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Automatic Defect Recognition System for Real Time Radioscopy of Hancock Valve Welds

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Abstract

Automatic defect recognition (ADR) in the case of NDT, especially for Digital Radiography is currently a focus of much research at home and abroad. There are ADR systems available for Digital Radiographic inspection of products like casting. However in the case of many type weld joints, ADR is still considered as a challenging and complex process. This paper introduces an indigenously developed Automatic Defect Recognition System for Real Time Radioscopy (RTR) of Hancock valve body yoke weld joints, that have complex configuration. The RTR system with ADR consists of a constant potential X-Ray equipment, with swiveling arrangement, as the X-Ray source, Digital Flat Panel (DFP) as the Detector/Imaging device, with its associated Software for Image acquisition and Review of the Digital X-Ray images, and a special ADR software for Defect recognition and Evaluation of the Hancock Valve body-yoke weld joint. Automatic Defect Recognition Algorithm, scans through the Digital X-Ray Image of the Hancock Valve Weld joint, and recognizes the detects, if any, and takes the decision of Acceptance / Rejection, based on the Acceptance Standards. This Algorithm which is based on an Artificial Neural Network (ANN) is capable of learning continuously, and grow in capability, with every joint it evaluates. This will enhance the reliability of defect detection and evaluation. The preprocessor uses concepts from digital image processing, image analysis, and pattern recognition. It also involves validation of the system with a wide range of weld samples with various types of discontinuities. This system replaces manual evaluation and eliminates the associated problems like subjectivity, inconsistency, fatigue etc and accomplishes a faster and more reliable evaluation.

1. Introduction

Radiography is very well established as an NDT technique, using both film and electronic X-Ray detection systems. Mainly used in the petroleum, petrochemical, nuclear and power generation industries especially, for inspection of welds, 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. However, radiography is a slow, expensive and hazardous method, particularly for mass production where thousands of weld joints are to be inspected everyday. 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 relative to the size and thickness of the evaluated parts [1].

There has been a remarkable development in research in the field of radiography in the last few decades, resulting in many new technologies like Real Time Radioscopy, Digital Radiography, and Computed Radiography etc. These inventions have significantly enhanced the quality and productivity of Radiographic testing through reduction in cycle time by elimination of chemical film processing, and image processing applications.

Most radiographic exposures and film interpretations in RT are still carried out manually [2]. Human interpretation of weld defects, however, is tedious, subjective and is dependent upon the experience and knowledge of the inspector· [3] Human inspectors are not always consistent and effective evaluators of products because inspection tasks are monotonous and exhausting. Typically, there is one rejected in hundreds of accepted products. It has been reported that human visual inspection is at best 80% effective. In addition, achieving human '100%- inspection', where it is necessary to check every product thoroughly, typically requires high level of redundancy, thus increasing the cost and time for inspection [4]. -Here comes the importance of Automation of evaluation, which reduces human involvement, thus making the inspection more reliable and faster [5]

2. Hancock valve and it's quality assessment:

Hancock Valves form very important components of Steam Generators. These play a significant role by governing of flow of water, steam, flue gases at various locations, and maintain the pressure level under control by releasing of steam, gases etc. They are of different types-gate valves, globe valves, check valves etc, based on their functions. These are made of Carbon Steel(C <25%) an Alloy Steel materials (C < 15%). These are available in a range of dimensions. (Refer Figs. 1 to 3)

One of the major operations in manufacturing of these valves is the welding of Body and Yoke. The welding is carried out in two stages. First stage is the welding of the root, by a robotic welding machine, which is a fully automatic TIG welding process. The second stage, - the welding of the

