Growing Self Organized Maps for Radiographic Non Destructive Testing of Metallic Products

Sarin CR, Manu R Krishnan

***Abstract:** Manual inspection of metallic products can only be a time-consuming and is less reliable to find microscopic and internal defects, therefore is an expensive task; it can also suffer from operator performance. The proposed system apply image processing techniques to automatically inspect radiographic images and evaluate the data to find faults and is based on Improved Growing Self organized Maps Segmentation. The number of false detections is still high and will be addressed in future research. Monitoring the defect or damage at an early stage is a very important as it allows to implement operations to classify and correct defects and improves the safety, reliability, accuracy, and high throughput of the structure. This paper presents an improved intelligent methodology for Radiographic automated visual quality inspection and, which provides many advantages over traditional methods. The accuracy of conventional systems is very much depending on the selected features, which are extracted from defect images. Growing Self Organized Maps for Radiographic Non Destructive Testing is an advanced method suitable for crack detection, which gives a smoothed image to obtain uniform brightness, followed by removing isolated points to remove noise and morphological operations with fast operation.*

***Index Terms**— Automatic Quality Inspection, GSOM, NDT, Object detection*

I. INTRODUCTION

Quality assurance is the systematic monitoring and evaluation of the various aspects of a product to maximize the probability that the production process is attaining minimum standards of quality. Deviations from the normal quality that impair the operating characteristics of a metal or product and lead to a reduction in grade or to rejection of products should be considered as defects [1]. Imperfections in the manufactured products may build up during smelting of the metal ,production of castings; during pressure treatment or as a result of thermal, chemicothermal, electrochemical, and mechanical treatment and in the process of joining metals like during welding, soldering, riveting, and so on. Metal defects may be local, distributed in limited zones, or distributed throughout the entire volume or surface of a product [2]. They may turn out negatively on various properties such as electrical conductivity, magnetic permeability, strength, density, and plasticity etc.

Due the high expectations of both primary manufacturers and end consumers, defects cannot be tolerated even in million piece quantities with considerable interest in optimum use of materials and cost reduction. The requirement for defect free manufacturing has driven suppliers to seek out cost effective methods of 100% quality. With introduction of Quality and Management Systems to industries has led to major improvements in the reliability of plant as well as their availability, but mainly focused to be as good as the data used as input for these systems [3]. To achieve zero defects ("Zero PPM") output cost-effectively, manufacturers are making the commitment to move to online, automated Non Destructive Testing (NDT) methods. This type of online inspection requires accuracy, reliability, and high throughput. The quality monitored by NDT methods such as chemical, spectral, structural, and metallographic analysis is difficult to be performed in real-time operation [4]. More reliable, thorough monitoring is accomplished through the advanced image processing techniques in NDT by the structural analysis of products. Growing Self Organized Maps for Radiographic Non Destructive Testing

is a very efficient method of structural defect discrimination and lends itself very well to 98% inspection of industrial imperfections.

Automatic defect recognition (ADR) in the case of NDT, especially by Real Time Radioscopy is rapidly become the accepted way for controlling the quality through visual or computer-aided analysis of images automatically [5]. The purpose of this non-destructive testing method is to identify microscopic casting defects and cracks automatically, which may be even internal fault in nature, measure them by intelligent object detection, and feature extraction tools. The AVI is a quality control task to determine automatically whether a casting complies with a given set of product and product safety specifications [6].

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 [7].

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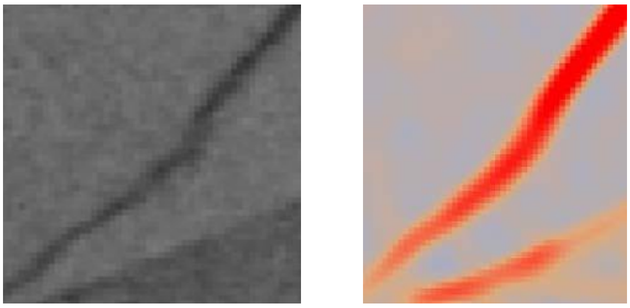
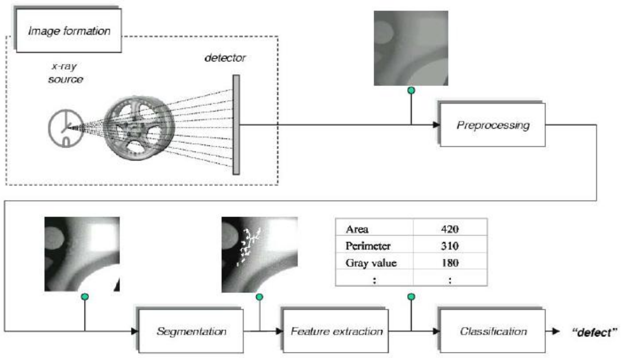


Figure: Voids in radioscopic images of metal wheels and enhanced image of defect.

