Welding Defect Detection by Segmentation of Radiographic Images

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Abstract

In the Non Destructive Testing (NDT), it is dealt with the detection of defects in metallic pieces especially for industrial use. These defects are mainly due to manufacturing errors or to welding processes. In this article we will focus on this second category of defects using segmentation techniques applied to the welded joints. The segmentation remains among the most difficult tasks in image processing, especially in the case of noisy or low contrasted images such as radiographic images of welds. In segmenting this type of images, many researchers used neural networks and fuzzy logic methods. The results are impressive, however the methods require a complex implementation and are time consuming. In this work, we propose a new method of segmentation of digitized radiographic images which is based primarily on histogram analysis, contrast enhancement and image thresholding. Computing time is optimized by using integral images to calculate the local thresholds. Although the method gives comparable results to those obtained by previous methods in terms of visual segmentation quality, it is found much more simple to implement.

1. Introduction

In the field of non destructive testing (NDT) applied to metallic pieces, the most important stage concerns the detection of welding defects which may affect the well functioning of these pieces. This could be very hazardous when dealing for example with rail roads, gas pipes, wheels, etc. Fortunately, radiography remains among the most adapted NDT processes for the control of welds of metallic pieces, because of its simplicity and its speed of implementation. In parallel, the development in the field of information technologies in particular in image processing, made it possible to invent new radiographic inspection methods able to detect and identify automatically welding defects by increasing the quality of information while decreasing diagnosis duration.

However, in image processing, the segmentation remains a very delicate stage, especially in the case of noisy and low contrasted images, as it is the case for the radiographic images. Several researchers in [8], [4] and [9] used neural networks and fuzzy logic methods to solve this problem. The results are impressive, but require a complex implementation and an important computing time.

In a previous work [1], we showed that the segmentation using global and local thresholding applied to digitized images of welded joints, led to comparable results to those obtained by previous authors but in a more efficient way in terms of implementation complexity, regardless of the computing time requirement.

In this article, we attempt to improve the efficiency in terms of computation complexity by associating the concept of integral images in the search of the local threshold. In the proposed approach, we first pre-process the image using histogram analysis and contrast highlighting by a homomorphic filtering. Second, we isolate the weld bead by performing on the resulting image a global thresholding using Otsu’s method. A last stage consists of applying an appropriate local thresholding technique based on integral images that performs the final segmentation (figure 1).

Figure 1. segmentation method steps
2. Method

2.1 Weld bead isolation

The first task in the pre-processing of a radiographic image concerns the selection of the region of interest (ROI), which is a reduced zone of the image where the processing will be applied. This will allow the operator to process on the useful parts of the image, and thus reducing computation complexity. Our objective is to focus on the segmentation of the defects caused by the welding processes only. The defects being outside the weld bead are mainly due to parts manufacturing. For this reason we chose to limit the ROI to the weld bead. Within this ROI, we isolate the weld bead from that of the defects by using a segmentation method based primarily on the contrast highlighting techniques, thresholding and morphological operations.

2.1.1 Denoising and homomorphic filtering

When observing a radiographic image of welding defects, we note that the intensity of a homogeneous area varies randomly due to the noise. Moreover, the image can be characterized by a low contrast, a non uniformity, a basic gradient related to the piece’s thickness or by a granular aspect due to the digitization equipment. The maximum of these disturbances can be eliminated in the pre-processing stage, in which we manage to denoise and highlight the image by the homomorphic filtering. The segmentation of the weld bead can be facilitated by reinforcing the resemblance between pixels belonging to the same area, or by accentuating the dissimilarity between pixels belonging to different areas [3]. There are several methods for highlighting contrast and correcting the non uniformity. However, we preferred the homomorphic filter for its speed of calculation and its double effect of contours reinforcement. In theory, we can model our image $g$ like the product of two characteristics:

- Illumination $i$: incidental light quantity on the looked scene.
- Reflectance $r$: light quantity reflected by the objects of the scene.

$$g(k, l) = r(k, l).i(k, l)$$

In this equation, it is practically impossible to distinguish $i$ and $r$ on the basis of $g$. Let define:

$$z(k, l) = \ln(g(k, l)) = \ln(r(k, l)) + \ln(i(k, l))$$

By Fourier Transform we have:

$$TF(z) = TF(\ln(r)) + TF(\ln(i))$$

rewritten as:

$$Z(u, v) = R(u, v) + I(u, v)$$

By filtering $Z$ by a homomorphic filter $H(u, v)$ built using a FIR (finite impulse response), and performing an inverse Fourier Transform (ITF), we obtain the following equations:


$$Zf(k, l) = ITF(H(u, v).R(u, v)) + ITF(H(u, v).I(u, v))$$

$$= if(k, l) + rf(k, l)$$

The processed image is represented by:

$$gt(k, l) = exp(zf(k, l))$$

$$= it(k, l).rt(k, l)$$

Figure 2. Homomorphic filter principle

The transfer function of $H(u, v)$ will tend to decrease the low frequencies related to the image and to accentuate the high ones due to the noise. We will thus use a low-pass filter (average M) before and after the homomorphic filter (figure 2). The final result will be a contrast highlighting.