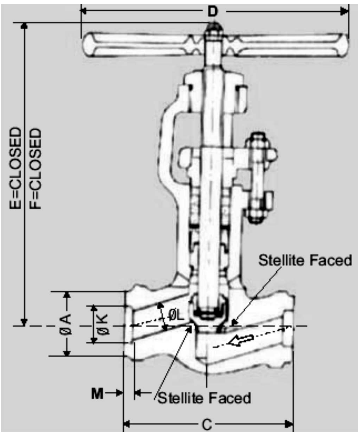

Fig. 1 : Structure of Hancock Valve welds

Fig. 2 : Body Yoke Weld joint

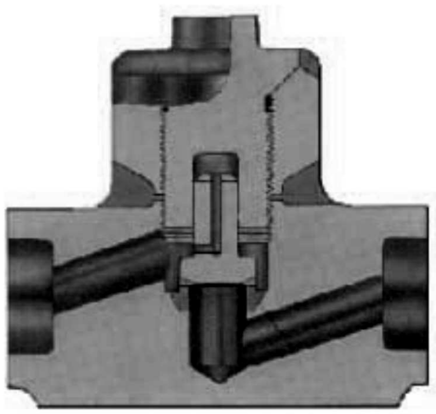

Fig. 3 : Cross section of Body Yoke Weld joint

subsequent passes of this joint, is done by MMAW process manually. Major defects occuring in these weld joints are Slag, Incomplete Penetration (ICP), Lack of fusion(LF), Porosities, Gas Holes, Filler wire inclusions, Excess Penetration etc. Body Yoke joint is considered as a critical weld and therefore the quality assessment requires 100% Radiographic Testing, as per Code. As per the existing practices 10% are tested by conventional Film Radiography and remaining by Real Time Radioscopy.

3. Real Time Radioscopy (RTR) of Hancock welds

RTR system for Hancock Valve consists of constant potential duel focal (large focal size 3 mm x 3 mm and small focus 0.8x 0.8 mm) X-Ray machine with capacity 320kV, 10mA, and an Imaging Device, which is usually an Image Intensifier (in lieu of film). There is a swiveling system, for mechanical manipulation of the relative positions.Image Intensifier, converts the X-Ray image to light image, and then from Light image to Digital image by a CCD camera. The X-ray images are displayed on a video monitor and the image is viewed in concurrent with irradiation. These are evaluated by experienced, RT Level-II qualified inspectors, decision of acceptance /rejection taken as per standards [6] and the feed back is given to the welder. The thickness range usually is 19 mm to 35 mm Steel .The Radiographic technique used here is Double Wall Double Image [7].

4. Automation of Evaluation Hancock Valve welds and need for better Imaging devices:

Manual evaluation, has limitations like subjectivity and automated evaluation, results in faster results, elimination of human dependency and therefore subjectivity and enhanced reliability. Therefore, it was decided to go in for an Automatic Defect Recognition System which will scan through the Digital X-Ray Image of the Hancock Valve Weld joint, and recognizes the detects, if any, and takes the decision of Acceptance / Rejection, based on the Acceptance Standards.

There is ADR technology available for Castings [8] especially Aluminuium Wheels, Magnesium components [9] and weld joints [10]. However, there were no such customized packages available as such, for ADR of Hancock Valve welds. Taking into consideration the complex configuration of this weld joint, it is necessary to have a custom made Algorithm specially designed for this task. The algorithm must incorporate in itself the tremendous domain expertise available, and must also be subject rigorous validation process. Therefore it was decided to indigenously develop an ADR system, specifically for these joints. For the ADR system for Hancock Valve welds, quality of X-Ray image should be good. Though the conventionally used RTR system with Image Intensifier meets the basic Image Quality requirements, it is viewed unfavorably in the case of an Automatic inspection system, due to its inherent limitations like limited resolution, poor signal-to-noise Ratio (SNR), low contrast, nonlinearity, limited dynamic range, etc. Although, using image-processing techniques, image quality is considerably improved, due to the degradation of Image Intensifiers over a period of time the image quality, despite image processing, the images does not meet the sensitivity requirements as per code. Hence, for development of ADR system, it is decided to go in for Digital Radiography with Digital Flat Panel Detectors as imaging devices (in lieu of Image Intensifiers).

