2012 10th International Conference on Frontiers of Information Technology

# Welding Defect Detection and Classification Using Geometric Features

J. Hassan
Department of Electrical Engineering
Pakistan Institute of Engineering and Applied Sciences
Islamabad, Pakistan
*junaid.hassan@engineer.com*

A. Majid Awan
National Center for Non- Destructive Testing
I-9/2 Islamabad, Pakistan
*awanmajid@hotmail.com*

A. Jalil
Department of Computer and Information Sciences
Pakistan Institute of Engineering and Applied Sciences
Islamabad, Pakistan
*abduljalil1961@hotmail.com*

*Abstract*— **In this paper we present a welding defect detection system using radiographic images. Main goal is to craft a dependable system because a human evaluator is not a stable evaluator besides other humanoid constraints. We present a novel technique for the detection and classification of weld defects by means of geometric features. Firstly noise reduction is done as radiographic images contain noise due to several effects. After this we tend to localize defects with maximum interclass variance and minimum intra class variance. Further we move towards extracting features describing the shape of localized objects in segmented images. Using these shape descriptors (geometric features) we classify the defects by Artificial Neural Network.**

**Index Terms**—*welding; radiography; features extraction*

## I. INTRODUCTION

Welding serves to be the backbone of industry. From nuclear reactors to space shuttles we cannot realize any brainchild in absence of welding. Welding defect detection is of prime importance in modern world. Radiography is longstanding technique to look out for defects present inside a material. We need special trained personnel for inspection of radiographs which not only slow down the process but also makes it human dependent. Humanoid inspection of radiographic images carries many limitations, one of the most important is it becomes a highly subjective process. These constraints incline us to develop automatic procedures which are not dependant on humans to maximum extent. A computerized process for analysis of radiographs will be helpful in a fast and reliable inspection process. As radiographic images have a bad contrast so it is a challenging work to inspect them even in digital domain. Many people across the globe have put their effort in this field to realize an automated system looking for defects through radiographic images. As conventional image processing techniques are not suitable for welding defect detection due to the nature of radiographic images, the proposed algorithm in this paper highlights a new dimension in welding defect detection using morphological operations.

The following sections present related work by scholars in this field, Section (III) explains proposed algorithm with experimental methodology. It also covers acquisition of radiographic images, image pre-processing, weld seam extraction, morphological operations leading to features extraction. Section (IV) and Section (V) describe classification and Results respectively.

## II. RELATED WORK

Many of the authors/developers suggest extraction of weld seam from the radiographic images when looking for the welding defects. The reason presented for this step is quite obvious, as defects are present only in weld seam which are to be detected and classified later. Extracting weld seam provides a form of ROI (region of interest) in the radiographic images. Liao and Ni proposed an algorithm for extracting weld seam [1]. The scheme was developed by observing the intensity plots in which weld seam looks more like Gaussian than other objects present in the image. Similarity measure between an object and its intensity plot is defined in terms of MSE (mean square error). The concept behind this method is: value of MSE (for objects present in image) is inversely proportional to the Gaussian nature of the object. So lower the value of MSE; the object tends to be more Gaussian in nature. Hence object with the lowest MSE is chosen to be weld seam. Another approach was presented by Mahmoudi and Regragui [2]. They proposed to perform global thresholding using otsu's method after performing homomorphic filtering. Homomorphic filtering normalizes brightness and increases contrast simultaneously. Wang et al devised another technique for weld seam extraction [3]. The technique is based on intensity values of different areas present in the image. Weld image is classified into three different areas i.e. base metal area, the weld area and lead plate area. Base metal appears brighter than both weld area and lead plate area. The lead plate area is the darkest area in the image. Binary image is automatically computed from gray level histogram. Adaptive segmentation is used, which works on the principle that variance inside the class is least while outside of class is the largest one. In [4] a system was proposed for automatic identification of weld defects using digital image processing, feature extraction and pattern classification. Image processing techniques for

