is used instead of Eq. 4, the reduction of the number of additions is correspondingly:

\[
    \eta = \frac{1}{11} [(2N_1+1)(2N_2+1) + 2] = 0.36. N_1. N_2.
    \]

The new approach, offered here, is aimed at the method simplification. For this, it is proposed instead of applying one, two-dimensional filter to use two, one-dimensional filters - the first one in the horizontal direction and the second one in the vertical direction, represented by the relations:

\[
    y(i,j) = g[y(i,j) - \frac{1}{(2N_1+1)} \sum_{m=-N_1}^{N_1} y(i+m,j)] + \mu_y;
    \]

\[
    z(i,j) = g_2[z(i,j) - \frac{1}{(2N_2+1)} \sum_{n=-N_2}^{N_2} z(i,j+n)] + \mu_y,
    \]

where: \( g = g_1 \times g_2 \), and \( y(i,j) \) is the pixel \((i,j)\) of the image obtained as a result of the first filtration (in the horizontal direction), with mean brightness \( \mu_y \).

By analogy with Eq. 7, Eqs. 9 are presented in recursive form:

\[
    y(i,j) = y(i-1,j) - \frac{g_1}{A_1} \left[ x(i-N_1-1,j) - x(i+N_1,j) \right];
    \]

\[
    z(i,j) = z(i,j-1) - \frac{g_2}{A_2} \left[ y(i,j-N_2-1) - y(i,j+N_2) \right],
    \]

where:

\[
    A = A_1 \times A_2; \quad A_1 = 2N_1 + 1, \quad A_2 = 2N_2 + 1.
    \]

As a result, the filtration is significantly accelerated because of the reduced number of operations performed:

\[
    \eta = \frac{2N_1 + 3}{3} + \frac{2N_2 + 3}{3} = \frac{2(N_1 + N_2) + 6}{3} =
    \]

\[
    = 0.66(N_1 + N_2) + 2.
    \]

If \( N_1 = N_2 = 63 \), then \( \eta \approx 85 \), i.e. in result of the recursive approach, the number of additions is more than 80 times smaller than for the case with non-recursive approach. The algorithmic efficiency is enhanced as a result of the double use of the same filter. The so described filtration causes some distortions at the image edges. In order to avoid them, the matrix of the processed image should be artificially made larger [9] adding pixels in both directions (horizontal and vertical). As a result, the original matrix of size \( M_1 \times M_2 \) becomes of
The easiest way is to add zeros in both directions, but the results obtained usually contain some distortions, called zero-padding artifacts. The better way is to use image replication [11] of size equal to that of the filter window side.

The filter parameters \( N_1, N_2 \) and \( g_1, g_2 \) are defined in accordance with the background shading, which should be corrected.

4 Image Segmentation

In result of the background correction, the image histogram usually has only one maximum, which corresponds to the image background (after the correction) and the detection of a second maximum, which to point at the likely defect(s) is not possible. For this reason, the segmentation is based on the so-called “triangle” algorithm [11].

A modification of the algorithm, developed by the authors for this application only, is given below. The segmentation threshold is determined:

1. The image histogram \( H(x) \) is calculated for \( x = 0, 1, ..., Q-1 \), where \( Q \) is the number of gray levels;

2. In the image histogram \( H(x) \), are defined the following 3 points:
   - First point \( (H_0, x_0) \) – the maximum of the histogram (usually the mean value of the corrected background illumination);
   - Two points \( (H_1, x_1) \) and \( (H_2, x_2) \), which are defined by the relations:
     \[
     H_1(x_1) = H_2(x_2) = \psi H_0(x_0),
     \]
     \[
     H_1(x_1) < H_0(x_0) > H_2(x_2) \text{ for } x_1 < x_0 < x_2.
     \]

The value of the parameter \( \psi \) is usually \( \psi = 0.1 \);

3. The equations of the two straight lines, which join the two pairs of points, \( (H_1, x_1) \), \( (H_0, x_0) \) and \( (H_2, x_2), (H_0, x_0) \) correspondingly, are defined. For this is used the well-known relation:
   \[
   Ax + BH + C = 0,
   \]
   where, for the first line:
   \[
   x_1 \leq x \leq x_0, A = H_1 - H_0,
   \]
   \[
   B = x_0 - x_1, C = H_0 x_1 - H_1 x_0,
   \]
   and for the second one:
   \[
   x_0 \leq x \leq x_2, A = H_2 - H_0,
   \]
   \[
   B = x_0 - x_2, C = H_0 x_2 - H_2 x_0.
   \]

4. The distance to both lines is calculated for each point of the histogram \( (H, x) \), using Eqs. (16-18) below, specially developed for this application:

   \[
   D(x) = \frac{Ax + BH + C}{\sqrt{A^2 + B^2}},
   \]
   where the values of \( A, B, \) and \( C \) are defined by the equation of the corresponding straight line.

