

Weld defect detection in industrial radiography based digital image processing

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Abstract—Industrial radiography is a famous technique for the identification and evaluation of discontinuities, or defects, such as cracks, porosity and foreign inclusions found in welded joints. Although this technique has been well developed, improving both the inspection process and operating time, it does suffer from several drawbacks. The poor quality of radiographic images is due to the physical nature of radiography as well as small size of the defects and their poor orientation relatively to the size and thickness of the evaluated parts. Digital image processing techniques allow the interpretation of the image to be automated, avoiding the presence of human operators making the inspection system more reliable, reproducible and faster. This paper describes our attempt to develop and implement digital image processing algorithms for the purpose of automatic defect detection in radiographic images. Because of the complex nature of the considered images, and in order that the detected defect region represents the most accurately possible the real defect, the choice of global and local preprocessing and segmentation methods must be appropriated.

Keywords—Digital image processing, global and local approaches, radiographic film, weld defect.

I. INTRODUCTION

THE industrial radiography is a non-destructive method that uses the penetrating and ionizing inspection radiation to detect internal discontinuities, especially in welded joints (porosity, cracks, lack of penetration, etc.). Mainly used in the petroleum, petrochemical, nuclear and power generation industries especially, for the inspection of welds, the radiography has played an important role in the quality assurance of the piece or component, in conformity with the requirements of the standards, specifications and codes of manufacturing. The reliable detection of defects is one of the most important tasks in non-destructive testing, mainly in the radiographic testing, since the human factor still has a decisive influence on the evaluation of defects on the film. An incorrect classification may disapprove a piece in good conditions or approve a piece with discontinuities exceeding the limit established by the applicable standards [1]. The expert radiograph has as role to inspect each film in order to detect the presence of possible defects which he must then identify and measure. This work is made particularly delicate because of a low dimension of certain defects (a fissure can have a thickness lower than $200 \mu m$), a bad contrast and a noised nature of the radiographic film. The expert often works in extreme cases of the visual system and, that is why the subjectivity in the mechanisms of detection and measurement is not negligible.

Perfect knowledge of the geometry of these weld defects is an important step which is essential to appreciate the quality of the weld [2].

The radiographic image processing is especially used to improve the image quality, making the analysis process easier, which consists of detecting and classifying defects on the film. In the conventional method, the analysis is done exclusively by the radiograph inspector. The progresses in computer science and the artificial intelligence techniques have allowed the defect classification to be carried out by using pattern recognition tools, which make the process automatic and more reliable, as it is not a subjective analysis [1]. Digital image processing covers the set of the processes of improvement and extraction of qualitative information in digital images, according to the required users and needs, to give us, either new images or particular evaluations.

The purpose of the use of digital image processing techniques is not only to detect and identify the defects automatically [3] but also, on the one hand, to offer a better visualization of information and on the other hand to formalize the methods of radiographic expertise in order to make them robust and systematic [4].

In the further sections, the steps of image processing (digitization, preprocessing, segmentation and post-processing) dedicated to the welded joint radiographic film, will be detailed.

II. DIGITIZATION

Generally, the radiographic films are very dark and their density is rather large, therefore an ordinary scanner cannot give a sufficient lighting through a radiogram. Of course, specialized scanners adapted to take high quality copies of radiograms exist, but they are expensive. Here, we have used a scanner AGFA Arcus II, (800 dpi, 256 gray levels). The major part of the radiographic films that we have digitized, were extracted from the base the standard films provided by International Institute of Welding (IIW).

After digitization, the principal characteristics of our images are:

- Small contrast between the background and the weld defect regions. These last are characterized by unsharpened and blurred edges.
- Pronounced granularity due to digitization and the type of film used in industrial radiographic testing.
- Presence of background gradient of image characterizing the thickness variation of the irradiated component part.

III. PREPROCESSING

For the reasons evoked in the preceding paragraph, it becomes difficult, if not uncertain to detect, during the radiogram visualization, the presence of the small defects and to determine accurately their sizes. That is why, it is often necessary to start with the preprocessing stage in order to reduce or eliminate the noise enclosing in the film and improve its visibility. This procedure permits to obtain an image which would facilitate later the identification of the weld defects being able to be present in the welded joint.