5. Digital Flat Panel Detector for ADR system

Digital Radiography [11] is the State of art technology based on Digital Flat Panel Detector (FPD) systems in which the X-ray image is displayed directly on a computer without intermediate imaging optics or mechanical scanning. The incident X-Rays are converted into electric charge and then converted to a digital image through a large area panel sensor. Compared to other imaging devices FPD provides high quality digital images, greater signal to noise ratio and dynamic range of 12 to 16 bit [12], which provides high sensitivity for radiographic application. The present system uses an Amorphous Silicon Flat Panel (model: XRD 0820MN 14, Perkin Elmer make), with major specifications - *Active area:*

204.8 x 204.8 mm^2*, Pixel matrix: 1024 x 1024, Pixel pitch: 200 microns, Dynamic Range: 80dB, Applicable Voltage range: 15 – 450kV*. The Images obtained by Flat Panels Image Acquisition and Review computers are in DICONDE format.

6. ADR Algorithm [13-24]

The Automatic Defect Recognition algorithm has several steps as shown in Fig. 4. The approach followed is - digital image processing, feature extraction, and pattern classification. Image processing techniques are used to extract the principal objects (weld defects here) from radiographic images. Usually, defects in the original X-ray image are low in number compared to its background information, and mixed with noises coming from various processes in the formation of X-ray images. Digital image processing techniques are employed to reduce the noise effects and to improve the contrast, so that the principal objects in the image can be more apparent than the background. Feature extraction is necessary to obtain a set of features that can describe the characteristics of welding defects. The features which are used are Area, Aspect Ratio, Roundness, Number of defects identified etc. The defect types are Pores, Slag, Lack of Fusion, ICP etc. Pattern classification methods are needed to analyze feature data and make a prediction of the defect type. Pattern classification algorithms might differ in efficiency and accuracy. Thus we identify potentially defective regions and extract these features of the defects. These defect regions may be found at different locations, may have different orientations and often have imprecise boundaries. Pattern classification methods are needed to analyze feature data and make a prediction of the defect type. Artificial Neural Network (ANN) algorithms were explored in this study. In the first version an ANN was employed for the decision support that has an override option by an expert. The training files are periodically updated. A Radial Basis Function (RBF) network is trained to classify the weld defects based on the extracted features. A separate Rule-based Algorithm is also developed for the same purpose of the defect recognition. RBF network is an artificial neural network that uses radial basis functions as activation functions. It approximates an unknown function as a linear combination of radial basis functions. The processing time for each image is approximately 2-3 seconds in a Pentium PC. The ANN algorithm is a self-learning algorithm that can constantly update itself on exposure to