978-0-7695-4927-9/12 $26.00 © 2012 IEEE
DOI 10.1109/FIT.2012.33

noise reduction and contrast enhancement were used along with BSM (background subtraction method) for segmentation. Features describing the shape, size, intensity and location of welding defects, distance from centre, standard deviation, major axis, width and length, elongation, heywood diameter, average intensity and standard deviation of intensity were used. Pattern classification was carried out using two techniques namely fuzzy k-NN and MLP neural network. Shafeek et al proposed another technique using software support [5]. AutoWDI (automatic welding defect inspection) and AutoWDA (automatic welding defect assessment) were used as primitive tools for automatic inspection of weld defects in gas pipelines. Form factor and regularity factor were used for defect identification which was further used for final detection of defects. One more method for detection of weld defects using multiple thresholds was proposed in [3]. They proposed a method using Hough transform to remove noisy pixels in coarse defect region. Features extraction was done with multiple thresholds. Features extraction was followed by SVM (support vector machine) to classify defects. Some suitable features were used in their technique to estimate accuracy of classification of weld defects. Position, ratio of aspect, roundness, area and angle were used for estimating the accuracy of classification for weld defects by Silva et al [6]. Some features were normalized prior to the classification. Another approach for defect detection in x-ray images using fuzzy reasoning was presented by Lashkia [7]. He proposed a technique rich with the special features that uses common sense fuzzy reasoning rules offering an intrinsic understanding of classification logic. Classification is done on basis of visual representation i.e. thread like zone with low contrast are cracks while roundish zone having high contrast are blow hole defects. Vilar et al proposed another system for classification of weld defects in radiographic images [8]. The algorithm starts with preprocessing of images through Wiener and Gaussian filtering. Preprocessing is followed by weld extraction step which mainly uses otsu's method. The last stage is feature extraction; features extracted are area, centroid, major axis, minor axis, eccentricity, euler number, solidity, extent and position. Following features extraction PCA (principal component analysis) is performed to reduce the dimension of input feature vector of classifier. Classification is done using multi-layer feed-forward ANN. Valavanis and Kosmopoulos presented another technique for multiclass defect detection and classification in weld radiographic images using geometric and texture features [9]. The paper describes methodology to extract 43 descriptors corresponding to texture measurements and geometrical features for each segmented object and given as input to the classifier. Texture and geometric features allow better modelling of various defects. SBS (sequential backward selection) has been used to avoid computationally intractable exhaustive feature selection. Yahia et al proposed another welding defect detection method using radiographic images with neural approach [10]. This method essentially works on edge detection method based on MPC (multi-layer perceptron). A database of different pictures is prepared with a picture size of 3x3 which are considered elementary contours. These elementary contours are learned by multi-layer neural network. 48 forms of basic contours are used in this paper. Image segmentation is done by threholding (binarization) by maximizing interclass variance.

## III. Experimental Methodology

Figure 1 shows the hardware system used in our proposed algorithm for the acquisition of radiographic images. We have used a GE film digitizer for this study, model: FS50B (maximum optical density: 4.7; maximum resolution for films; 50um) to digitize set of films from International Institute of Welding (IIW) and weld samples with known defects from NCNDT [11,12,13]. The films are digitized at 14 bit grey level (72 dpi, 2900x950 pixels).

The films are transferred to PC for further processing by the proposed algorithm. Figure 2 shows the key steps of proposed algorithm. Digital image processing tools are used to de-noise the radiographic images. Morphological techniques form the basis of this defect detection algorithm. Features like area, major axis length, eccentricity, solidity, convex area, convex hull, position are extracted. Table I shows some of the extracted features. Optimal features are input to artificial neural network. ANN is prior trained for different types of defects classification.

### *A. Image Preprocessing*

The radiographic images contain noise, some by reason of digitization process and other caused by natural interventions. Also the radiographic images have a poor contrast so it is necessary to reduce the noise and enhance contrast. Median filtering is a non-linear filtering and is used for reduction of noise [14]. For contrast enhancement we have used high boost filtering [15]. High boost filtering sharpens the edges and considerably increases contrast. Contrast enhancement makes more visible the irregularities present in images.

