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Automatic Defect Detection and Counting In Radiographic Weldment Images

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ABSTRACT
Digital Image Analysis is one of the most challenging and important tasks in many scientific and engineering applications. Extracting the Region of Interest (ROI) from the image and recognition in image processing are very important steps**.** When these tasks are manually performed, it is tedious and difficult involving human experts. This paper focuses on automatic defect detection and counting in radiographic weldment images thus considering defects in weldment images as object of interest. To detect defects in radiographic weldment images, thresholding and segmentation algorithm is used and a new procedure is introduced for counting number of defects in the input images. The results obtained from the proposed work are impressive with respect to the computational time and defect detection rate. The performance of the proposed algorithm is found better than the existing defect detection algorithms.

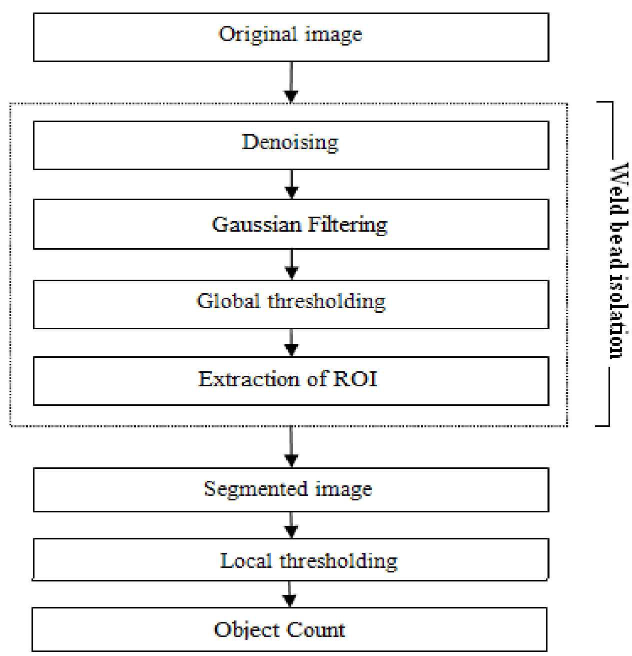
General Terms
Image Processing, Segmentation, Detection

Keywords
Defect, Weldment, Region of Interest (ROI)

1. INTRODUCTION
In Non-Destructive Testing (NDT) of metallic pieces, the most important stage is the detection of welding defects which may affect the well functioning of these pieces [1, 2]. Defects in metal can be very hazardous in railroads, gas pipes, wheels, etc. Fortunately, radiography is 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, developments in information technology in particular image processing, have made it possible to invent new radiographic inspection methods that can automatically detect and identify welding defects by increasing the quality of information while decreasing the duration of diagnosis.

However, in image processing, segmentation remains a very delicate step, especially in the case of noisy and low contrast images, as is the case of radiographic images.The existing methodologies of defect detection are quiet complex as they involve neural networks and fuzzy logic [6, 9,10]. The results are impressive, but require a complex implementation and significant computing time. The proposed work aims to improve the efficiency in terms of computation complexity by associating the concept of extracting the weld bead before identifying defects in it. In real time environment, welded metals coming out from a furnace are red hot and to manually check the welding defects first requires welded metal pieces to cool down which easily consumes four to five hours. Besides it take considerable amount of time to manually check for defects and also accuracy will be less. Hence, the proposed work aims for automatic defect detection in weld beads by using thresholding concepts of image processing. This reduces time to a great extent and also gives accurate result. Atiqur and Mobarak Hossai [4] describe a method to detect the defects automatically and to control the quality of ceramic tiles. Defects such as pin hole defects, blob defects, crack defects, spot defects, edge defects and corner defects are discussed and the defect detection rate is observed to be better than the existing method**.** An effective weld defect classification algorithm developed by Rafel[7] et al., (2009) showed twenty five shape descriptors for the classification. The system developed a multi-layer perceptorn (MLP) neural network for training the shape parameters from the simulated images of weld defects and achieved maximum classification accuracy.

2. PROPOSED WORK
2.1 Framework for the Proposed Work
Figure 1. Framework for the proposed work



2.2 Procedure for Defect Detection and Counting

2.2.1 Denoising and Gaussian filtering

This is the step taken before any major image processing task. The problem here is to perform some basic tasks in order to render the resulting image more suitable for the job to follow. In this case it may involve enhancing the contrast, removing noise. This is sometimes referred to as image restoration. An image may be restored by the damage done to it by a known cause say for example removing of blur caused by linear motion or removal of optical distortions. Thus, Restoration techniques are oriented toward modeling the degradation and applying the inverse process inverse process in order to recover the original image. Here we used Gaussian filtering in light of its simplicity and speed of execution.

