ANALYSIS OF VARIOUS FLAWS DETECTION USING SEGMENTATION TECHNIQUES IN WELD IMAGES

Sangita Dubey[1], Kamal Shah[2]
[1]Department of Electronics and Telecommunication, Mumbai University, Thakur College of Engineering and Technology, Mumbai, India
[2]Professor, Dean R&D, HOD, Information Technology, Kandivali (E), Mumbai, India

ABSTRACT

It is necessary to detect suspected defect regions in the radiographic weld images to find the type of flaws. In this paper different segmentation techniques are studied in detail. Various techniques are implemented on radiographic NDT images of weldments for the detection of flaws produced during the welding process. It is necessary to detect suspected regions in the radiographic weld images to find the type of flaws and its causative factors. This requires processing of radiographic images by a suitable approach. Various flaw detection techniques are Flaw detection using Morphological edge based segmentation techniques, Region Growing Segmentation, Morphological Watershed Segmentation Techniques, Support Vector Machine (SVM) Classifier and Artificial Neural Network (ANN). All this techniques has some advantages and disadvantages which are discussed in the paper. Finally it is suggested that if edge based segmentation, region growing Segmentation, morphological operations and Watershed Segmentation are performed simultaneously then maximum number of flaws can be detected.

KEYWORDS: *Radiographic images weld flaws; segmentation techniques; edge-based segmentation; region growing; watershed segmentation; SVM; ANN.*

I. INTRODUCTION

Radiography testing is one of the most important testing techniques for welding inspection. It is based on the ability of X rays or Gamma rays to pass through metal and produce photographic records. Radiography testing can examine the internal structure of weld. Conventionally experienced interpreters evaluate the weld quality but it is time consuming and less efficient method. Currently there is a great deal of research on development of automated system for detection various flaws in radiographic images and analysis of quality of welding. During welding process following nine types of flaws are mainly observed. These nine flaws are

1. Slag Inclusion
2. Worm Whole
3. Porosity
4. Incomplete Penetration
5. Under Cuts
6. Weaving Fault
7. Cracks
8. Slag Line
9. Lack of Fusion

These Flaws can be detected by various Techniques. One of the well known Techniques for detection of Flaws is Segmentation. Segmentation [1] is a process in which regions or features sharing similar characteristics are identified and grouped together. . Image segmentation is based on thresholding, edge detection, region detection or combination of any of these techniques. The segmentation should separate the region that are homogeneous to the particular criteria chosen for analysis, of segmented area should be considerably less than the variation at borders. The segmented area should have smooth shedding and texture. There should not be large variation in homogeneity criteria within a single segment. Small data must be clear for further analysis and the position of border obtained after segmentation must match with local maxima, ridges and saddle points of local gradient the measurements. Segmentation basically divides an image into segments having of the following characteristics.

1. Looks uniform.
2 .Belongs to single object.
3. Have some uniform attributes.
4. All pixels related to it are connected.

Most segmentation techniques are either based on discontinuity or similarity criteria.

For detecting types of Flaws in radiographic image various segmentation techniques are applied. All this techniques have some advantages and disadvantages. We will see advantages and disadvantages of these techniques.

II. Flaw Detection using Morphological Edge based Segmentation Techniques [2]

In this method first the flaw boundaries are determined by applying the canny operator [3] after choosing an appropriate threshold value. The boundaries are then fixed using a morphological image processing approach i.e. dilating few similar boundaries and eroding some irrelevant boundaries decided on the basis of pixel characteristics. The flaws detected by this approach are categorized according to their properties.