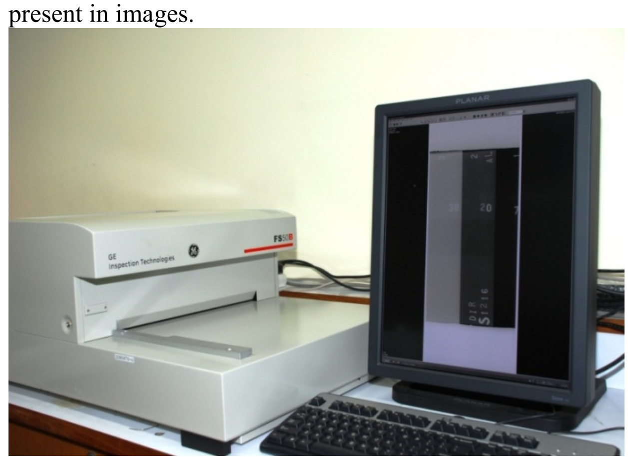


**Fig. 1 GE FS50B Film Digitizer**

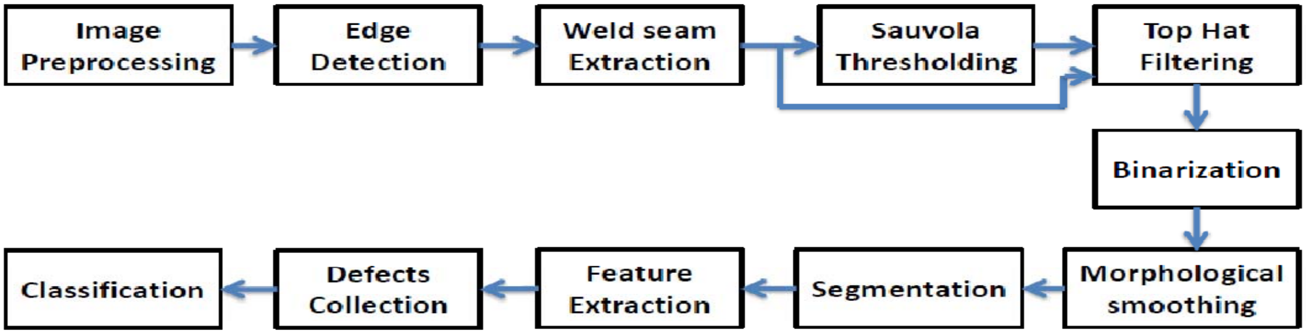



Fig. 2 Proposed Algorithm

*B. Weld seam extraction*

Here we propose a new technique for weld seam extraction. The technique is appealingly intuitive and is based on gradient of radiographic images. We have used Canny edge detector due to its superior characteristics over other edge detectors. Canny's aim was to present an optimal edge finding algorithm keeping in view three parameters for optimization which are good detection, good localization and minimal response [16]. We look for high values in gradient image in a way to locate the densest rows containing the high values. Weld seam can be easily extracted through this proposed technique. As most of our edges are vertical so median filtering in image preprocessing step does not alters these vertical edges, in this all these vertical edges remain intact which are crucial for weld seam extraction. This method works well on digitized images as there is considerable contrast between weld seam and background (base metal).

*C. Sauvola thresholding*

Following weld seam extraction we perform Sauvola thresholding on the acquired image. This step provides us with an important result: whether defect present is of higher value than background (weld seam) or holds lower gray level values in comparison with gray level of weld seam. Sauvola thresholding was chosen due to its superior properties as a local thresholding technique [17]. Equation (1) governs the threshold

$$\mathrm{T} = \mathrm{M}\left[1 + \mathrm{K}\left(\frac{\mathrm{s}}{\mathrm{R}} - 1\right)\right] \qquad (1)$$

where the formula is run on NxN window. M is mean, s is standard deviation in window and R shows the maximum possible standard deviation of grey level [10]. This step inherently classifies one or two types of defects from others. If defects are of high gray level values than background then we use the original weld seam extracted image.

*D. Morphological operations*

The key step in proposed technique lies is morphological operations. Top Hat filtering is applied on weld seam extracted image which is subtracting the morphologically opened image from original image [18]. Equation (2) shows top hat filtering mathematically.

$$\text{Top Hat} = \mathrm{I} - (\mathrm{I} \circ \mathrm{B}) \qquad (2)$$

Arithmetic operation and morphological smoothing provide us with a segmented image in binary form containing defects and non-defects. The algorithm looks out for defects in a passive manner, we don't directly localize defects present in weld seam but the algorithm localizes all those regions which can be candidate for defects. All the high valued pixels in binary image obtained (defects and non-defects) are sectioned on connected component basis.

*E. Features extraction*

Features are extracted for all the elements which are sectioned on connected component basis in segmented images. Geometric features are extracted for all the sections which include area, major axis length, minor axis length, eccentricity, solidity, convex area, convex hull, perimeter, centroid, euler number, orientation, extent and extrema. As all the sections acquired in segmented images through above process are defect candidates so there is a need to discriminate between defects and non-defects out of these candidates. Table I depicts some of the geometric features which are extracted from the segmented images.