2.2.2 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 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. [8][3] Wang's method and Otsu's method are among the mostly used techniques for global thresholding. While the first method proves to be effective, it has a 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 moment's defined by:

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

and

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

$$p_i = \frac{n_i}{N}$$

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:

$$\nu^2 = \frac{[m_T * s(t) - m(t)]^2}{s(t)[1 - s(t)]}$$

$$m_T = m(256)$$

The global threshold t is obtained by the maximum of value of v^2.

2.2.3 Segmentation of ROI

Segmentation refers to the operation of partitioning an image into component parts or into separate objects. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The two important concepts of segmentation are thresholding and edge detection. Thresholding refers to turning a grayscale image into a binary(black and white) image by first choosing a gray level T in the original image and then turning every pixel black or white according to whether its gray value is less than or greater than gray level T. So here input is grayscale image and output is binary image.

After applying Otsu's global thresholding as discussed above, we get a binary weld image containing 1's where weld bead is present. Using this we isolate the weld bead and then go for next step of local thresholding. Thus, here we assume where consecutive 1's are present as weld bead i.e. area of interest and we will isolate it by calculating mean of weld bead boundaries.

2.2.4 Sauvola's local thresholding

After the weld bead isolation, the further processing will only be performed inside this smaller region, thus reducing 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's neighbors. For better detection of small and large defects inside the bead, local thresholding methods remain superior. These methods calculate the value of the threshold for each pixel based on the information contained in its local neighbors.[1,5] Sauvola proposed a formula to calculate the local threshold t(x, y) from the local average m(x, y) and standard deviation s(x, y) according to the equation:

$$t(x,y) = m(x,y)[1 + k(\frac{s(x,y)}{R} - 1)]$$

Where k>0 is a parameter and R is the maximum of s(x,y). But this might be time consuming, so we go for another approach.

Assuming g(x, y) is the intensity of the pixel at the position (x, y), the integral image Ig 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 at the top-left of this position in the original image g. Thus the intensity at the position (x,y) can be written as:

$$I_g(x,y) = \sum_{i=0}^{x} \sum_{j=0}^{y} g(i,j)$$

And the local average mg(x, y) in a window of neighbors of size w is written as:

$$m_g(x,y) = \frac{1}{w^2} \sum_{i=x-w/2}^{x+w/2} \sum_{j=y-w/2}^{y+w/2} g(i,j)$$

The square of the local standard deviation in a window of neighbors of size w is defined by:

$$s^2(x,y) = 1/w^2 \sum_{i=x-w/2}^{x+w/2} \sum_{j=y-w/2}^{y+w/2} (g(i,j) - m_g(x,y))^2$$

$$= 1/w^2 \sum_{i=x-w/2}^{x+w/2} \sum_{j=y-w/2}^{y+w/2} g^2(i,j) - m_g^2(x,y)$$

If we put

$$m_{g^2}(x,y) = \sum_{i=x-w/2}^{x+w/2} \sum_{j=y-w/2}^{y+w/2} g^2(i,j)$$

Then finally we have

$$s^2(x,y) = 1/w^2(m_{g^2} - m_g^2)$$

Thus by using above equations we can calculate threshold. It is to be noted that window size is taken as 4 and as window size w increases, time of execution also increases exponentially.

2.2.5 Defect Counting

This module counts the number of defects and count is displayed. Desired features are extracted from the previous segmented image. It is done by checking each pixel if it is 0 and then it is checked with all its boundary pixels whether they are 0 thereby reducing redundant pixels giving more count. By applying above method number of defects in the region of weld bead is counted. Procedure for defect count is shown below.

$$\sum_{i=2}^{col-2} \sum_{j=2}^{row-2} \text{if Tbw(j,i)} == 0$$

if Tbw(j-1,i-1)~=0 && Tbw(j-1,i+1)~=0 && Tbw(j-1,i)~=0 && Tbw(j,i+1)~=0 then increment counter and display the number of defects present in the given input image un till condition satisfies.

3. RESULTS AND DISCUSSION

Thirty samples are tested with the proposed methodology. Fig 10. shows number of the correctly ROI extracted samples, not correctly ROI extracted samples and counting the number defects for the given input image, not correctly counted the defect count in the given sample. And also computational times for various samples are shown in Fig 11. The proposed steps for detecting and counting the defects in weldment images (2 samples) are shown below as snapshots.