Nevertheless, the first task in image preprocessing is the selection of the region of interest (ROI), i.e. which be considered as the parts of the image where the radiograph interpreters suspect the presence of imperfections. The selection of the ROI saves the operator to make treatments on the useless parts of the image, permitting reduction of the computing time. The second advantage is to save the treatments based on the global approaches to use the irrelevant regions of the image, which can negatively influence the output results.

A. Noise reduction

Noise in the radiographic image is characterized by its high spatial frequency and its lack of spatial correlation [5]. Radiographic images show substantial variation depending on the testing technique adopted as well as the material being inspected, which makes it difficult to choose a standard filter for noise elimination [6]. Therefore, the right choice is normally made empirically; bearing in mind that use of these filters must not alter the relevant information on those images [7]. The application of a median type low pass filter is carried out in this paper. This filter performs better than the major averaging filters because it can remove noise from input images with a minimum amount of blurring effect. Fig. 1 illustrates the neighborhood used by median filter in our application, where the horizontal and vertical lines are preserved and Fig. 2 illustrates the result of median noise removal operation on a radiographic film.

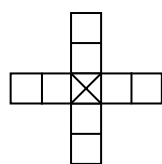


Fig 1 Neighborhood used by median filter

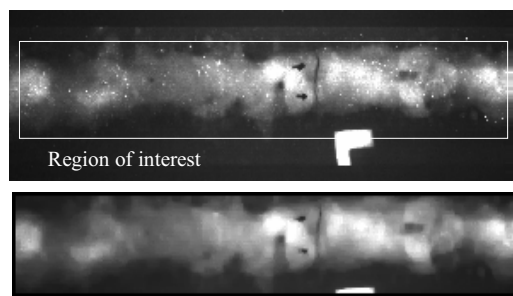


Fig. 2 Noise removal by of a median filter

B. Contrast enhancement

The goal of contrast enhancement is to improve the intensity contrast in the input image, highlighting the defect regions whilst leaving the unimportant background regions intact. In our work, we have developed two techniques of contrast enhancement based on global and local approaches.

B1. Contrast image enhancement by dynamic stretching

The below example relate the advantage bearing by Look Up Table transformation in the visibility improvement of radiographic images. The defect in Fig. 3a is hardly visible to the naked eye. The histogram in Fig. 3b is condensed at low gray level values because of the dark aspect of the input image. After application of LUT, the original dynamics is expanded, giving better visibility of output image in Fig. 3d.

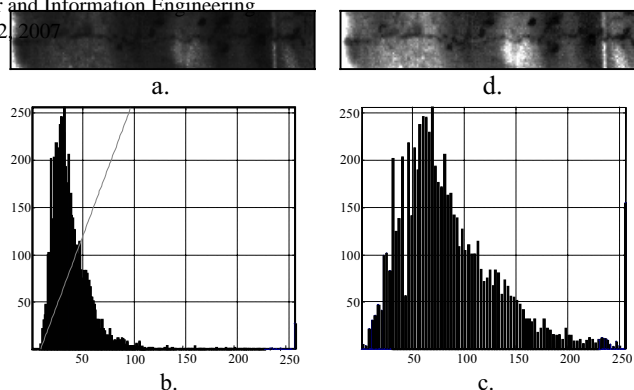


Fig. 3 Contrast enhancement by dynamic stretching

a. Region of interest. b. Normalized histogram of a. and LUT function (in gray line). c. Stretched Histogram. d. Enhanced image.

B2. Local contrast enhancement

The method discussed in the previous paragraph is global, in the sense that pixels are modified by a transformation function based on the gray level distribution over an entire image. While this global approach is suitable for overall enhancement, it is often necessary to enhance details over small areas [8]. For this purpose, the contrast enhancement method developed below is based on the gray level statistical properties of pixels taken in the neighborhood of each pixel in the image.

