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WELD DEFECT DETECTION IN RADIOGRAPHY BASED ON PROJECTION PROFILE AND RST INVARIANT BY USING LVQ

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ABSTRACT

X-ray radiography is commonly used in (NDT) Non-destructive Testing, for identifying defects in weld. When the X-ray is passed through the weld object, the area where the defects are occurred will be having different intensity profile, than the nearby pixels. Most of the X-ray radiographic images will be having some forms of noise components embedded in it. Median filter is applied for noise removal, followed by gamma correction for image enhancement which made the image more operative. For the segmentation of the weld defect, watershed method is performed. Through watershed segmentation process, the defective regions are segmented out, without oversegmentation problem. Standard derivation and mean of the Projection Profile of the radiographic image along with RST invariants features are used for feature extraction. In this work, we fed the feature extracted to a Learning Vector Quantization (LVQ) for training, with four different output classes, where each class corresponds to different classes or types of weld defects like Cluster Porosity, Slag inclusions, Lack of Penetration (LOP) and Burn-Through. The result shows that the proposed system is highly efficient in classifying different types of weld defects.

Keywords: *Weld defects, Radiography, Learning Vector Quantization (LVQ), Watershed, RST invariant*

1. INTRODUCTION

Radiography image is created on the principle that, when X-ray or γ-ray passes through an object, it gets attenuated, depending on the absorbency of the metal. The intensity profiles of the defective region will be having a different pattern of gray level intensity with majority of black intensity. Interpretation of radiographic images by human with naked eyes is error prone and unreliable, since the image will be noising and edges will be obscure. Computer-aided process of weld-defect detection is a very effective and useful technique. Image processing technique is widely used nowadays for the identification of weld defects in rail roads, gas pipes etc. Various research work and projects were conducted in image enhancement and segmentation methods for weld detection. Image enhancement is the process of making the image more visible and at the same time to make it easy to understand the abstruse image contents. Segmentation of image is to partition the image into various objects and recognition is the process of labeling the segmented image based on some features extracted.

Several researchers have carried out various works on the recognition of weld defect using FBPN neural network, SVM, k-means clustering etc. All the works are impressive and effective, but they have its own drawbacks. In this article we propose a method for finding weld defects, with good efficiency and less complexity.

In 2001 R R da Silva, M H S Siqueire et al [1] proposed linear classifiers for recognition of weld defect, in which a hierarchical classifier algorithm and non-hierarchical classifier algorithm are compared where hierarchical classifier is giving better performance. In 2004 T.W.Liao developed a Fuzzy based inspection method for weld-defect recognition where fuzzy rule is constructed by using fuzzy c-means [2]. The performance of fuzzy system was compared with MLP neural network. In 2009, Abdelhak Mahmoudi and Fakhita Regragui developed a segmentation method for weld defects

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Detection which is fast and efficient. The result showed that, the algorithm is faster, effective and practical, which is a necessary step before characterizing defects [3]. In 2010, Xin Wang, Brian et al. developed a Support Vector Machine Classifier based methodology for identification of weld defects in radiographic images [4]. This methodology was tested by 25 radiographic weld images, where 96.98% of the existing weld defects are detected, with 14.07% of false alarm.

In the proposed method, we first pre-processed the image using median filter and performed gamma-correction with a gamma value of 0.3. Second, we partitioned the image into objects of defective areas, by performing Watershed Segmentation method, without having over segmentation [5]. The segmentation obtained by Watershed method performed better than region growing when applied to the same radiograph. Horizontal and Vertical Projection profile of the segmented image is performed for the different pattern of segmented defects.

Cluster porosity weld defect occurs due to the presence of moisture, which turns into gas, which will be further trapped in the weld when heated. The Cluster Porosity as the name indicates are usually present as cluster or group which appears like regular porosity. Burn-Through is a weld defect which arises due to overheating, which makes the weld metal to penetrate the weld zone. Burn-Through appears to be a dark spot, surrounded by whitish grayscale intensities. Lack of Penetration defect happens when the weld metal fails to penetrate the joints. It usually appears as a dark straight line of medium width. Slag Inclusion defect occurs due to the presence of non-metallic element in weld metal [6] [7].

The features extracted are standard deviation and mean of Projection Profile along with RST invariant moments. These features extracted are fed to the LVQ, which is a supervised learning method of kohenon network, which uses competitive learning technique. The objective of LVQ based training and classification method performed, is to develop software to improve the process of automated weld defect detection.

2. PROPOSED SYSTEM FOR WELD DEFECT DETECTION

The proposed system is having five different phases, which is shown in the following Figure. 1.