Figure 2: Depicts a normal radiographic weld gray scale image containing defects

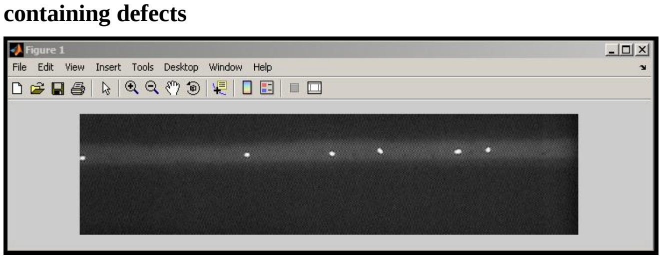


Figure 3: Depicts the binary image after performing filtering and Denoising

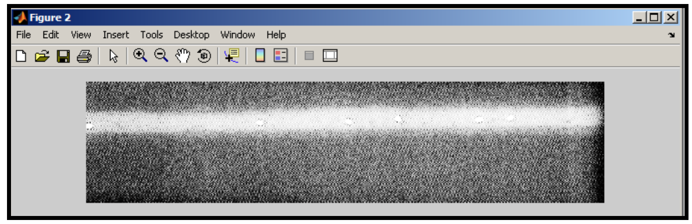


Figure 4: Depicts binary image of weld bead after applying Ostu's global thresholding

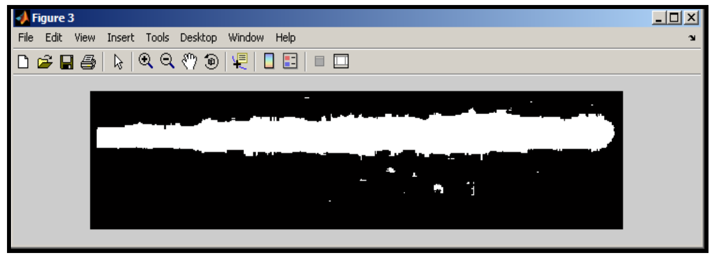


Figure 5: Depicts isolated weld bead.

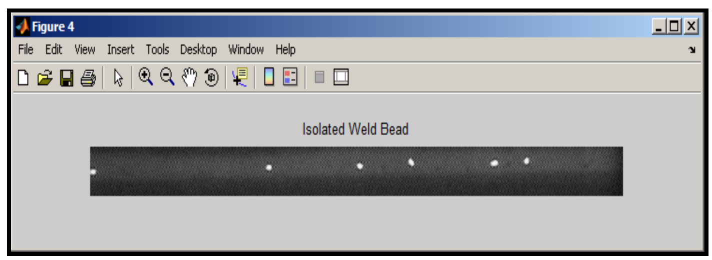


Figure 6: Depicts the image showing defects after applying Sauvola's local thresholding

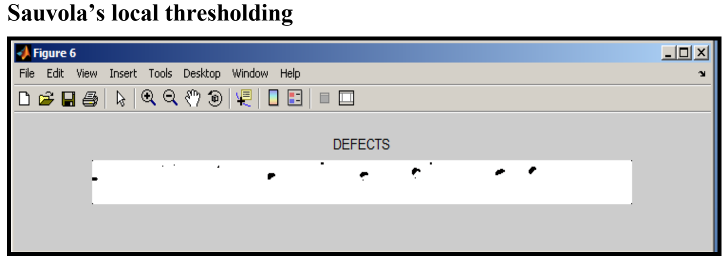


Figure 7: Depicts the image showing defect count of Fig 6

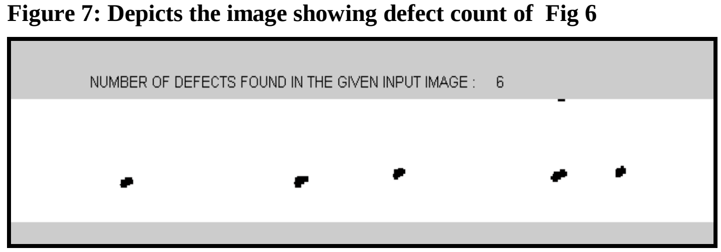


Figure 8: Depicts another normal radiographic weld gray scale image containing defects.

