Detecting Defects in Digital Radiographic Images

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***Abstract*—It has been noticed that digital x-ray images of faulty welds in pipes tend to be darker than the rest of the image. Rather than simple thresholding, in this work a light pixel is converted to white if there are light pixels within its immediate neighborhood. The effect is that the flaw appears black and the background appears white, this enabling the flaw to be easily detected. However, this method will have the effect of eroding any rough edges on the flaw i.e. black pixels that stick out from the main body of the flaw. This method works well for large flaws, while not with fine cracks.**

***Index Terms*— Defect Detection;Flaws in the weld; NDT; X-ray image.**

I. Introduction

The quality management of manufactured products is one of the main aims in the production process. To make the process more objective rather than relying on the subjective opinion of the people, automatic inspection and analysis techniques must be used. Despite accepting some faults in the production process, some applications have stringent safety tolerances.

Whenever two metals are welded together, the weld is not perfect - a lot of flaws can appear in the welding materials due to, for example, a lack of fusion weld into the material or the emergence of some bubbles or cracks inside the weld that can run the risk of causing the pipe to fracture. The mechanism that used to detect the flaws in the weld is Nondestructive testing (NDT), and it is one of the most common techniques is radiography where an image (such as an X-ray image) is produced.

Radiography utilizes the radiation generated by X-Ray device passes through the object and is absorbed to a large or small degree depending on the thickness and type of material that passes through it. Therefore, the image is formed, and it can be collected using either Radiography film or various electronic means **[1].**

Although these images can be inspected visually by humans, research into the automation of this process, particularly now that the images are often digital, leads to image processing being applied to the NDT. This research aims to use a new image processing technique to isolate and detect defects in welds.

From experience, it is noticeable that in radiographic images, the pixels fall into two classes. The first class represents the flaw and the second class represents the rest of the welded object, which we call the background. The goal of this research is to be able to correctly classify the regions by finding some kinds of compatibility among the probability distributions of the image pixels.

The use of statistics and knowledge about the image shows that the values of the defect area are generally lower compared to the values of the background i.e. the defects appear darker when compared to the rest of the pixels in the local region. We will try to strengthen the two regions using simple thresholding without the need to use edge detection techniques as primary stage for defect detection or the need for pretreatment represented by using noise removal techniques.

II. Previous Work

Many researchers attempted to improve the quality of photographic images by the use of image processing techniques so that a human operator can more easily detect and distinguish defects [2][3][4].

Due to the low contrast and blurred edges of the defect region with background fluctuations, the optimal threshold for segmenting image and identifying the specific defect of air bubbles has been considered [5]**.**

Previous research [6] used the knowledge of the specific context of the photographic image, in which welds in pipes were used. It is usually standardized and subjected to Gaussian noise when obtaining a proper image over a small region area. This means that the majority of pixel are located between (± 2) standard deviation. In this case, the suggested working principle is that most of the photographic images are darker in the upper and bottom part and lighter in the central region because of the curvature of the pipe. This indicates that the horizontal pixel values do not change significantly, but there is a significant change in the vertical direction. Hence, to detect the defects, the statistical focus is on the horizontal direction. However, the results of this hypothesis is only suitable for detecting vertical defects rather than for horizontal defects.

A researcher [7] presented a method to detect defects without segmentation based on the sliding window approach. He analyzed 5000 windows from 10 x-ray images in which the size of each window was 24*24. A Local Binary Pattern (LBP) was extracted from these windows. These features input to the Support Vector Machine (SVM)to classify defects from no-defects labeled with '1' '0' respectively.

A method for detecting line weld defects by extracting the features of the x-rays using different thresholding values has been proposed in [8]. Then, SVM was used to classify the defects from the non-defects. Furthermore, Hough transform has been applied to delete the noise pixel in the coarse defect area.

Many features (edge chain code (ECC) and geometric moment invariants (GMI)) were extracted as a shape features from defects objects and optimized. In order to test these optimized features, neural networks were used as a mean of comparison and discussing system performance relative to these characteristics [9].

Redounane [10] proposed the use of the first part of the application of ANN configuration to detect the edge of X-Ray images that contain defects of welding. He assumed that the application of neural networks dedicated for classifying defect of welding uses supervised learning algorithm. This algorithm is represented by multilayer ANN, which is trained by error back-propagation algorithm after applying image analysis and extracting invariant moment features as data input. Defects of welding such as porosity, lack of fusion, inclusions have been investigated as ANN training data.

The researchers in [11] considered the problem of defects classification as pattern recognition system. It looked like improving the quality of the images of welding using digital image processing after which 12 properties were drawn. There properties describe the location, shape, size in addition to information related to the intensity. The last stage is the use of two algorithms for classification, fuzzy k-nearest neighbor and multi-layer Perceptron neural networks to classify six types of defects. Because, there is a small number of samples for these types, cross validation and bootstrap techniques were used to verify the performance of the classifiers and conclude that MLP neural networks achieve better results than fuzzy classifiers.