This local contrast enhancement method maps the input image $f(x,y)$ into a new image $g(x,y)$ using:

$$g(x,y) = A(x,y)[f(x,y) - \mu(x,y)] + \mu(x,y) \quad (1)$$

$$\text{where } A(x,y) = k \frac{M}{\sigma(x,y)} \quad 0 < k < 1, \quad (2)$$

$\mu(x,y)$ and $\sigma(x,y)$ are respectively the gray level mean and the standard deviation of $f(x,y)$ in the neighborhood $W \times W$. M is the global mean of $f(x,y)$, and k is a constant value.

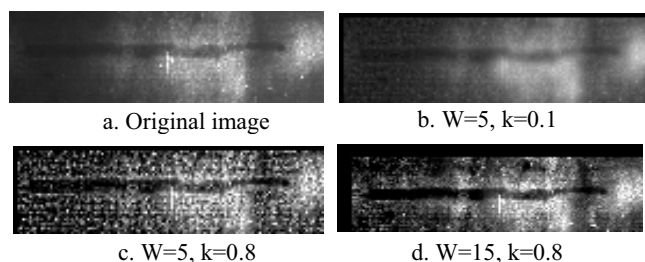


Fig. 4 Local method for contrast enhancement

The application of the local gain factor $A(x,y)$ to the difference between $f(x,y)$ and the local mean amplifies local variations. Since $A(x,y)$ inversely proportional to the standard deviation of the intensity, areas with low contrast receive larger gain. The mean is added back in (1) to restore the average intensity level of the image in the local region.

According to Fig. 4, the implementation results of the local contrast enhancement depend on the amplification factor k and the size W of the considered neighborhood. A little value of W and a big value of k give a textured aspect of the modified image (see Fig. 4c). For a little value of k , the effect of smoothing by neighborhood averaging becomes prevalent (see Fig. 4b). We obtain better results with k and W rather larges (see Fig. 4d). However, it is necessary to take in account the border effect when we choose a great neighborhood that is why, the selected region of interest must be relatively large in order to compensate the masked areas caused by local contrast enhancement algorithm.

$$\sigma_T^2 = \sum_{v=0}^{V-1} (v - \mu_T)^2 p_v \quad (8)$$

The segmentation constitutes one of the most significant problems in image processing, because the result obtained at the end of this stage strongly governs the final quality of interpretation [9].

The radiographic film images contain weld defects placed in background with different intensities. For such images, intensity is a distinguishing feature that can be used to extract the defects from the background. Therefore, a thresholding technique becomes a strong candidate for efficient radiographic image segmentation.

Thresholding is the process of partitioning pixels in the images into object and background classes based upon the relationship between the gray level value of a pixel and a parameter called the threshold. Because of its efficiency in performance and its simplicity in theory, thresholding techniques have been studied extensively and a large number of thresholding methods have been published [10].

These methods can be divided, among others, into two categories: global methods and adaptive local methods. Global methods compute a single threshold value for the entire image, and pixels having a gray level value less than the threshold value are marked belonging to one class, otherwise the other class. Local methods, on the other hand, compute a threshold value for each pixel on the basis of information contained in a local neighborhood of the pixel.

Based on the properties of the radiographic images, we have implemented three different thresholding algorithms. One of the methods is the Otsu global thresholding and the two others are the Niblack's and Sauvola's local adaptive thresholding.

A. Global thresholding by Otsu method

Otsu suggested minimizing the weighted sum of within-class variances of the object and background pixels to establish an optimum threshold. Recall that minimization of within-class variances is equivalent to maximization of between-class variance. This method gives satisfactory results for bimodal histogram images.

Let the pixels of the image be represented by V gray levels $\{0, 1, 2, \dots, V-1\}$. The number of pixels in level v is denoted by n_v , and the total number of pixels is denoted by N .