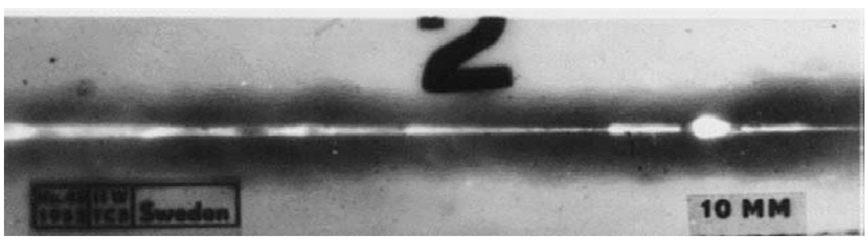

Fig1. Original image

Fig. 2. Binary gradient mask of the original image [2]

Fig. 3.Dilated image of Binary gradient mask of the original image

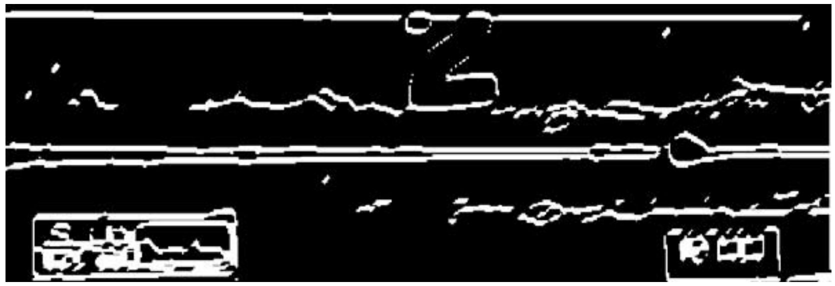

Fig. 4. Segmented images

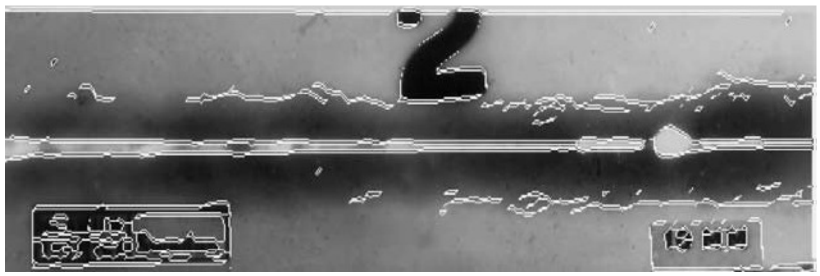

Fig. 5. Superimposition of the segmented image on the original image.

2.1 Advantages

This technique gives good result for Slag Inclusion, Worm hole ,porosity(in case of big pores),best result in case of Incomplete penetration .Lack of Fusion are identified. Weaving Faults are identified very clearly. Slag lines are identified. It gives good result in slag inclusion

2.2 Disadvantages

This technique lacks in formation of close contour. In case of worm hole shape of wormhole is not properly given. Small porosity holes are identified but with many extra features. Undercuts are not properly identified, many extra edges are obtained. Some information regarding Lack of Fusion is missing. In case of Weaving Fault some information is missing at the corner of the image. Along with Slag Line few other edges are identified.

III. FLAW DETECTION USING REGION GROWING SEGMENTATION [4]

Using Region growing method we merge the adjacent detected pixels on homogeneity criteria to obtain flaws. Region starts with seeds. The seed value is determined with help of histogram analysis [5].The peaks and valleys of histogram help in determining the seed value.

Fig.1 shows a radiographic image of weldments having incomplete penetration. Flaws are clearly identifiable after the application of algorithm .The segmented image, depicting the flaws is shown in Fig. 2.