2.1.2 Otsu’s global thresholding

Global thresholding methods calculate only one threshold for the whole image. The pixels which have a gray level value lower than this threshold are allocated to one class; the other pixels belong to another class. As long as the histogram of gray levels of an image presents quite distinct classes, the choice of the threshold will be better. Wang’s method and Otsu’s method are among the mostly used techniques for global thresholding [7],[5]. While the first one proved its effectiveness, it requires however high computation cost. We chose instead Otsu’s method for its simplicity and low computation requirements. In Otsu’s method, separation is based on calculation of the first and second order moments defined by:

$$s(t) = \sum_{i=0}^{t} p_i$$

and,

$$m(t) = \sum_{i=0}^{t} i * p_i$$
with,
\[ p_i = \frac{n_i}{N} \] (10)

Where \( n_i \) represents the number of pixels of level \( i \), and \( N \) the number of points in the image.

We thus calculate for the 256 gray levels of the image the value:
\[ \nu^2 = \frac{(m_T - m(t))^2}{s(t)[1 - s(t)]} \] (11)

where
\[ m_T = m(256) \] (12)

The value of the global threshold \( t \) is obtained for the maximum of \( \nu^2 \).

### 2.1.3 Regions detection and morphology operations

Global thresholding detects also some objects outside and inside the weld bead. These objects can be removed by applying morphological methods. These objects can be removed by applying morphological methods widely described in the literature [3]. Our aim is to eliminate all small areas and keep the largest area regarded as being the weld bead. For that, we apply in a first stage a number of erosions by using structuring elements of small sizes, until there remains only the greatest area. In a second stage, we apply the same number of dilations to the area of the bead so that it takes again its original form.

### 2.2 Sauvola’s local thresholding

After the weld bead isolation, the processing will be performed inside this region and thus the size of the new image to be processed is obviously reduced which diminishes the computing time. Although Otsu’s global thresholding made it possible to detect defects inside the bead, this process does not exploit the information contained in the processed object neighbors. For a better detection of the small and large size defects inside the bead, local thresholding methods remain the best. These methods calculate the value of the threshold for each pixel while being based on the information contained in its local neighbors. Sauvola [6] proposed a formula to calculate the local threshold \( t(x, y) \) starting from the local average \( m(x, y) \) and standard deviation \( s(x, y) \) according to the equation:
\[ t(x, y) = m(x, y)[1 + k(\frac{s(x, y)}{R} - 1)] \] (13)

where \( k \) is a parameter of positive value and \( R \) the maximum value of \( s(x, y) \).

A direct threshold’s calculation with this formula is time consuming. To overcome this problem, it is possible to use integral images [2]. Assuming \( g(x, y) \) the intensity of the pixel at the position \((x,y)\), the integral image \( I_g \) of the image \( g \) is defined by the image in which the intensity at a position is equal to the sum of the intensities of all the pixels located on the top-left of this position in the original image \( g \). Thus the intensity at the position \((x, y)\) can be written as:
\[ I_g(x, y) = \sum_{i=0}^{x} \sum_{j=0}^{y} g(i, j) \] (14)

This can be calculated recursively by applying the following relation:
\[ I_g(x, y) = I_g(x-1, y)+I_g(x, y-1)-I_g(x-1, y-1)+g(x, y) \] (15)

Since the local average \( m_g(x,y) \) in a window of neighbors of size \( w \) is written:
\[ m_g(x, y) = \frac{1}{w^2} \sum_{i=x-w/2}^{x+w/2} \sum_{j=y-w/2}^{y+w/2} g(i, j) \] (16)

then, according to the integral image \( I_g \), we can write:
\[ m_g(x, y) = (I_g(x+w/2, y+w/2) + I_g(x-w/2, y-w/2) - I_g(x+w/2, y-w/2) - I_g(x-w/2, y+w/2))/w^2 \] (17)