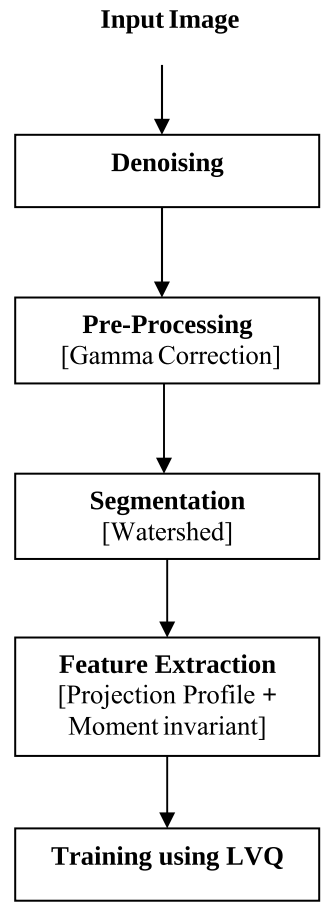

Figure 1. Weld Detection system

2.1. Denoising

The radiographic images are basically low in contrast, dark and noisy. Image enhancement is an inevitable part in automatic defect detection, since the defects are unidentifiable directly, due to noises and low image contrast [8].In this method, a median filter is used to remove the noise. Median filter is an order-statistics filter, where the value of a pixel is replaced by the median of neighboring gray level pixel values.

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2.2. Pre-Processing

During preprocessing process, Power-law transform is performed, where a narrow range of dark input values are mapped to a wider range of output values [9]. Power-law transform is also known as gamma correction, where different transformation curves are obtained for various gamma values. In our requirement we applied gamma value of 0.3, which gave better enhancement.

2.3. Segmentation

Segmentation is a difficult task in image processing since most of the images will be noisy and low contrast images [10][11]. Many segmentation methods like neural network, fuzzy logic based, SVM based are effective but time consuming. In our proposed system we performed Watershed segmentation [12].

2.4. Feature Extraction

Feature extraction is done using Projection Profile and Geometric invariant moment.

2.4.1. Projection profile

The vertical projection profile of the watershed segmented image is performed. From which standard deviation, mean and co-variance are computed as a features. The standard deviation, mean and co-variance show the statistical nature of the segmented defective region. Cluster Porosity, Slag Inclusion, Burn through and Lack of Penetration are all having different pattern. Features are the information or data which are extractable, and it should reduce the bulk data into smaller dimension, without losing vital information [13]. The relevant features are fed to an ANN for classification or pattern recognition. Artificial Neural networks (ANN) are widely used for Pattern Recognition [14]. The nodes in ANN are analogous to the neurons in the brain. The results obtained after training and testing by Radial Basis Function Network (RBFN), Feed Forward Back Propagation Network (FBPN) and Learning Vector Quantization (LVQ) shows that, the performance of LVQ is better than both RBFN and FBPN.

2.4.2. Moment invariant

Hu.M.K. in 1962 introduced the concept of Geometric moment invariant, for pattern recognition [15].

Two dimensional moment μ_{pq} for a digital image f(x,y) of size M×M can be expressed as:

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p . (y-\bar{y})^q f(x,y)$$

$$\bar{x} = \frac{m_{10}}{m_{00}} \qquad \bar{y} = \frac{m_{01}}{m_{00}}$$

Central moments after applying scaling normalization are as follows:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00^{\gamma}}}, \gamma = [(p+q)/2]+1$$

Seven moment invariant features ($M_1, M_2 \ldots, M_7$) are given below in terms of central moments:

$$M_1 = \eta_{20} + \eta_{02}$$
$$M_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$
$$M_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$
$$M_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$
$$M_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[((\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$
$$M_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$
$$M_7 = (3\eta_{21} - \eta_{30})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{30})^2] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} - \eta_{03})^2]$$

2.5. LVQ Based Training

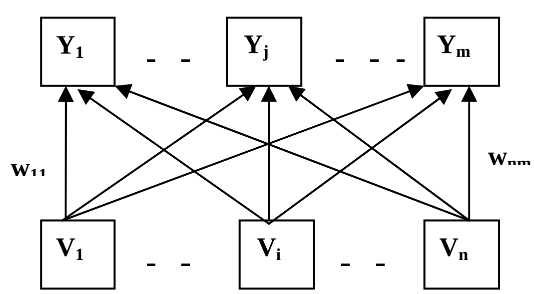

Figure 2. LVQ Neural Network

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The LVQ classifier is based on the principle of nearest neighbor, which is demonstrated in the Figure. 2, where Euclidean distance is basically used for calculating distance [16]. Kohonen network is an unsupervised way, where LVQ (Learning Vector Quantization) network is a supervised technique, where target values are available for the input values. The architecture of LVQ and Kohonen self organizing neural network are similar, but the output neurons are considered to be class type. During the training process while updating the weight the target value is compared with the index of winner neuron unit.

2.5.1. Training algorithm for LVQ

Steps:

1. Set the initial value of weight matrix and learning rate.
2. Execute steps from 3 to7 until end condition is true.
3. Execute steps from 4 to 5 for each 'V',where 'V' is the input vector.
4. Using squared Euclidian Distance calculate J as follows

   4.1 $D(j)=\sum(wij - Vi)$,where

   D(j) is squared Euclidian Distance
   w_{ij} is the element of weight matrix
   V_i is the element of input vector

   4.2.Find J with D(j) is minimum

5.W_j is updated as follows:

   5.1 .if ($T=C_j$) then
   T is the target and C_j is winner index
   5.1.1 $w_j(N)=w_j(O)+\alpha\ (V-w_j(O))$

   5.2 .if ($T!=C_j$) then
   5.2.1 $w_j(N)=w_j(O)-\alpha\ (V-w_j(O))$
   where ,$w_j(O)$ is old value of w_j
   $w_j(N)$ is new value of w_j

6. Decrement the learning rate

7.Check for end condition, which may be fixed number of iterations.