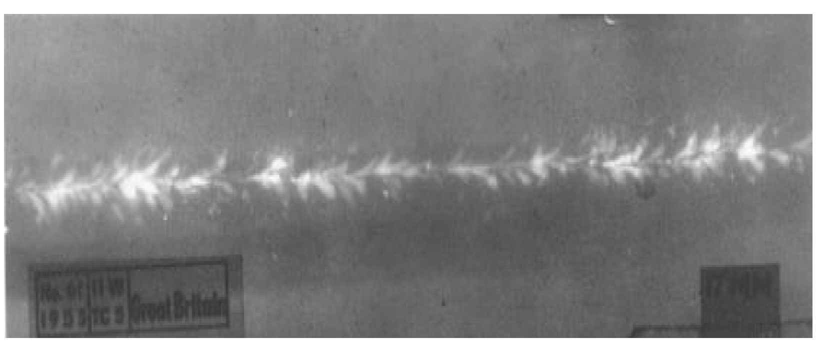

Fig. 6 Original X-Ray image having Gas- cavity (worm hole) type flaws

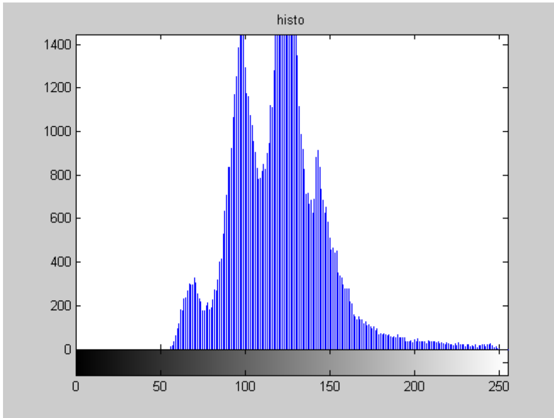

fig.7 Histogram of fig.6

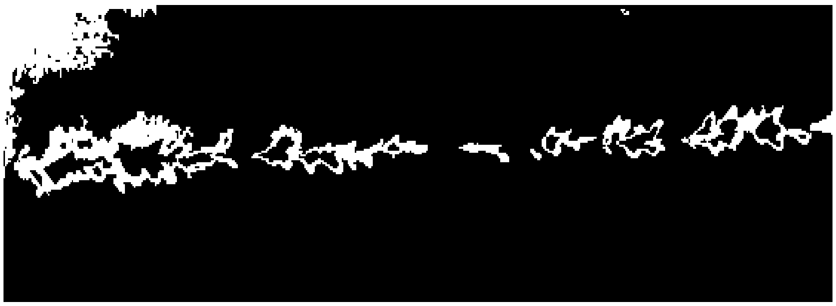

Fig. 8 Segmented images after region growing on image of Fig.6

3.1 Advantages

Worm Hole identifies the flaws with proper shape, helpful in more accurate determination of dimension. It gives good result in case of big porosity. Incomplete penetration flaws identified. Undercuts flaws are identified, gives best result.

3.2 Disadvantages

Slag Inclusion is not identified they results in over segmentation or loss of information. Small pores are not identified. Cracks are not identified. Weaving Fault and Slag line are identified but results in over segmentation. One more disadvantage is, limitation of this algorithm is that the threshold value has to be judged by expert, based on histogram of the image.

IV. Flaw detection using Morphological Watershed Segmentation Techniques [6]

The steps involved for the process are given in diagram shown below.