To simplify, the gray level histogram is normalized and regarded as probability distribution function

$$p_v = n_v / N, \quad p_v \geq 0, \quad \sum_{v=0}^{V-1} p_v = 1 \quad (3)$$

Suppose we divide the pixels into two classes C_0 and C_1 by a threshold value at k ; C_0 denotes pixels with levels $[0, 1, \dots, k]$ and C_1 denotes pixels with levels $[k+1, \dots, V-1]$. The probabilities of class occurrences ω and class mean levels μ for both classes are given by:

$$\omega_0 = \sum_{v=0}^k p_v; \quad \omega_1 = 1 - \omega_0; \quad \mu_0 = \frac{\mu_k}{\omega_k}; \quad \mu_1 = \frac{\mu_T - \mu_k}{1 - \omega_k} \quad (4)$$

$$\text{where} \quad \mu_k = \sum_{v=0}^k v p_v; \quad \omega_k = \sum_{v=0}^k p_v; \quad \mu_T = \sum_{v=0}^{V-1} v p_v \quad (5)$$

To measure the thresholding performance, a criterion measure is introduced by Otsu:

$$\eta = \sigma_B^2 / \sigma_T^2 \quad (6)$$

$$\text{where} \quad \sigma_B^2 = \omega_0 (\mu_0 - \mu_T)^2 + \omega_1 (\mu_1 - \mu_T)^2 \quad (7)$$

is the total variance.

We search for the optimal threshold k^* , which maximize η , or equivalently maximizing σ_B^2 , since σ_T^2 is independent of k . It only remains to compare the value of all the image pixels to the threshold thus found.

B. Local thresholding by Niblack and Sauvola methods

In some radiographic images, the background intensity is variable, and the overlapping between the two classes is therefore large, due to the weld thickness variations, the weak sizes of the defect and the geometrical considerations related to the used radiography technique. In such case, by a global thresholding, we do not obtain the desired results. That is why a local adaptive thresholding technique can be employed to overcome the problem. The method of Niblack is fast to implement and easy to apply.

The main idea of Niblack's thresholding method [11] is to vary the threshold value over the input image, based on the local mean $\mu(x,y)$ and local standard deviation $\sigma(x,y)$. The threshold value at pixel (x,y) is computed by

$$T(x, y) = \mu(x, y) + k\sigma(x, y) \quad (9)$$

where k is an adjustable parameter which depends on the image content. The size of the neighborhood must be sufficiently small to preserve the local details but also, it must be enough large to remove the noise. In this method, the problems are the light textures in the background, which are considered as object with small contrast.

To overcome these problems, Sauvola proposed a new improved formula to calculate the threshold

$$T(x, y) = \mu(x, y)[1 - k\alpha] \quad (10)$$

where $\alpha = 1 - \sigma(x, y) / R$

k : positive value parameter. R : dynamic range of the variance.

The contribution of the standard deviation becomes adaptive. In this method, hypothesis on the gray levels of the object and the background are used to eliminate the noise produced by light textures of the background because μ reduces the threshold value in the light background regions.

According to the results presented in Fig. 5, we note that the Otsu method gives good results for well contrasted images. In the case of radiographic images with non uniform background intensity, the methods of Niblack and Sauvola are recommended. Nevertheless, in the Niblack's method, the problem lies in the light textures of the background, which are assimilated to objects with low contrast.

To overcome this problem, the method of Sauvola can be applied. It should be also known that the performances of these methods are related to choice of the size neighborhood W and the parameters k and R . For the Niblack method, we have taken: $W = 15$ and $k = -0.2$. In the Sauvola method, the values of $W = 15$, $k = 0.5$ and $R = 128$ are selected. This choice was made in an empirical way. All the parameters chosen for these methods must answer the dilemma between robustness (non sensitiveness to noise) and precision (space definition of the segmented areas).