**TABLE I**
GEOMETRIC FEATURES EXTRACTED FOR CLASSIFICATION

| Sr. No | Name | Notation | Description |
|---|---|---|---|
| 1 | Area | $A = \sum_{i=0}^{n}\sum_{j=0}^{n} a_{i,j}$ *for* $a_{i,j}=1$ | actual no. of pixels in the region |
| 2 | Major axis | $L = \sum_{i=0}^{n}\sum_{j=0}^{n} p.(a_{i,i} - u)$ | scalar specifying length of big axis |
| 3 | Minor axis | $e = \sum_{i=0}^{n}\sum_{j=0}^{n} q.(a_{i,i} - u)$ | scalar specifying length of small axis |
| 4 | Solidity | $S = \sum_{i=0}^{n}\sum_{j=0}^{n} a_{i,j}/A_c$ *for* $a_{i,j}=1$ | proportion of the pixels in the convex hull that are also in the region |
| 5 | Perimeter | $P$ = no. of pixels forming boundary of object | distance around the boundary of the region |

| | | | |
|---|---|---|---|
| 6 | Convex area | $A_c = \sum_{i=0}^{n} \sum_{j=0}^{n} a_{i,j}$ *for* $a_{i,j}=1$ | specifies the number of pixels in ConvexImage |
| 7 | Eccentricity | $E = \sqrt{1 - b^2/a^2}$ | specifies the eccentricity of the ellipse that has the same second-moments as the region |
| 8 | Orientation | $o = angle\ of\ L$ | the angle between the $x$-axis and the major axis of the ellipse |

## IV. Classification

We have used area, major axis length, minor axis length, and solidity to acquire defects only from segmented image. Table II presents the bounds for the features to discern between defects and non-defects from the set of defect candidates (sections in segmented image). A section satisfying all the conditions mentioned in Table II is considered a defect. For classification we have used five features from Table I. We have used feed forward ANN for classification between different defects. A multi-layer multiple input neuron model is used for the classification of defects into different categories. The feed forward back propagation network works on LM (Levenberg-Marquardt) algorithm. Geometric features are used for the classification of defects. Geometric and statistical features are combination of machine learning with computer vision and are widely used for solution of visual acuities. In our system we have used convex area, major axis, minor axis, solidity and eccentricity for classification purpose. The above mentioned features are very helpful to visualize a defect and its type. We have used an input feature vector with depth five, and used two hidden layers each having five threads. The output vector is of depth two.

**TABLE II**

Limits for a True Defect Candidate

| Sr no. | Defects bifurcation from candidates | | |
|---|---|---|---|
| | **Feature** | **Threshold** | **Status** |
| 1 | Area | > 90 | Defect |
| 2 | Major axis | < 60 | |
| 3 | Minor axis | < 10 | |
| 4 | Solidity | < 0.85 | |

## V. Results

The results for the proposed algorithm are shown in Fig. 3 and Fig. 4. Figure 3 shows the results of algorithm for weld seam extraction part. From top to bottom, we have original image then gradient image is shown, finally the image of extracted weld seam is shown. Figure 4 shows the results of the proposed algorithm for welding defects detection. The left column shows the original radiographic image holding welding defects. The images in second column show images after thresholding. The third column depicts the final image (segmented images) obtained after morphological smoothing of thresholded images. Morphological smoothing retains all the segments which are doubtful for defects and removes the other segments. In Fig. 4 first two rows contain heavy metal inclusion defect, third row image has crack defect while fourth and fifth row show us lack of fusion and long crack defect.