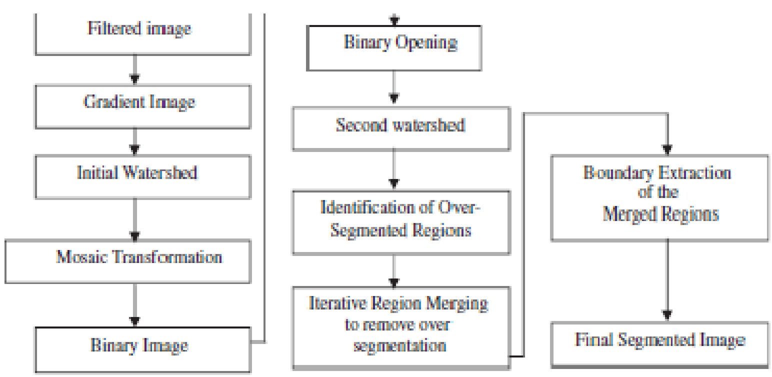

Fig 9.proposed multi-stage watershed segmentation approach

The basic concept of watershed is based on visualizing an image in three dimensions [7] i.e. two spatial coordinates versus gray levels. In such a topographic interpretation, three types of points are considered, such as,
(a) Points belonging to a regional minimum
(b) Points at which a drop of water, if placed at the location of any of those points, would fall with certainty to a single minimum; and
(c) Points at which water would be equally likely to fall to more than one such minimum.
For a particular regional minimum the set of points satisfying condition (b) are called catchment basin or watershed of that minimum. The points satisfying condition (c) form crest line on the topographic surface and are termed as watershed lines or divide lines.
In this process, pre- processed filtered weld image is used to reduce the noise level efficiently. The smoothed image is used for gradient calculation. Any one gradient operator like Sobel, Prewitt or Gaussian derivative is used in this segmentation. Since the noise level is efficiently reduced by filtering, these operators perform well on filtered images .Initial Watershed segmentation transformation gives many small homogeneous regions that result in over segmentation or undesired small regions in homogeneous regions. The watershed transform applied on another level, will help to merge the fragmented regions. The boundaries produced by the segmentation at this stage do not have same weight. Those, which are inside the homogeneous region, are weaker. In order to compare these boundaries, the neighborhood relation between them is used, which is built on the basis of connectivity graph from partitioned or mosaic image. Mosaic image is compared by assigning the average of pixel to each corresponding region, resulting from watershed image.
The mosaic image pattern is further thresholded by Otsu's thresholding [7] method and converted in to the binary image. Binary image morphology and watershed top hat transformation is used to find the bright objects. It finds peaks in the image function that differ from local background. Watershed segmentation takes account of sources of information and supersedes the top- hat method [8].
Second Watershed separates partially overlapping objects. With the help of morphological opening small objects are removed. The separation of small objects is followed by removal of sporadic variations along the object edge. The Euclidean distance map (EDM) of the resulting image is calculated. At the location of overlap in the binary image, the inverse EDM has a ridge where the two catchment basins of each overlapping objects meet. Therefore, each basin is labeled uniquely and ridge separating them as watershed.
The resulting watershed labeled image is marked by the binary morphological eroded image to match the object and background boundaries and to overcome false separation of the overlapping regions. The marked image gives the region shape with the clue of false separation boundaries. From this resulting image, the region properties are calculated for designing estimation criteria of region merging post processing. Region merging post processing is used to compensate over segmentation problem. The following images shows the process discuss above.

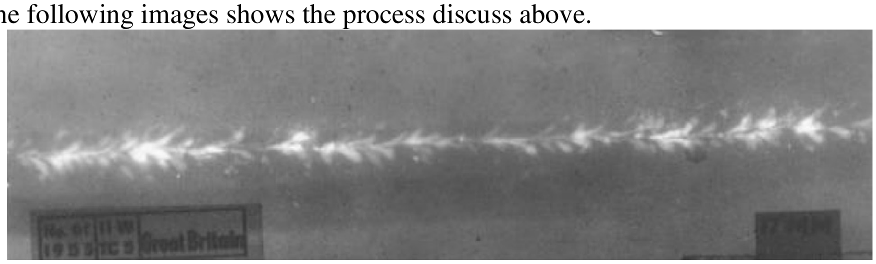

Fig10. Filtered and gradient X-ray weldment image showing wormhole-type gas cavities

