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Vijay R. Rathod
Dept. of Electrical Engineering, Indian Institute of Technology, Roorkee, Roorkee – 247667 INDIA, Sunil5718@gmail.com

R. S. Anand
Dept. of Electrical Engineering, Indian Institute of Technology, Roorkee, Roorkee – 247667 INDIA, maheshkumargubbala@gmail.com

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Feature Extraction and Classification of Flaws in Radio Graphical Weld Images Using ANN

Vijay R.Rathod, R.S. Anand
Dept. of Electrical Engineering, Indian Institute of Technology, Roorkee, Roorkee – 247667 INDIA
Email: Sunil5718@gmail.com, maheshkumargubbala@gmail.com

Abstract - In this paper, a novel approach for the detection and classification of flaws in weld images is presented. Computer based weld image analysis is most significant method. The method has been applied for detecting and discriminating flaws in the weld that may corresponds false alarms or all possible nine types of weld defects (Slag Inclusion, Wormhole, Porosity, Incomplete penetration, Under cuts, Cracks, Lack of fusion, Weaving fault Slag line), after being successfully tested on80 radiographic images obtained from EURECTEST, International scientific Association Brussels, Belgium, and 24 radiographs of ship weld provided by Technic Control Co. (Poland) were used, obtained from Ioannis Valavanis Greece.. The procedure to detect all the types of flaws and feature extraction is implemented by segmentation algorithm which can overcome computer complexity problem. Our problem focuses on the high performance classification by optimization of feature set by various selection algorithms like sequential forward search (SFS), sequential backward search algorithm (SBS) and sequential forward floating search algorithm (SFFS). Features are important for measuring parameters which leads in directional to understand image. We introduced 23 geometric features, and 14 texture features. The Experimental results show that our proposed method gives good performance of radiographic images.

Key words- Radiographic images weld flaws, segmentation, region growing, morphological edge detection, multistage watershed transformation, and Artificial Neural Network.

I. INTRODUCTION

Welding plays an important role in industries as it is used for joining metal parts permanently. A Welder joins metal by intense heat produced by a multitude of different welding processes, which produce an extremely strong permanent bond. Because of its strength welding is used to construct and repair ships, aircrafts, automobiles, join steel and reinforcing rods in buildings, bridges and highways, nuclear power plants, pipeline system conveying gases, liquids, refineries, automobile manufacturing and repair, aerospace, underground trains and a host of many other welding applications [8] .

With the advent of digital computer technology and in resultant fast and extensive computing facility, image-processing field has found its application in many areas including the weld inspection. In such a case image processing plays a very vital role in finding the features of digitized weld images (obtained either from radiographic methods or ultrasonic methods) defined in terms of the defects in them and characterizing the defects with their type and geometrical information. Image segmentation is an important step for quantitative and qualitative weld image analysis and classification of multiple weld flaws. The accurate segmentation provides more meaningful information in X-ray images for industrial purpose.

Radiographic NDT techniques are used for detection of flaws in gas pipelines, nuclear canisters, fuel oxidizer and gas tank, multi layered vessels, nuclear petrochemical, aerospace industries and other welds. The integration of quality, reliability and durability of welding plays a very important role in industrial applications. To get a state of the art technological development in the field, a chronological overview of these methods for NDE (Non destructive evaluation) weld inspection is presented below [8].

In 2009, Alaknanda, et al proposed novel method of flaw detection in radiographic weldment images using morphological watershed segmentation [8]. Rafal Vilar described an automatic system of classification of weld defects [7].

In 2010, Ioannis Valavanis, et al recently proposed other method for detection and classification of defects in weld radiographs. The method has been applied for detecting and discriminating defects such as worm holes, porosity, linear slag inclusion, gas pores, and lack of fusion or crack, But the technique has not been able to focus on incomplete penetration and other type of flaws [1]. H.Kasban, et.al developed feature extraction methodology using cepstral approach [2]. S.Margret Anouncia presented a knowledge based model for image interpretation but accuracy of classification is unstable [4]. P.N.Jebarani Sargunar [5, 6] developed Gaussian mixture model (GMM) classifier to classify the defects in input image.

N.M.Nanditha, proposed comparative study on the suitability of feature extraction techniques for tungusten inclusion and hotspot detection from weld thermographs [3].

In the above context, the present research work proposes to contribute towards the application of image processing techniques for identifying flaws in the radiographic X-ray images. To date there are no satisfactory results for detection, feature extraction and classification of all the possible nine types of flaws. The Proposed method also aims to improve the process of automated welding detection system.