The researchers in [12] discriminate between the defects from the non-defects. All images are segmented using background subtraction algorithm based on three features defect areas, the average of gray level difference to its surrounding district and the gray level standard deviation was extracted. These features were then introduced to the SVM methods to discriminate real defects. Like many researchers, the author [13] suggested extracting the seam weld from the radiographic images when searching for defects. The reason is that the defects exist only in the area of seam weld. The median filter was used to remove the noise while the high boost filter was used to improve the contrast, which makes irregularities more clear. For the seam weld extraction, the researcher applied Sauvola thresholding to detect the edges followed by top hat filtering.

The authors in [14] presented a method for detecting defects through a number of steps beginning with improved radiographic image matching. The drawback of this method is the time consumed.

III. Methodology

Most researchers focused on determining the most suitable threshold value for the segmentation of color and monochrome images [15] [16]. Unimodal distribution exists when the image consists mostly of a large background with small but important areas. For example, the extraction of the borders of different types of cells is a complex process in medical application since these cells are close to each other. At the same time, they have poor borders definition.

When the body of the border is sharp, the gray level will fall quickly from the inside to outside. But in the case of deformed body border, the gray level will fall slowly from inside to outside. This case appears in the thermal imaging (slow radiate heat from the target to the cold ocean).

Taking into consideration of the above reasons and drawbacks, we used a suitable technique to detect the defects. In this paper, we consider that the value of the grayscale pixel element and its neighbors are good set of attributes for classification. Therefore, the response of each element is reinforced by taking into account the neighboring elements. Figure 1 shows the diagram of this proposed method.

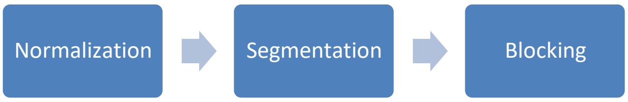


Figure 1: Diagram of the proposed defect detection method

The initial step is the normalization of the image pixel values which takes the form of the proportion of the amount of element grayscale to the number of the gray levels.

$$Nor = \frac{g}{N-1} \qquad (1)$$

Where $0 =< Nor =< 1$

$g\ is\ ith\ pixel\ gray\ level, N\ is\ the\ no.of\ gray\ levels$

The second step is the initial allocation of a defect point or background point. This is done through segmentation using threshold value.

$$Object \qquad if\ Nor\ > Threshold$$

$$Background \qquad Otherwise$$

To strengthen the defect points, or background points we take the benefits from the neighboring region. Compatibility factor is calculated by taking the average of the center element with neighborhoods.

$$comp(k) = \sum_{i=1}^{n} Nor_i\,(k) \qquad \ldots k = 1\ or\ 0 \qquad (2)$$

Where (0) refers to the background, (1) refers to the object (defect).

The last step is mapping values that exceed the highest value in the gray levels.

$$efect = 1\ \ldots\ldots\ if \quad comp(k) > Highest\ gray\ level \qquad (3)$$

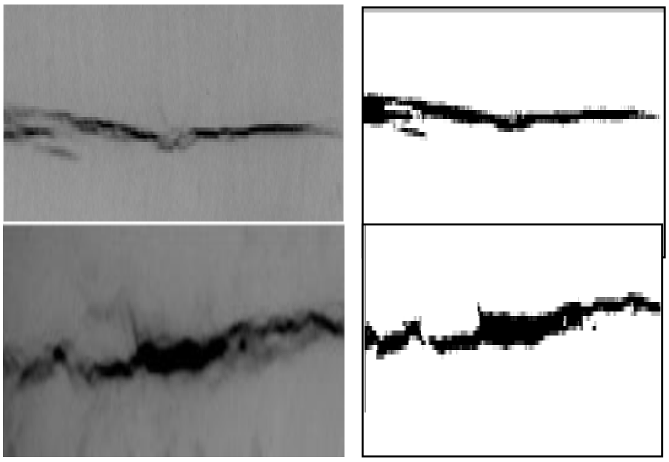
$$Background = 0 \qquad Otherwise$$

IV. Results

Using [17] data set, many experiments have been carried out and the impact of this method on the images with poor contrast has been observed. Through experiments, the total values of the eight neighborhoods may exceed (1) (i.e. exceed the highest gray level of intensity 255). Therefore, the solution is to use a thresholding, which maps the maximum values of (255). This approach does not affect the outcome, because the purpose of the research is to identify and strengthen the area of the defect values.