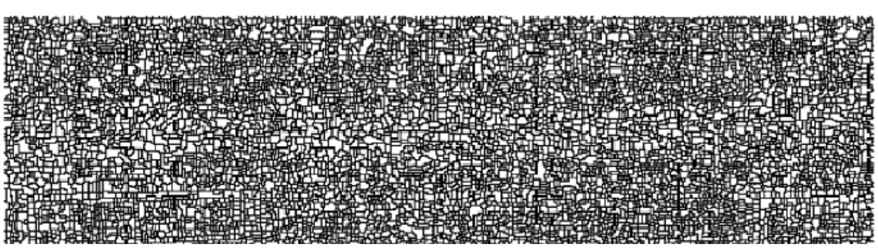

Fig. 11. Initial watershed-transformed mosaic image of gradient image

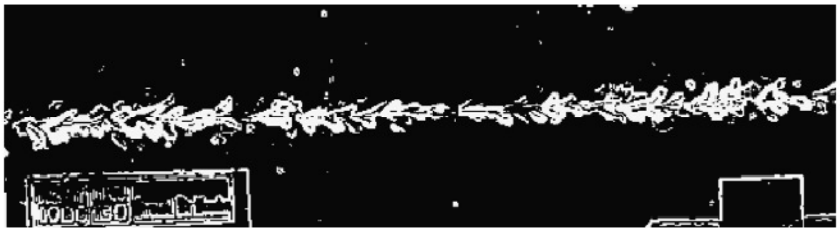

Fig. 12. Binary image of Fig.4

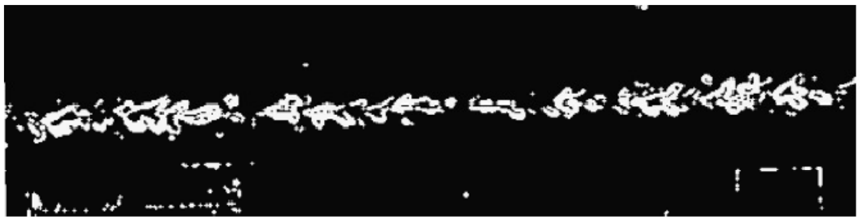

Fig. 13. Opening of image (removal of extraneous region)

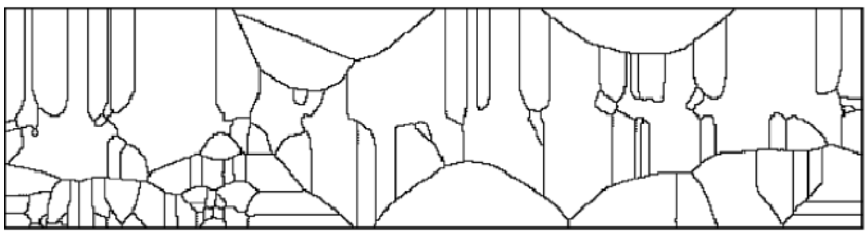

Fig. 14. Second watershed segmentation to obtain better result of flaw

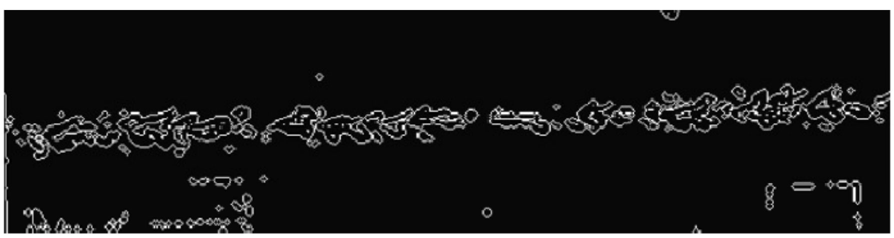

Fig.15. Boundary extraction of the merged region of second watershed segmentation.

4.1 ***Advantages***

a. Slag Inclusion: Flaws identified properly and clearly. Best suited.
b. Worm Hole: Flaw identified with less distortion, shape and size properly given, best results.
c. Porosity: Small pores clearly identified with proper boundaries. Cracks identified in few cases.
d. Lack of fusion: Flaw completely detectable, best results, all details are present.
e. Weaving fault: Flaw is identified clearly in most of the cases, more details available, best results. Slag line: Flaw is identified clearly, best suited.

4.2 Disadvantages

a. Porosity: Boundary of big pores are not identified clearly.
b. Incomplete penetration: Flaw information missing, over segmentation.
c. Undercuts: Flaws not properly identified, over segmentation.
d. Cracks: are not identified in some cases.

V. RECOGNITION OF WELDING DEFECTS IN RADIOGRAPHIC IMAGES BY USING SUPPORT VECTOR MACHINE CLASSIFIER [9]

A Support vector or Machine Classifier

An automatic computer-aided detection system based on Support Vector Machine (SVM)[10] is implemented to detect welding defects in radiographic images. After extracting potential defects, two group features: texture features and morphological features are extracted. Afterwards SVM criteria and receiver operating characteristic curves are used to select features. Then Top 16 best features are used as inputs to a design SVM classifier.