On the basis of presented overview of developments in the weld inspection our work tries to fill the following gaps.

Detection of all the nine types of common flaws(Slag Inclusion, WormHole, Porosity Incomplete penetration, Under cuts, Cracks, Lack of fusion, Weaving fault Slag line), in the weldments, especially incomplete penetration type of flaws.[8]

Feature extraction using segmentation approach and classification by neural network, has been tried out. Effectiveness and efficiency of system is likely to improve using these techniques,

II. SEGMENTATION METHODS

For detecting the flaws and their type in radiographic images (having different types of flaws), three segmentation techniques have been applied here. Every segmentation technique has its own advantages and disadvantages i.e. results obtained are of varying quality. Taking this into account, comparative study has been performed here to find the best segmentation technique for a particular type of flaw.

First of all, edge based segmentation was used on the images. It gave good results in few types of flaws while few others were not clearly identifiable by this technique. In this technique, the edge detection is the prior step to provide the edge pixels; after that these edges are modified to produce the close curves representing the boundaries between adjacent regions. But, to convert the weak edge pixels into the close boundary is very difficult task of segmentation In such low-quality images, edge based segmentation algorithms do not identify the border accurately and the grouping process presents serious difficulty in producing connected close contour. This makes it difficult to find the dimensions of the flaws accurately.

The complement of the boundary-based method is the region-based segmentation. Under this category, region-growing method has been implemented here. Region growing method always provides closed contour and makes use of relatively large neighborhood for decision making, but selection of seed point is difficult in this case. The accuracy of the technique depends on the selection of seed point, which is time consuming. It suffers from pixel sorting orders for labeling and seed selection.

Watershed transformation based image segmentation is another technique, which has been applied here. It is a widely used in image processing because it is a simple intuitive method. It produces complete division of image in separate regions even if contrast is poor so no contour joining is required. But it has few drawbacks also like over-segmentation, sensitive to noise, poor detection of thin boundaries and poor detection of significant areas with low contrast.

III. COMPUTER AIDED AUTOMATED WELD DEFECT RECOGNITION SYSTEM

In the computer aided automated weld defect recognition system, some image preprocessing techniques are used to remove noise and enhance the image quality of the image, here noise reduction is mandatory in the beginning and then contrast enhancement. Ioannis Valavanis[1] enhanced image first then gone for noise reduction, but it is not preferable since noise has to be reduced in the beginning before enhancement. Then concept of application of three segmentation techniques i.e. morphological edge based segmentation, region growing segmentation and multistage watershed segmentation has been implemented on radiographic NDT images of weldments for the detection of flaws, produced during the welding process. These methodologies are compared and concluded to be effective for all possible nine types of weld flaws detection. After defect detection, geometric, related geometric and texture features are extracted and given as input to classifiers and identified exact defect types. [2-7].

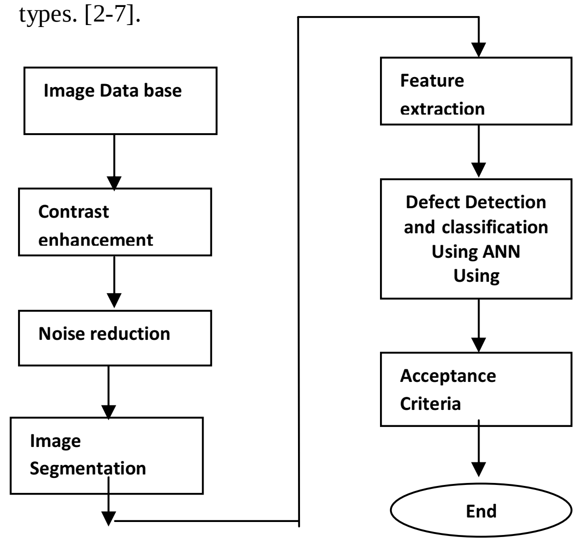

Fig 1.General process flow of radiograph based automated weld defect recognition system

IV. FEATURE EXTRACTION AND CLASSIFICATION

The 14 most commonly used texture features and 23 geometrical features are extracted from weld defect are defined and described. Texture feature used to partition images into regions of interest and to classify those regions, provides information in the spatial arrangement of color or intensities in an image, characterized by the spatial distribution of intensity levels in a neighborhood, repeating pattern of local variations in image intensity and cannot be defined for a point.