On the other hand, the square of the local standard deviation in a window of neighbors of size \( w \) is defined by:
\[ s^2(x, y) = 1/w^2 \sum_{i=x-w/2}^{x+w/2} \sum_{j=y-w/2}^{y+w/2} (g(i, j) - m_g(x, y))^2 \]
\[ = 1/w^2 \sum_{i=x-w/2}^{x+w/2} \sum_{j=y-w/2}^{y+w/2} g^2(i, j) - m_g^2(x, y) \] (18)

If we put
\[ m_g^2(x, y) = \sum_{i=x-w/2}^{x+w/2} \sum_{j=y-w/2}^{y+w/2} g^2(i, j) \] (19)

then,
\[ s^2(x, y) = 1/w^2 (m_g^2 - m_g^2) \] (20)

Thus, by using equations (17) and (20), we can calculate the threshold expressed in the equation (13). Calculation will be independent of the size \( w \) since we will carry out only two additions and two subtractions in the equation (17). Similarly the first term in equation (20) can be calculated by employing the integral image of \( g^2 \).
3 Results

We tested the proposed approach using images provided by the Laboratory LIAIRI of the Centre National de l’Energie des Sciences et techniques Nucléaires (CNESTEN, Morocco). The image in figure 3(a) of size 370x650 pixels, present porosity defects. It will be processed according to the steps detailed in the subsections bellow.

3.1 Weld bead isolation

Figure 3(a) and (b) represent, respectively, a low contrasted image and its corresponding histogram. After homomorphic filtering, we observe an increase in contrast in the filtered image (figure 3(c)) which yielded a better classes separation as shown by the histogram in figure 3(d). We can thus easily apply Otsu’s method to isolate the weld bead. In fact, in figure 4, we can see clearly that the weld bead is well detected, however this stage of processing shows unavoidable small objects located outside and inside the bead that could be considered as defects. These defects can be removed through morphological methods, taking into consideration that their area is significantly small compared to the bead surface area (figure 5(a)). For more computation efficiency, we reduced the size of the image by eliminating the outside of the bead as reflected in figure 5(b).

3.2 Defects segmentation

Recall that Otsu’s method performs global thresholding which is not adequate to detect precisely the defects inside the bead. For this reason we applied a local thresholding to highlight the small and large defects. However, direct application of this method may detect false defects especially near the edge of the bead due to the non homogeneity of the whole image of figure 5(b). To overcome this problem, we attempted to characterize this image with a unimodal histogram by allotting to the pixels being outside the bead (dark pixels), the grey level value the most represented inside the bead. This yielded the resulted image shown in figure 6(a), on which we applied Sauvola’s thresholding. Figure 6(b) shows the application of Sauvola’s thresholding by choosing the window size of the local neighbors equal to 19x19 pixels.

3.3 Effectiveness of the method

To test the efficiency of the proposed method, we applied it to other radiographic images presenting different types of defects (porosities, cracks, lack of fusion and penetration). Based on the results shown in figure 7 and similar results obtained by processing several other images, the method is revealed very efficient in defect detection.

4 Discussion

The choice of the weld bead isolation finds its justification in the fact that welding defects can only be inside the bead. Another reason, is that the size of the image is reduced which diminishes computation cost. The radiographic images, being low contrasted, have a histogram that
Figure 7. (a) Sauvola’s thresholding on the image of figure 6(a). (a) With window’s size $w=7\times 7$ and (b) $w=19\times 19$ pixels.

Figure 8. Examples of different types of defects detected by our method. on the right, original images. on the left, the corresponding segmented defects inside the weld bead with $w=15\times 15$ pixels. for an image of size $200\times 250$ pixels the cost is 0.3 seconds.

Figure 9. Influence of the window’s size on computing time

The method is very sensitive to the window’s size; larger size allow detection of larger defects. The proposed method, on the basis of several tests, is revealed to be efficient especially in terms of segmentation quality and processing speed. In fact, thanks to the use of integral images, the computing of the local threshold is made completely independent of the size $w$, contrary to the direct application of the equation (13) (Figure 8).

5 Conclusion

In this article, we proposed a segmentation method of radiographic images of metal’s welded joints, combining global and local techniques of thresholding. Application of the approach using a large data base showed its effectiveness in detecting various types of defects. Furthermore, the use of integral images during local thresholding improved significantly computing time. This latter is also revealed to be not dependent on the size of the processed window in the welded bead image, which is very beneficial in detecting small and large size defects. In the automation process in NDT, this work of segmenting radiographic images of welds was a necessary step before characterizing defects. This will be our goal in a future work.

References