SVM is based on the structural risk minimization principle from computational learning theory, or better, and on minimization of the misclassification probability of unseen patterns with an unknown probability distribution of data.

In its simplest, linear form, an SVM is a hyperplane that separates the data maximizing the distance between the hyperplane and the closest points of the training set. Using a Lagrange function, the optimal hyperplane can be represented by a classifier function given by equation[11].

$$\text{f(x)=sgn}\left(\sum_{x_i \in SVS} a_i y_i k(x_i, x) + b\right) \tag{1}$$

$$\text{b=}-\frac{1}{2}\sum_{x_i SVS} a_i y_i \left[K(x_r, x_j) + k(x_s, x_i)\right] \tag{2}$$

where x_i is the i^{th} training example and y_i is the correct output of the SVM for the i^{th} training example. x_r is any support vector from positive examples and x_s is any support vector from negative examples. K(x_i,x_j) is a kernel function to construct a mapping into a high dimensional feature space and to enable operations to be performed in the input space rather than the potentially high dimensional feature space. Some of the commonly used kernels include Linear, Gaussian RBF (Radial Basis Functions), polynomial functions, and sigmoid polynomials. Usually an RBF kernel is favored, because they are not sensitive to outliers and do not require inputs to have equal variances. So, Gaussian RBF kernel function is choose. Platt [12] developed a fast algorithm for training a SVM called Sequential Minimal Optimization (SMO), which made it possible for PC users to practice complex applications.

5.1 ***SVM based feature selection:***

In order to improve the prediction performance of the predictors and providing faster and more cost-effective predictors, an SVM-based feature selection algorithm is applied. However, this algorithm relies on a backward feature selection, which is computationally tractable but not necessarily optimal. The performance of the feature selection is improved by combining result. SVM-based feature selection with a Receiver Operation Characteristic (ROC) feature selection process.

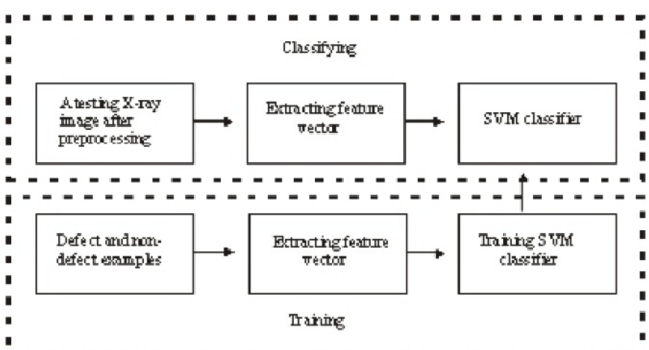

Fig 16. The procedure of training and classifying

The SVM is provided with many statistics that allow one to estimate their generalization performance from bounds on the leave-one-out error, *L*. The leave-one-out error is the number of classification errors produced by the leave-one-out procedure which consists in learning a decision function from *m-1* examples, testing the remaining one and repeating until all elements served as a test example. The leave-one-out error is known to be an unbiased estimator of the generalization performance of a classifier trained on *m-1* examples. One of the most common *L* error bounds for SVM is the

radius/margin bound (for a decision function with non-zero bias *b*). The ROC analysis is commonly used to measure the performance of a two-class classification. In our case, each feature is analyzed independently using a threshold classifier. In this way, a hypothetical flaw is classified as a 'no-defect' (or 'defect') if the value of the feature is below (or above) a threshold value.
Following images shows the difference between the original and segmented image after applying svm.