4.1 Texture features

The purpose of feature extraction is to reduce the original data set by measuring certain properties, or features, that distinguish one input pattern from another pattern. The extracted feature should provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image into a feature space. 14 features based on the first order histogram and the gray level co-occurrence matrices (GLCM) have been used in this work. Co-occurrence matrix depicts Joint histogram of gray levels of a pair of pixels with a given spatial relationship. It captures the statistics of the gray level spatial variation. Co-occurrence matrices calculate the joint probability of adjacent pixels along a given direction θ having co-occurring values i and j.[3]

Four matrices were calculated, for θ = 0, 45, 90, and 135 degrees, and combined in an averaged co-occurrence matrix since no directional variations in texture were expected. The 14 textural measures defined by Haralick were computed for each lesion.

V. ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN), often just called a "neural network" (NN), is a mathematical model or computational model based on biological neural networks, in other words, is an emulation of biological neural system. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

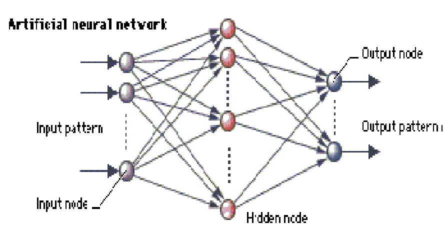

Fig 2 ANN Architecture.

Training Of Artificial Neural Networks

A neural network has to be configured such that the application of a set of inputs produces (either direct or via a relaxation process) the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to 'train' the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. We can categorize the learning situations as follows:

Supervised learning or Associative learning

In which the network is trained by providing it with input and matching output patterns. These input- output pairs can be provided by an external teacher, or by the system which contains the neural network (self-supervised).

Unsupervised learning or Self-organization

In which an (output) unit is trained to respond to clusters of pattern within the input. In this paradigm the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli.

Reinforcement Learning

This type of learning may be considered as an intermediate form of the above two types of learning. Here the learning machine does some action on the environment and gets a feedback response from the environment. The learning system grades its action good (rewarding) or bad (punishable) based on the environmental response and accordingly adjusts its parameters.

Neural networks have been successfully applied in a wide range of supervised and unsupervised learning applications. Neural-network methods are not commonly used for data-mining tasks, however, because they often produce incomprehensible models and require long training times. In this article, we describe neural-network learning algorithms that are able to produce comprehensible models, and that do not require excessive training times.

5.1. Classifiers

In this research work, neural network is analyzed for the classification applications.

The feature selection problem involves the selection of a subset of “d” features form a total of “D” features, based on a given optimization criterion. The D feature are denoted uniquely by distinct numbers from 1 to D, so that the total set of D feature can be written as

S={1,2,3…d}. X Denotes the subset of selected features and Y denotes the set of remaining features, so S= XU Y at anything. J(X) denotes a function elevating the performance of X. J depends on the particular application. Here, J(X) denotes the classification performance of defected flaw region as benign or malignant using the set of feature in X.

5.2 Sequential forward search (SFS) Algorithm

X=Φ;

J={J/1≤ i ≤ D};

Repeat

Choose the most significant feature y in Y such that J (XU{Y}) gives maximal classification performance.

Move y to X.

Until J(X) gives optimal classification performance

End

5.3 Sequential backward search (SBS) algorithm

Y=Φ**;**

X=={i/≤ i ≤ D};

Repeat

Choose the least significant feature x in X such that J(X-{x}) gives maximal classification performance. Move x to Y until J(X) gives optimal classification performance.

End

5.4 Sequential Forward Floating Search (SFFS) Algorithm

X=Φ;

J={iJ/1≤ i ≤ D;

K=0 // initialization

While (K<d)

{Find the most significant feature y in Y and add to X. find the least significant feature x in X. While (J (J (XK –{X})>J (XK-1)) {

XK-1 = XK- {X};

K-1;

find the least significant x.

VI. EXPERIMENTAL TESTING

Testing results using 14 texture features

For the first stage, only texture descriptors are used for testing, because they have commonly been used and considered as an effective way to classify different types of flaws in welding process. The results can be seen in Table 1. And classification based on above three segmentation methods is shown. 23 geometrical features and 14 Texture and its related geometrical feature can be extracted easily using proposed method.

Fig2. (a) Original image having incomplete penetration type flaw.

Fig 2. (b) Segmented image superimposed on original image after using edge based segmentation technique

Fig 2. (c) Segmented image superimposed on original image after using region growing technique.

Fig 2. (d) Segmented image superimposed on original image after using multistage watershed segmentation.