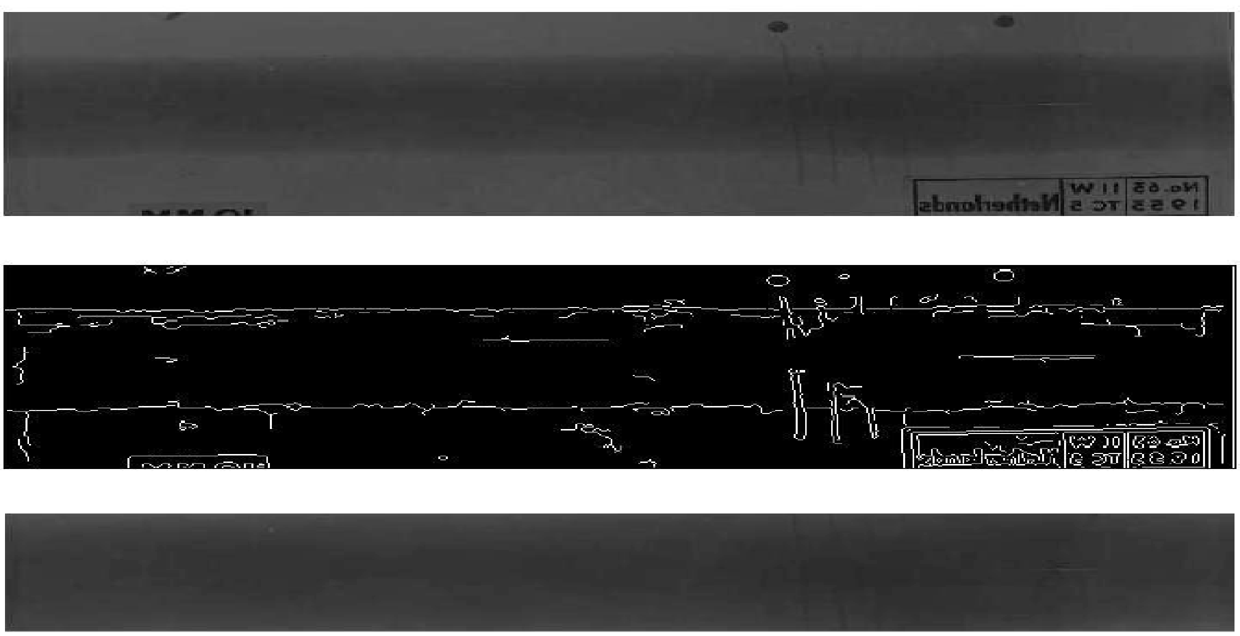
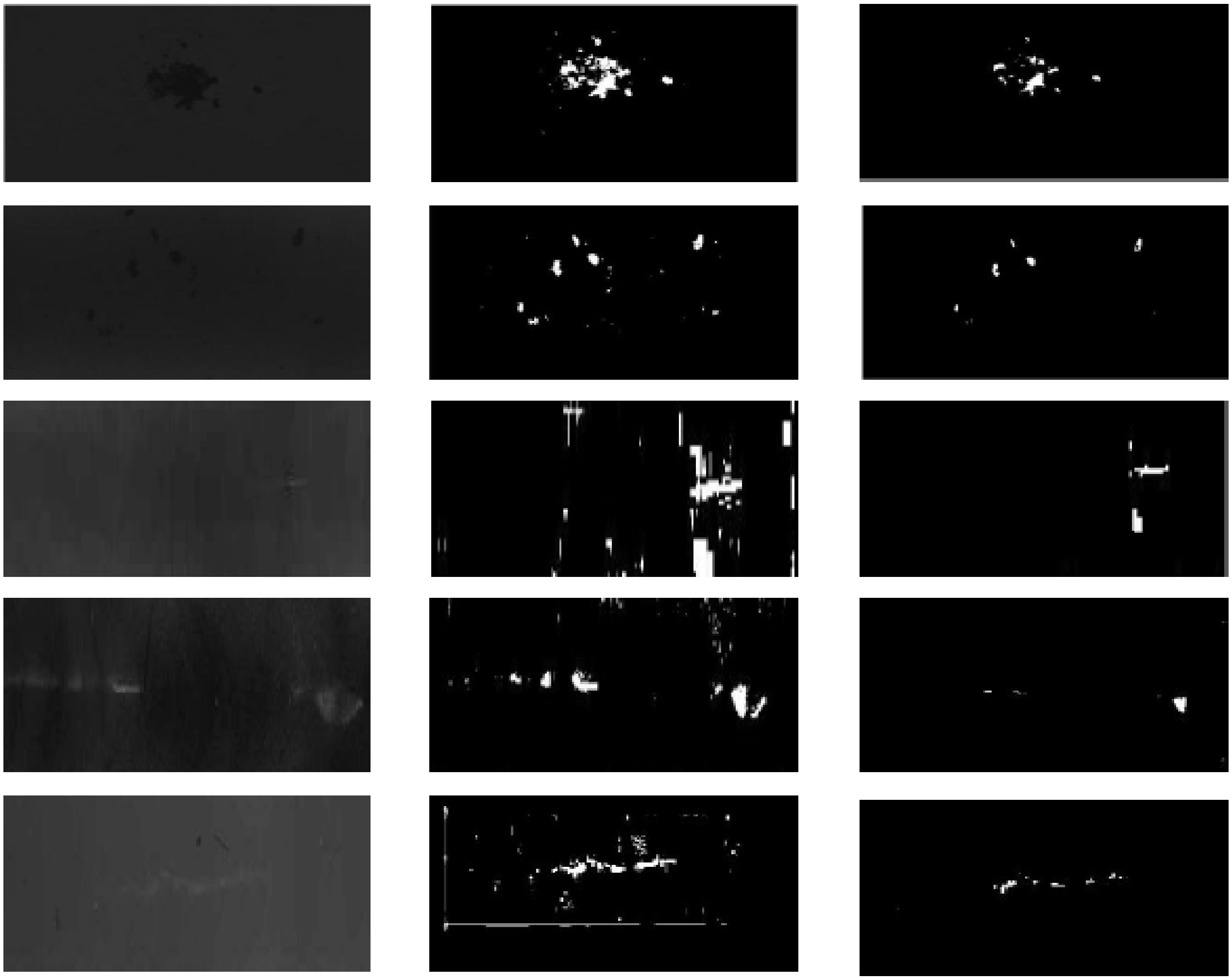