5. The value \( \theta \) of the variable \( x \) is defined, for which the distance \( D(\theta) = \text{max} \). This value is the found segmentation threshold, for which from Eq. 16 is obtained:

   \[
   \frac{H(\theta_1 + 1) - H(\theta_1)}{H_0 - H_1} \approx \frac{H_0 - H_1}{x_0 - x_1},
   \]
   for the range \( x_1 \leq x \leq x_0 \); and correspondingly:

   \[
   \frac{H(\theta_2 + 1) - H(\theta_2)}{H_2 - H_0} \approx \frac{H_2 - H_0}{x_2 - x_0},
   \]
   for the range \( x_0 \leq x \leq x_2 \).

Here \( \theta_1 \) and \( \theta_2 \) are the image segmentation thresholds, used to separate respectively the dark and the light welding defects.

6. For the visualization of the detected dark defects the image is binarized in accordance with the relation:

   \[
   p_1(i,j) = \begin{cases} 1, & \text{if } x(i,j) \leq \theta_1; \\ 0, & \text{if } x(i,j) > \theta_1; \end{cases}
   \]

   The detected white defects are visualized accordingly:

   \[
   p_2(i,j) = \begin{cases} 1, & \text{if } x(i,j) \geq \theta_2; \\ 0, & \text{if } x(i,j) < \theta_2; \end{cases}
   \]

7. The so detected dark and light defects comprise one general binary image \( p(i,j) \), in accordance with the operation:

   \[
   p(i,j) = p_1(i,j) \oplus p_2(i,j).
   \]

5 Experimental results

The software implementation of the presented algorithms developed in the Technical University of Sofia proved their efficiency and reliability.

The experiments were performed using a significant number of test images (more than 100). The images, presented below, are only parts of the real test images because their original size was too large (more than \( 8,000 \times 2,000 \) pixels each, 16 bpp, .tif and .bmp formats).

On Fig.1, an X-ray photo of a vertical pipe, of size 350 \times 800 pixels containing a welding defect, is shown.

The result of the first preprocessing (the suppression of the additive Gaussian noise) is
shown in Fig. 2; and the image obtained after the background illumination correction (the compensation of the pipe shape) is shown in Fig. 3. The detected defects are shown on Fig. 4.

The test image is shown scaled down and the difference between Fig. 1 and Fig. 2 is not easily noticeable, but the object on Fig. 2 is smoother. The result of the background illumination correction (Fig. 3) and the final image (Fig. 4) show the results obtained. The extracted defects could then be easily measured and counted, omitting the smallest (if decided of no importance). The values of the parameters, used for the processing of the test images, are: for the 2DAFF filter the brightness threshold was 35, and the filter window size was 5 pixels; for the correction of the uneven illumination in the image background was used filter of size 99 pixels in both directions (horizontal and vertical).

On Fig. 5 is shown a part of the test image of a pipe, containing a pore. The example image is of size 600 x 300 pixels. The detected defect is shown on Fig. 6. The values of the main parameters are same as these, pointed above. The contour of the extracted defect is shown on Fig. 7. For the contours extraction is used again the algorithm for background illumination correction, but the filter size is 7 pixels. In result, the processing retains the brightness transitions.

The accuracy of the presented method is illustrated on Fig. 8, where the contour of the extracted defect is overlapped on the original image.
For the detection of cracks in images of metal parts is used similar approach. In this case the 2DAFF filter used for the noise reduction is not needed. The example text image with selected region of interest (ROI) is shown on Fig. 9 and the extracted cracks of the ROI (enlarged) – on Fig. 10. The size of the filter used for the correction of the uneven illumination is 77 pixels in both directions. The size of the test image is 1027×768 pixels.

6 Conclusion
The software implementation of the presented approach for nondestructive testing proved its efficiency and a capability for reliable defects detection. Compared with other similar methods, based on neural networks of different kind or with the FFT, the presented approach has lower computational complexity and its performance is much faster. The investigated combination of algorithms is a flexible tool for image analysis and defects detection. The processing depends on a relatively small number of parameters and permits automation for similar image classes, i.e. for series of photos taken at same conditions the parameters of the processing should not be changed.

The future development of these algorithms will be aimed at the creation of additional tools for the evaluation of the depth of the detected defects, based on the brightness evaluation. The extraction of features, representing the geometry or brightness qualities (contrast, position, aspect ratio, width-area ratio, length-area ratio, and roundness), together with additional specific information, set in accordance with the application, will permit the development of an expert system, able to evaluate such properties as slag inclusion, porosity, lack of penetration, undercutting, etc.

The method is suitable for processing of regular photos as well, when detection of cracks is needed. The high accuracy of the method makes it suitable for medical applications, where the brightness changes with predefined threshold should be detected without taking into account the shape of the object.

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