The weights are updated on each step for the process of learning. The weights will move closer to the class which will be winning class or else it will move away from the class. Once the training is finished, the LVQ will be able to recognize any unknown features which are not trained already.

3. EXPERIMENTAL RESULTS

In this proposed approach welding discontinuities or defects such as Lack of Penetration (LOP), Burn-Through, Cluster Porosity, Slag inclusions are tested. In the radiographic input image with weld defects are first passed through denoising and preprocessing stages. Watershed method is used for segmentation which gave a better result than region growing. The output of Watershed segmented images are shown in the Figure. 3. Feature extraction process is a very important step where in proposed method only the first four moment invariant features are made into use ,since the remaining three moments are not so significant for our application. Standard deviation and mean of Projection Profile gives very relevant information about the pattern of the defect. These six features are fed to the LVQ, Feedforward BackPropogation Network [17] and Radial Basis Function Network for training [18].

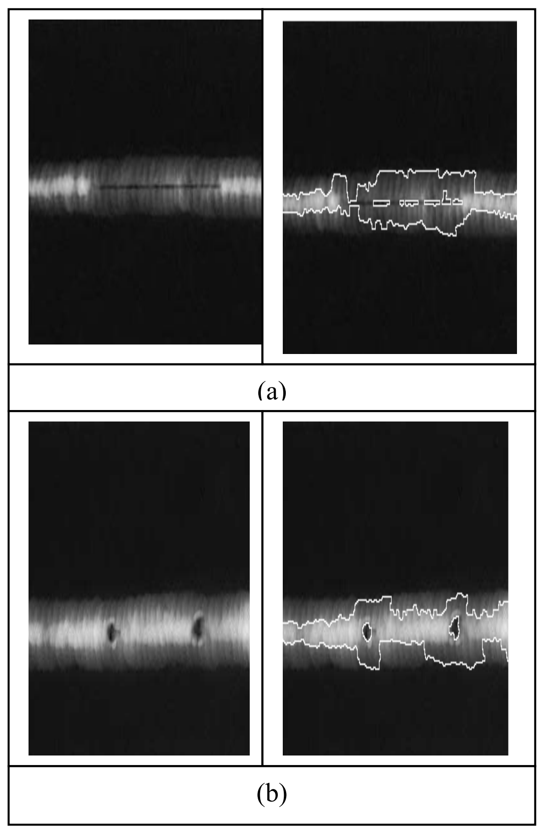

Figure 3. (a) Image with Lack of Penetration Welding Defect and Output Watershed Image (b) Image with Burn through Welding Defect and Output Watershed Image

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The learning error for LVQ is the lowest with less number of iterations when compared to RBF and FBPN. The learning error and testing error for LVQ is only 0.00017 and 0.001 which is very less when compared to other two networks. For RBF network the learning error is less but the classification error during testing is 2.63 which are high. The results are shown in Table1.The graph analysis of three approaches is shown in Figure. 4.

Table 1. Experimental Results

	LVQ	RBF	FBPN
Learning Rate	0.02	.3	0.3
Learning Error	0.00017	0.0002	1.12
Testing Error	0.001	2.63	0.9813

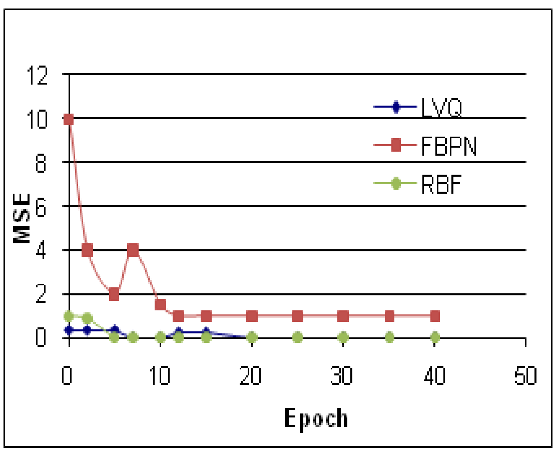

Figure 4. Comparison of LVQ, RBF and FBPN in terms of MSE

4. CONCLUSION

This paper presents a Moment invariant Projection Profile based weld defect detection system. The test images have been degraded by various types of noises. The experimental result shows that the proposed method is highly reliable for noisy images in defect detection. Watershed segmentation performs well for weld defect segmentation than region growing. The RST invariant and Projection Profile based features extracted are very efficient for recognition of weld defects like Cluster Porosity, Slag inclusions, Lack of Penetration (LOP) and Burn-Through. The learning error and the testing error show that LVQ based learning and testing is performing better than Radial Basis Function and Feedforward BackPropogation network. A recognition rate of nearly 99% can be achieved through this approach.

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