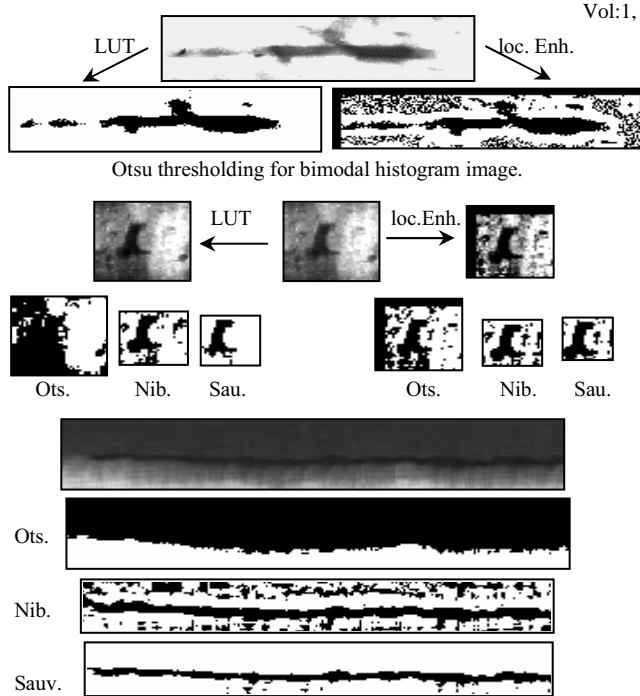


Fig. 5 Thresholding by Otsu, Niblack and Sauvola methods

V. POST-PROCESSING AND MORPHOLOGICAL OPERATIONS

After the thresholding stage, the binary image can contain:

- superfluous information that it is suitable to eliminate,
- or masked information that it is necessary to reveal and this, whatever the employed thresholding method.

The processing based on mathematical morphology makes possible to modify the binary image for this purpose. Dilation and erosion are two basic morphological operations [12]. Dilatations and erosions are often used in pairs to obtain morphological opening and closing.

Opening by a disk structuring element smoothes the boundary, breaks narrow parts, and eliminates small objects. Closing by a disk structuring element smoothes the boundary, fills narrow bays, and eliminates small holes.

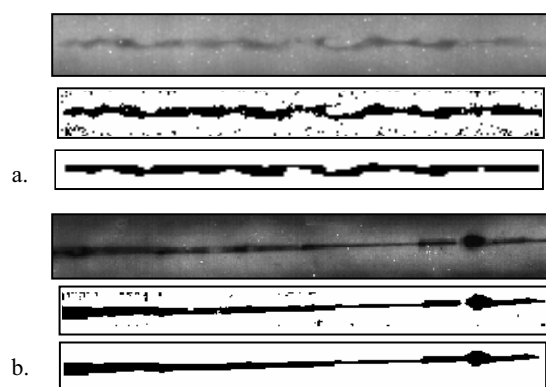


Fig. 6 Radiographic image post-processing

By referring to morphological operators properties, it thus becomes convenient to apply these operators in order to eliminate the noise and the small residual spots in the thresholded image. We must consider that at the end of this stage, we obtain only one connected region which represents the more accurately possible, the weld defect. The morphological operators of dilation, erosion, opening and closing allows: to remove the noise, to eliminate the small

residual spots and to connect closed regions likely to represent the same weld defect.

In Fig. 6a, one pass of median filter on the Sauvola thresholded image followed by an opening/closing using square structuring element (2×2 of ones) is sufficient to obtain the expected result. On the other hand, in the case of Fig. 6b, it was necessary to apply two passes of median filtering, followed by double dilation and double erosion using a rectangular structuring element (2×3 of ones). This choice is justified by the fact that in this last case, the structuring element must play a double role: eliminate the small irrelevant areas and connect regions which belong a priori to the same region representing the weld defect.

VI. CONCLUSION

By the light of the obtained results, we can recommend for the digitized radiographic image processing films the following operations:

- After the selection of the region of interest (ROI) where the defect is likely to be present, we apply a median filter smoothing with one or more passes according to the importance of the noise.
- We apply the dynamic stretching by Look Up Table transformation for uniform background images and the local contrast enhancement method for the images with variable brightness background.
- If the enhanced image histogram is bimodal, it is suitable to use the Otsu method for thresholding. If the defect region after contrast enhancement remains drowned in the background, it is recommended to apply Niblack or Sauvola thresholding methods. Moreover, this latter can be applied on images with noised background lowly contrasted.
- For the extraction of the defect region, we can apply in interactive way the morphological operators which eliminate the small holes and spots and connect the closely regions.

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