**Fig. 3 Original, gradient and extracted weld seam image (from top to bottom)**



Original Image Thresholded Image Segmented Image

**Fig. 4 Original, Thresholded and Segmented images of weld seams which contain heavy metal inclusion (1st & 2nd row), Cracks (3rd row), Lack of fusion (4th row) and long Cracking (5th row)**

## VI. CONCLUSION

The proposed algorithm is tested on more than 100 images containing various types of defects, the output efficiency of algorithm in detecting and classifying defects is found to be more than 91% in detecting and 96% in classifying defects separately. The combined accuracy of the proposed algorithm in detecting and classifying defects was observed to be 86%. Total time consumed by the proposed algorithm was averaged out to be 91 seconds on an Intel Core i5 processor with 4G.B RAM. The proposed algorithm works very well in case of low contrast images in both tasks i.e. extraction of weld seam as well as defect detection and classification as compared to existing techniques of welding defect detection.

## REFERENCES


[1] T. Warren Liao and Jiawei Ni. An automated radiographic NDT system for weld Inspection: Part I- Weld Extraction, NDT & E International, Volume 29, Isuue 3, June 1996, pages 157-162

[2] A Mahmoudi, F Regragui. A fast segmentation method for defects detection in radiographic images of welds In: The 7th ACS/IEEE International Conference on Computer Systems and Applications (AICCSA) Morocco: IEEE Computer Society

[3] Yan Wang , Yi Sun, Peng Lv, Hao Wang. Detection of line weld defects based on multiple threholds and support vector machine, NDT&E International 41 (2008) 517-524

[4] Gang Wang, T. Warren Liao. Automatic identification of different types of welding defects in radiographic images, NDT&E International 35 (2002) 519-528

[5] H.I. Shafeek, E.S. Gadelmawla, A.A. Abdel-Shafy, I.M. Elewa. Automatic inspection of gas pipeline welding defects using an expert vision system, NDT&E International 37 (2004) 301-307

[6] Romeo R da Silva, Marcio H.S Siqueira, Marcos Paulo Vieira de Souza, Joao M.A. Rebello, Luiz P. Caloba. Estimated accuracy of classification of defects detected in

welded joints by radiographic tests. NDT&E International xx(2004) 1-9

[7] V. Lashkia. Defect detection in X ray images using fuzzy reasoning, Image and Vision Computing 19 (2001) 261-269

[8] Rafael Vilar, Juan Zapata, Ramon Ruiz. An automatic system of classification of weld defects in radiographic images NDT&E International 42 (2009) 467-476

[9] Ioannis Valavanis, Dimitrios Kosmopoulos, Multiclass defect detection and classification in weld radiographic images using geometric and texture features, Expert Sytems with Applications 37 (2010) 7606-7614

[10] N.B Yahia, T. Belhadj, S. Brag, A. Zghal. Automatic detection of welding defects using radiography with a neural approach, Procedia Engineering 10 (2011) 671-679

[11] http://www.ge.com

[12] http://www.iiwelding.org

[13] http://www.paec.gov.pk/ncndt

[14] B. Chanda and D. DuttaMajumder. Digital Image Processing and Analysis. Prentice-Hall India

[15] Rafael C Gonzalez & Richard E woods, Digital image Processing, 3rd edition, Prentice Hall India, 2008

[16] Mark Nixon & Alberto Aguado, Feature Extraction and image processing, 2nd edition, Associated Press

[17] J.Sauvola and M Pietikainen. Adaptive Document Image Binarization. Pattern Recognition, Volume 33, Issue 2, 2000, pages 225-236

[18] Rafael C Gonzalez & Richard E woods and Stevin L Eddins, Digital image Processing using MATLAB, Dorling Kindersley (India) Pvt. Ltd 2006