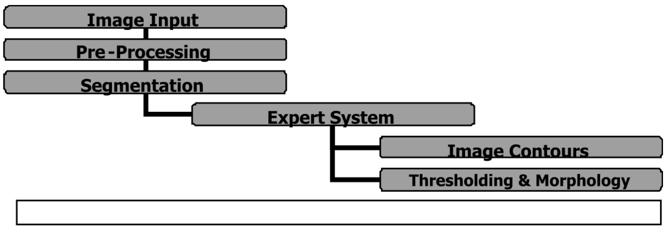

Fig. 4 : Steps of ADR algorithm

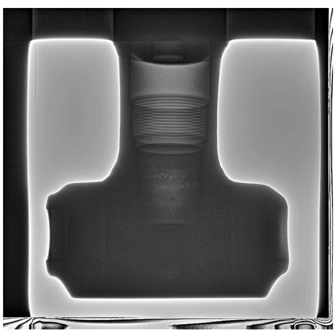

Fig. 5 : Original Image

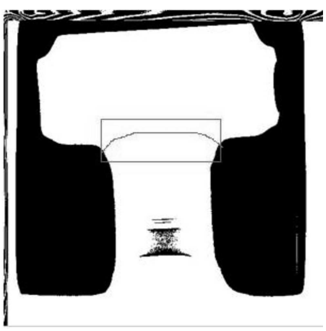

Fig. 6 : Image after rotation and registration

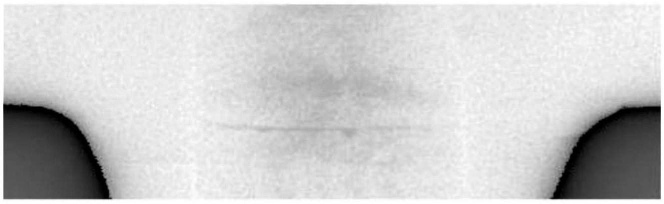

Fig. 7 : RoI (Weld Region) after Segmentation

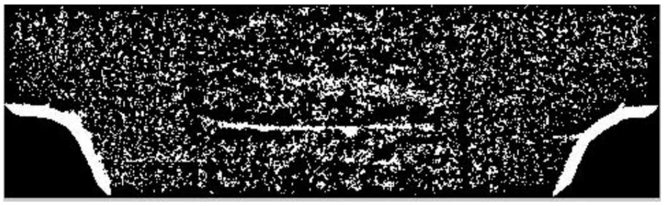

Fig. 8 : Binary Image

Fig. 9 : Final Image with Defects detected

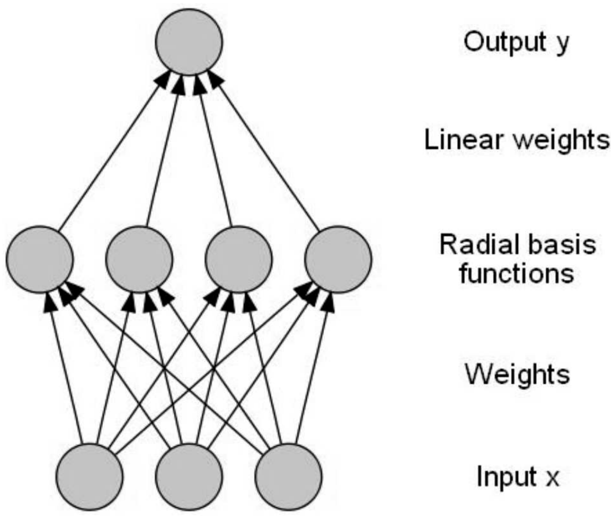

Fig. 10 : Structure of RBF Neural Network

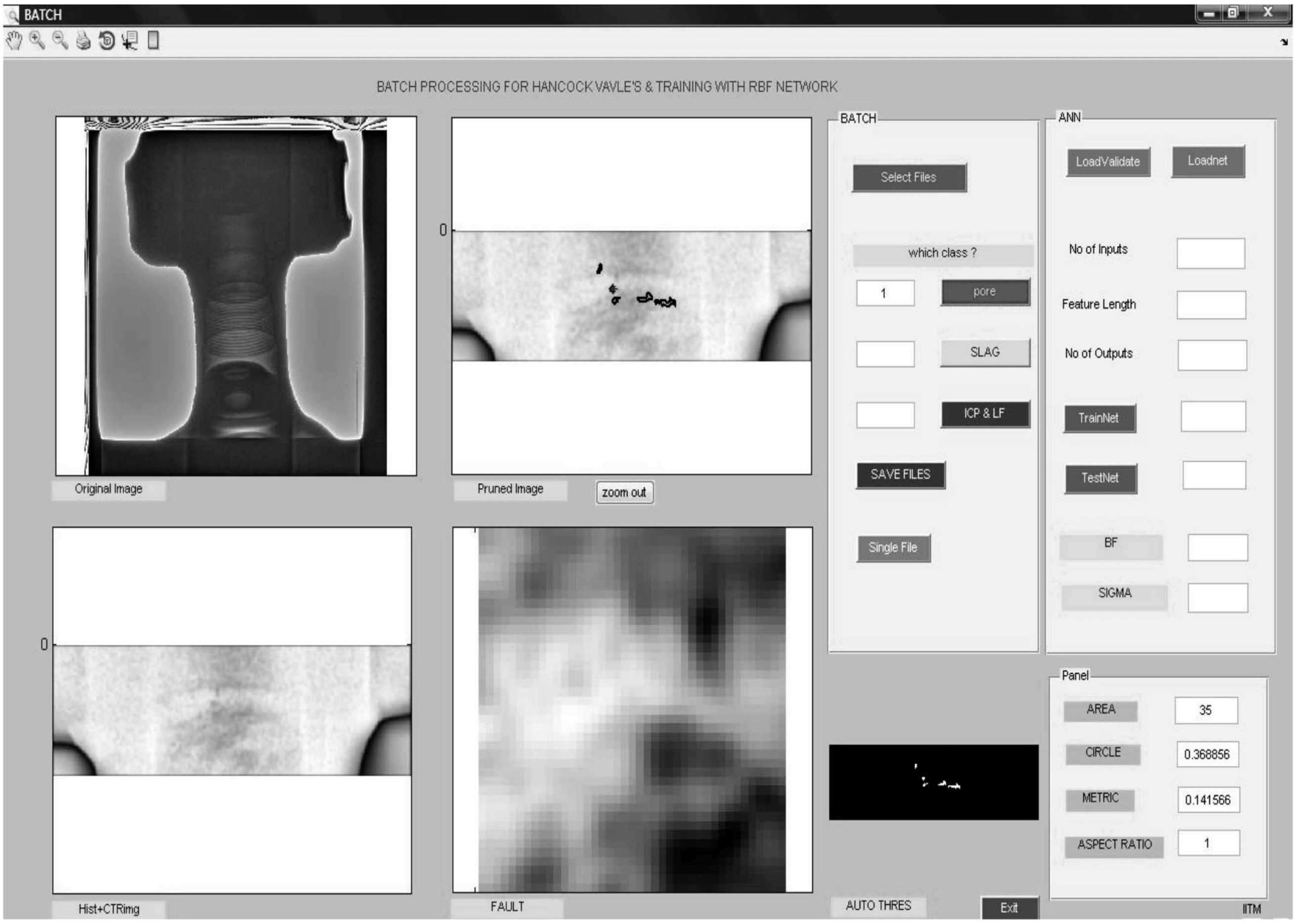

Fig. 11 : ADR Batch processing and ANN training tool kit

new data. This property of the ANN enables the ADR to remain robust against subtle and acceptable process changes over a period of time.

RBF classifier can be trained by fewer training samples to obtain optimal classification, so it has the advantage over small samples. It transforms the nonlinear classification problem in sample space to linear classification problem in feature space. Therefore, training is typically computationally less expensive compared to other neural networks like the multiplayer perceptron.

8. Experimental Results

To evaluate the performance of the present system for Automatic Defect Recognition, defect features of 120 weld images are selected. Defect types include Slag, Pore, Cluster of pores, ICP (Incomplete penetration), LF (Lack of Fusion). The system uses a Radial Basis Function network to classify the defects. The network is trained by varying the number of hidden nodes (or Basis Functions), and the parameter

Table 1 : RBF Network Results

**No of Training samples*	*No of Testing samples*	*No of inputs*	*No of out puts*	*Bias Function*	*Sigma*	*Training %*	*Testing %*
140	73	4	3	40	10	90.71	80.82
445	257	3	3	47	29	82.92	82.8794
445	257	5	3	115	31	85.12	81.3230
257	257	7	3	164	38	87.42	81.7121
236	328	3	3	29	46	84.75	86.28
39	16	3	2	10	10	84.62	93.75
597	**251**	**3**	**2**	**62**	**50**	**98.4925**	**86.45**