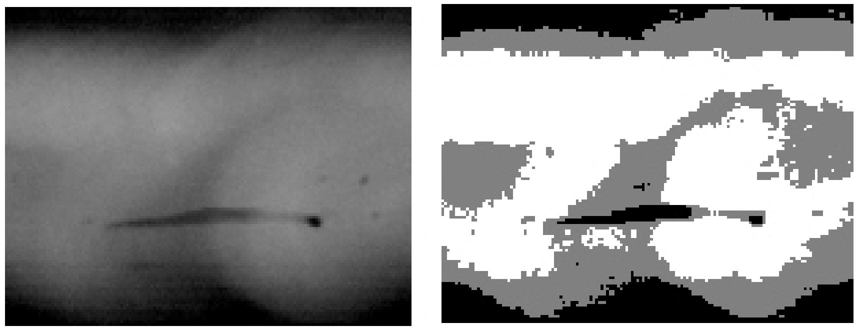

Fig 17. Original image Image after segmentation

5.2 Advantages
Using SVM most of the flaws are detected i.e. The method has detected and discriminated defects such as worm holes, porosity, linear slag inclusion, gas pores, and lack of fusion or crack.
5.3 Disadvantages
But the technique has not been able to focus on incomplete penetration and other type of flaws. This algorithm relies on backward feature selection, but it is not necessarily optimal. Also this method requires complex implementation and also time consuming.

VI. ANALYSIS AND INTERPRETATION OF WELD FLAWS USING ANN:[13]

The procedure to detect all the types of flaws and feature extraction is implemented by segmentation algorithm which can overcome computer complexity problem. And classification carried out by Counter propagation Neural Network. Features are important for measuring parameters which leads in directional to understand image.

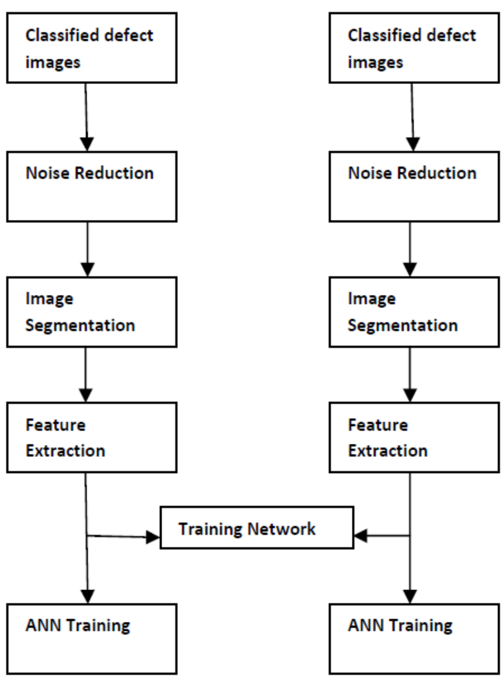

Fig 18. General process flow of radiograph based automated weld defect recognition system

6.1 Conventional CPN

The CPN neural network is a hybrid neural network which employs both the supervised and unsupervised training methodologies. It consists of the input Kohonen layer which uses the "winner take-all" strategy and the output Grossberg layer which uses the error signal for weight adjustment. The error signal is used to update only the output layer weights. Thus, this network is named as Counter Propagation Neural Network to show that it is contrary to the conventional BPN.[14].
A CPN consists of three layers: the input layer,the competition and the output layer.

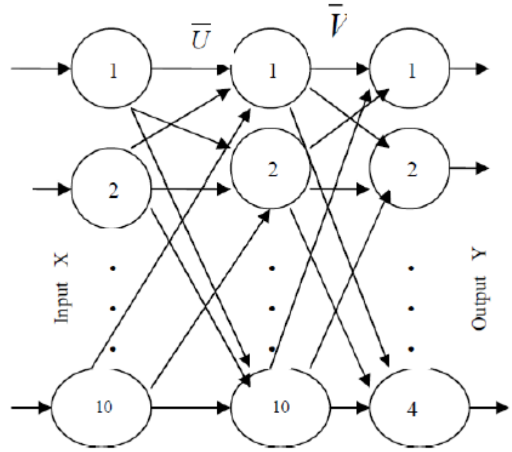

Fig19. CPN Layers

6.1 Advantage

The flaws such as Slag Inclusion, Incomplete Pentration, Lack of Fusion, and Slag Line are detected, best results.
The flaws such as Porosity, Cracks, and Weaving Fault are detected, good results.

6.2 Disadvantages

The flaws, Wormhole and Undercuts didn't show good results. It involves lots of complex calculations and time consuming.