Fig3. (a) Original image having worm hole type flaw.

Fig 3. (b) Segmented image superimposed on original image after using edge based segmentation technique.

Fig 3. (c) Segmented image superimposed on original image after using region growing technique.

Fig 3. (d) Segmented image superimposed on original image after using multistage watershed segmentation.

Table 1. Results of Texture & Geometrical classification for Image Database

Segmentation methods	**No. of sample images in Training / Testing Set**	**Classification Rate (%)**	
		Textures Features	**Geometrical Features**
Region Growing Segmentation	Training - 25% Classification - 75%	92.25	88.97
	Training - 50% Classification - 50%	88.23	89.13
Edge Based Segmentation	Training - 25% Classification - 75%	88.18	85.348
	Training - 50% Classification - 50%	91.0	88.11
Watershed Segmentation	Training - 25% Classification - 75%	88.13	85.34
	Training - 50% Classification - 50%	91.29	88.14

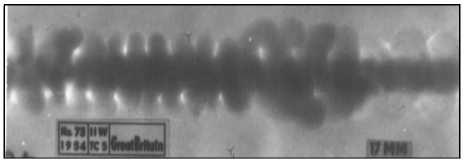

Fig2 (a) Original image having Weaving fault type flaw

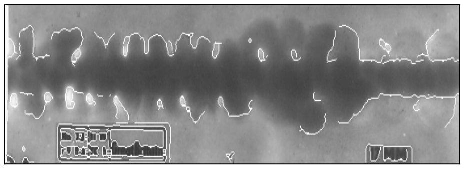

Fig 2 (b) Segmented image superimposed on original image after using edge detection

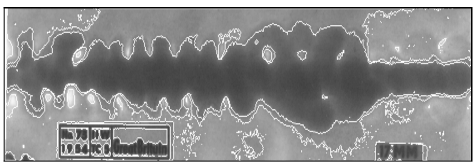

Fig 2 (c) Segmented image superimposed on original image after using region-growing technique

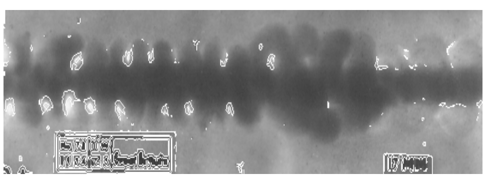

Fig 2(d) Segmented image superimposed on original image after using multistage watershed segmentation

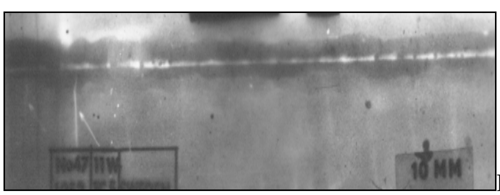

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Fig. 11 (a) Original image having incomplete penetration and crack type flaws

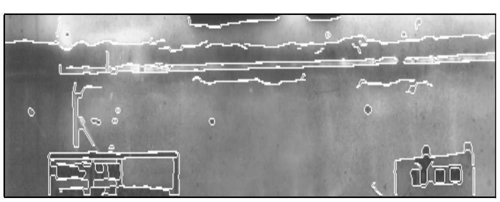

Fig.11 (b) Segmented image superimposed on original image after using edge detection technique

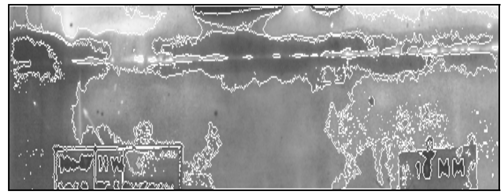

Fig. 11 (c) Segmented image superimposed on original image after using region growing technique

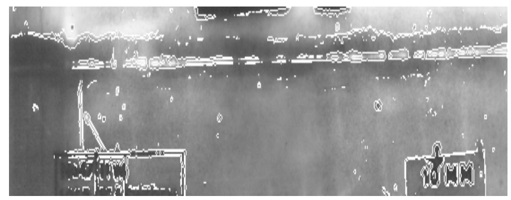

Fig. 11 (d) Segmented image superimposed on original image after using multistage watershed segmentation technique

VII. CONCLUSION

In this proposed method 14 Texture features, 23 geometrical features have been extracted from X-ray weld defect images. All 37 features have been studied and discussed. According to experimental testing, 92.25 % of defect samples can be classified using texture features and 88.97%using geometrical features.

The classification rate can be improved to 88.97 % and 92.25% step by step. All the test results mentioned prove that the defect identification ability can be increased using the proposed method.

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