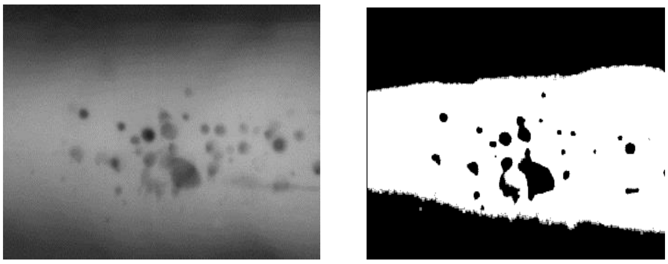
Figure 2 shows the creation of the clusters for the defect body and for the background, especially when a small portion of the original image is cut off and the background is approximately uniformed, while Figure 3 shows a good clustering in spite of more fluctuations in the background.

Figure 4 shows the effect of threshold factor value to segment defects. The smaller value than 0.5 leads to defect erosion. On the contrary, values larger than 0.5 result in dilation in the defect object with addition of deformities.



(a) (b)

Figure 2: Results of defect detection method (a) original X-ray images , (b) result image.



(a) (b)

Figure 3 Defect detection method .(a) Original image, (b) Result image.

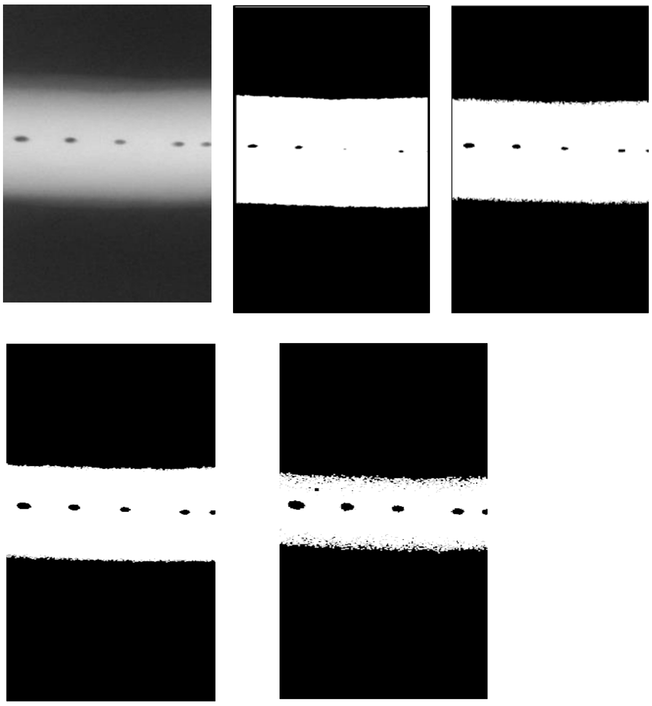
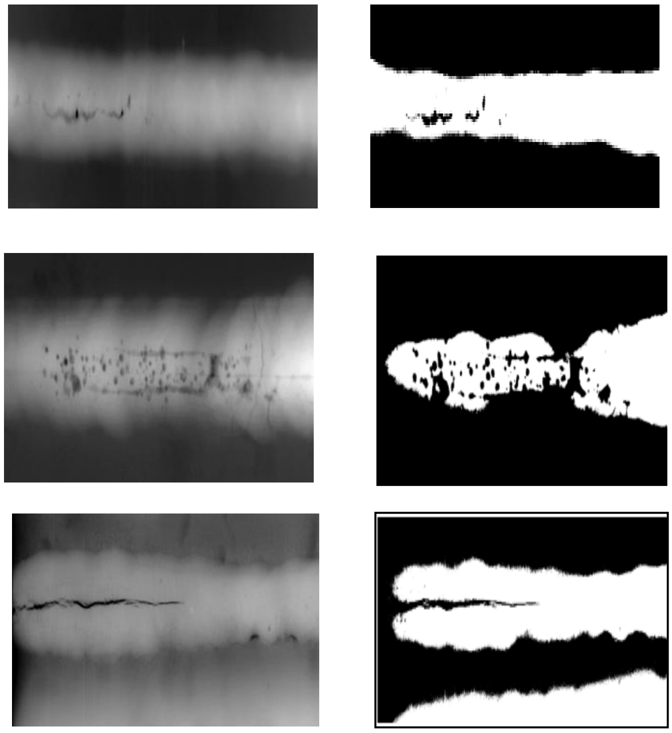


Figure 4: (a, b, c, d and e) Results of defect detection method on the X-ray images with different values of threshold (0.5, 0.6, 0.7, 0.8) respectively.

Using our method, it is noted that we can locate the weld and the defects within the body as a result of clustering, as shown in Figure 5.



(a) (b)

Figure 5: Result of defect detection method. (a) X-ray images (b) processed images

V CONCLUSION

The method describes the first stage in a flaw detection system. It starts with the raw image, which then converts the image to a binary image where the black pixels represent a flaw. The second stage requires either a human in a semi-automated system or a software in a fully automated system to determine whether the black pixels are actually a flaw and the types of flaw. That is an area of future research. Although the proposed method is much simpler than many of the alternative methods proposed in earlier research, it still seems to be able to extract the defects in the image relatively easily, thus enhancing the ability of either a human observer or an automated system to detect, locate and identify defects in welds.

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