*No of samples will be individual defect features

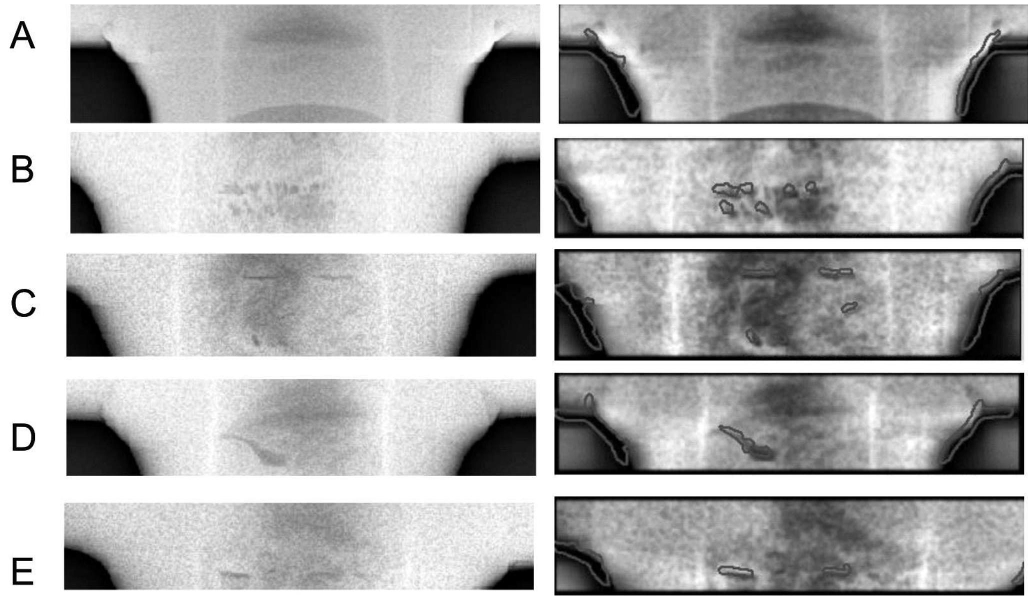

Fig. 12 : The results from the ADR software with the images on left side and ADR results superimposed on the images on the right side for different valve images (A) No Defect, (B) Cluster of porosity, (C) Planar Defect and gas hoes, (D) Slag, (E) Planar Defect.

known as the 'sigma factor' which determines the level of overlap between neighboring Radial Basis Functions.

The Fig. 11 shows a screenshot of the software for Batch programming and training the samples with RBF neural networks. The current defects will be indicated in blue star. We have to classify the defect in which class it falls and press the respective button as shown in the above figure and finally it will save a file with 120 x no of defects per image samples. To train the samples all you need to do is load the file and press 'load net'. Results from this software are given in the Table 1.

8. Conclusions and Summary

The ADR algorithm accomplishes its task in two phases, viz, Defect Recognition, and Defect classification. The Defect recognition process involves preprocessing, segmentation, Defect identification/separation and Feature extraction. The Defect classification is done in two steps-Basic and advanced classifications. The basic classification or coarse classification classifies the defects into two classes-Class 1 is slag and pore together, and class 2 is LF (Lack of Fusion) and ICP (Incomplete penetration). In case of this 2-class problem, the results are achieved with 93.75% accuracy. In Advanced classification, we use three classes: Class 1 is pore, class 2 is slag and class 3 is LF and ICP. In this case, the accuracy is 86.28%. However performance can be improved with continuous training by using more samples in each of these groups. It transforms the nonlinear classification problem in sample space to linear classification problem in feature space, and therefore training is not computationally intensive.

This study reveals that the transformation from manual evaluation with RTR system with Image Intensifier, to an ADR with DR system, results in improved Probability of defect detection and higher reliability through elimination of subjectivity etc. With continuous training with ANN technology the performance of the system has considerably increased and proven suitable for these welds. The ADR algorithm uses ANN in self-learning mode for continuous improvement of performance of ADR system. The system acts as a specialist package for Hancock valves. However the scope of this research works can be extended to other weld configurations also, especially for thin wall components, where RTR is being used for testing.

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