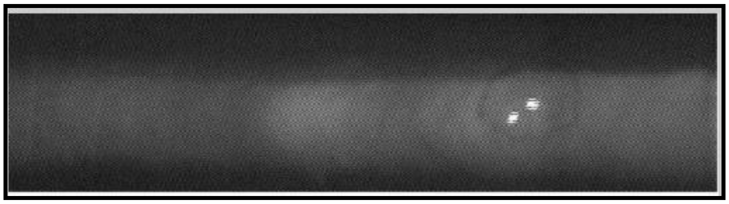


Figure 9: Depicts the image showing defects after applying Sauvola's local thresholding of Fig 8.

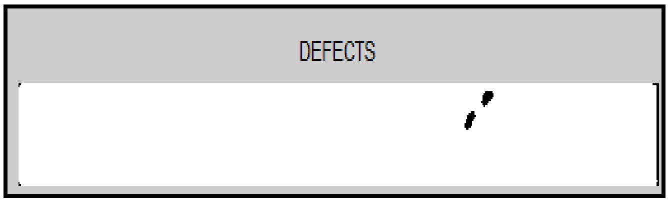


Figure 10: Depicts the image showing defect count of Fig 9.

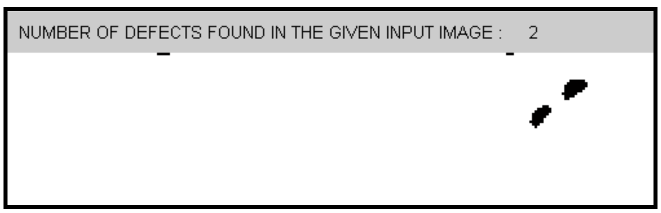


Figure 10: Depicts result analysis of different samples.

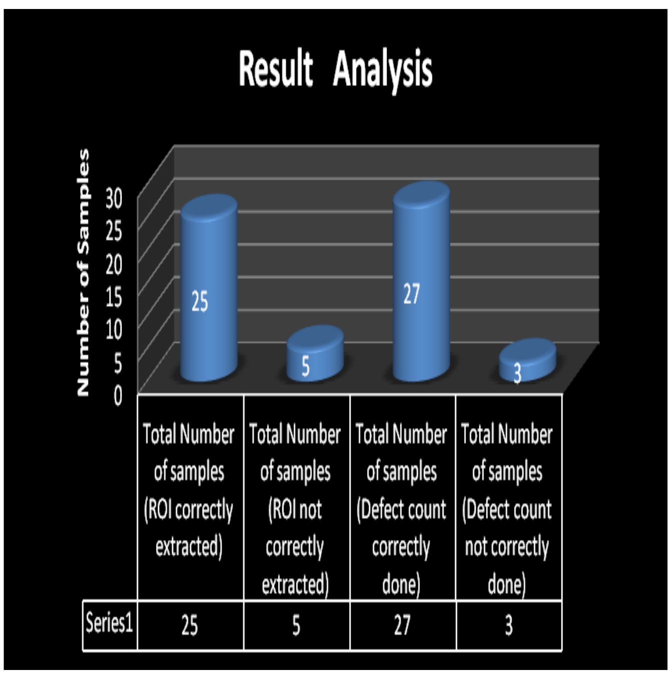
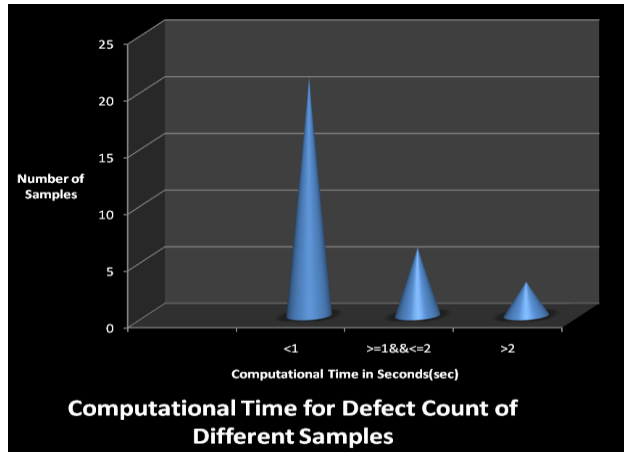


Figure 11: Depicts computational time for different samples.



4. CONCLUSION

A segmentation method of radiographic weldment images, combining global and local techniques of thresholding is thus proposed besides giving defect count. The proposed method significantly improves the efficiency in terms of computation complexity by associating the concept of processing only Region of Interest (ROI) instead of dealing with the whole image and by not using the concept of neural network as using neural networks results in high implementation complexity. Also the filtering technique used in the work helps in fast execution and the computation time for defect count of different samples is depicted in Fig 11. This same concept can be extended to other domains and finally arriving at object recognition and extraction.

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