VII. CONCLUSION

It has been observed that edge based segmentation is successful on few types of flaws like slag inclusion, incomplete penetration and transverse cracks. While region growing approach provides best results for lack of root penetration, undercuts and gas cavities, the watershed segmentation technique, on the other hand gives best results for wormhole type gas cavities, lack of fusion, slag inclusion and slag line. In the case of multiple flaws, individual types of flaws are successfully determined by specific segmentation technique only.SVM and ANN is very impressive, however this method requires complex implementations and are time consuming.

REFERENCES

[1] Gunn, S.R., 1997. Support vector machines for classification and regression. Technical report image speech and intelligent group Southampton University, Southampton, UK
[2] Platt J.C 1998. Sequential minimal optimization :A fast algorithm for training support vector machines .Technical report
[3] Vijay R. Rathod R.S. Anand Alaknanda, "Interpretation of Weld Flaws Using ANN"
[4] T.C.Liu,et al,"A new ART-counter propagation neural network for solving forecasting problem" *Expert Systems* with Applications 28(2005) 21-27
[5] Y. Boykov and V. Kolmogorov. An experimental comparison of mincut / max-flow algorithms for energy minimization in vision. *submitted IEEE Trans. Pattern Anal. and Machine Intell.*, 2004
[6] Alaknandaa, R.S. Ananda,, Pradeep Kumar," Flaw detection radiographic weld images using morphological approach" NDT&E International 39 (2006) 29–33
[7] John Canny. A computational approach to edge detection. Pattern Analysis and Machine Intelligence, IEEE Transactions on, PAMI-8(6):679–698, Nov. 1986

[8] Vijay Rathod," Flaws Detection Using Region Growing Segmentation Technique In Weldment Images"
[9] H. Jiang, J.Toriwaki and H.Suzuki "comper performance evaluation of segmentation method based on region growing and division" Sys. Compute. Jpn,Vol24,No 13, pp28-42,1993
[10] Alaknanda a, R.S. Anand a, Pradeep Kumar b" Flawdetection in radiographic weldment images using morphological watershed segmentation technique" journal homepage:www.elsevier.com/locate/ndtent
[11] Vincent L, Soille P. Watersheds in digital spaces: an efficient algorithm based on immersion simulations. IEEE Trans Pattern Anal Mach Intell 1991;13(5):583–98
[12]] Otsu N. A threshold selection method from gray-level histograms. IEEE Trans Syst Man Cybern 1979;9(1):62–6.
[13] Sonka M, Lavac VH, Bolye R. Image processing, analysis and machine vision. 2nd ed. London and New York: Chapman & Hall; 2003
[14]] Xin Wang, Brian Stephen Wong and Ching Seong Tan," Recognition of Welding Defects in Radiographic Images by Using Support Vector Machine Classifier" Research Journal of Applied Sciences, Engineering and Technology 2(3): 295-301, 2010.
[15] Boster B.I. Guyon and V. Vapnik ,1992.A training algorithm for Optial margin classifiers.Proccedings of the fifth annual ACM workshop on Computational Learning Theory ,Pittsburg,USA,pp:144152

Authors Biography

Sangita Dubey has received B.E. in Instrumentation Engineering from Vidyavardhini's College of Engineering (VASAI) in 1999, .She has teaching experience of around 12 years. Presently she is working as Assistant Professor in St.Gonsalo Garcia College Vasai. She is currently pursuing M.E. (Electronics and Telecommunications) in Thakur College of Engineering and Technology Mumbai University, Kandivli (E), Mumbai, INDIA. Her areas of interest are Mathematics and Image Processing.

Kamal Shah has received B.E. in Electrical Engineering from Regional College of Engineering (REC-Surat) in 1996, M.E (Electronics and Telecommunication) from Mumbai University in 2005.She has teaching experience of around 13 years. Presently she is working as Dean R&D, Professor It department . Her areas of interest are Digital Signal processing, Image Processing and Computer vision. She has 18 papers in National / International Conferences / International Journals to her credit. She is a member of various professional bodies like ISTE,IETE etc.

.