II. COMPUTER AIDED RADIOGRAPHIC TESTING

The principle aspects of an automated inspection unit are shown in Figure. Typically, it comprises the following five steps [8]:

1. A manipulator for handling the test piece,
2. An source, which irradiates the test piece with a conical beam to generate an image of the test piece,
3. An image intensifier which transforms the invisible image into a visible one,
4. A CCD camera which records the visible image and
5. A computer to process the digital image processing of the image and then classifies the test piece accepting or rejecting it.
6. Programmable controller (PLC) may also control the manipulator for positioning the test piece in the desired inspection position with more precision and accuracy, although a computer normally performs this task.



Detectors made of compound semiconductors such as CdTe and CdZnTe have shown outstanding performance for X and gamma ray spectrometry when operating at room temperature [9].

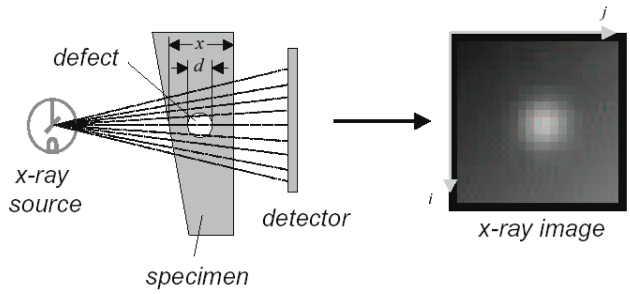
This paper proposes an idea of using intelligent object detection and feature extraction in image processing as a tool in the automated visual inspection and NDT of finished products. The paper introduces the Improved GSOM segmentation based automated visual quality inspection and NDT employed when inspecting metal products.

III. DIGITAL IMAGE PROCESSING IN TESTING

The aim of the Digital image processing system is to recognize the fault and its dimensions and features using artificial intelligent technique. The AI classifies the image obtained from the ITC is processed and pattern reorganization algorithms are executed to get to the classification of elements in image - 'Area with defects' and 'Background' [10-12].

A. Image Formation

The more common way of acquisition is through scanners, which works with light transmission – usually called transparency adapters. The material under test is exposed to radio waves, ITC detectors made of compound semiconductors such as CdTe, and CdZnTe senses the radiation intensity attenuated by the material. Another method also used is image acquisition by camera CCD (Charge Couple Device). A defect in the material modifies the expected radiation received by the sensor. The intensity distribution of is characterized by structural distribution of the product and defects such as voids, cracks or bubbles, show up as bright features which patterns a varying intensity provision image due to low attenuation.



The real-time acquisition of image in matrix representation and the size of the matrix correspond to the resolution of the image. Proposed system resolution is 286 × 384 pixels, each associated a value, usually for gray scale images it is between 0 and 255 for a scale of 28 = 256 gray levels. Here, '0' represents 100% black and a value of '255' corresponds to 100% white, matrix x be the digitized image, then the element x(i,j) denotes the gray value. The eye is only capable of resolving around 40 gray levels, however for the detection of ADC system, 216 = 65,536 gray levels are used, which allows one to evaluate both very dark and very bright regions in the same image increases system performance.

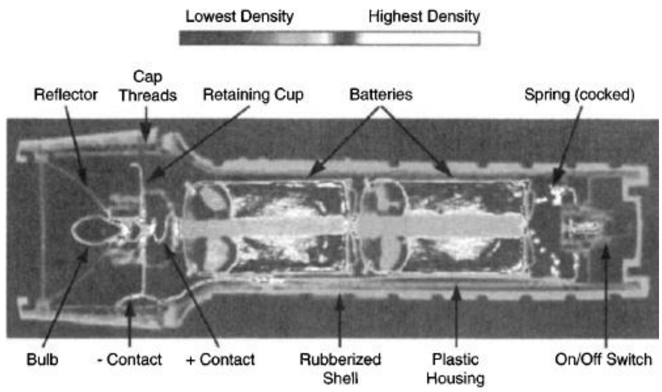


Figure: Differential absorption in a specimen.

B. Preprocessing

The image taken is preprocessed to improve the quality of the image before it is analyzed removes noise, enhanced the contrast, corrected the shading effect and restore blur deformation of images, seeking mainly the attenuation by elimination of noise and contrast improvement.

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C. Noise Removal

Noise follows Poisson law directly which can prove a significant source of image degradation and taken into consideration account during processing and analysis. The standard deviation of this distribution is equal to the square root of the mean. This means that the photon noise amplitude is signal-dependent. Integration removes image noise stationary images modeled using the stationary component and the noise component With a noise component of zero mean, average of the n images the stationary component is unchanged, while the noise pattern decreases by increasing n improves the signal-to-noise ratio by a factor. The larger the number n, the better the improvement, usually there added ($10 \leq n \leq 16$).

D. Contrast Enhancement

Contrast encasement will amplify the differences in the gray levels of the image whose gray values lay in a relatively narrow range of the gray scale. The function summarizes the gray level information of an image as histogram h(x) where x is a gray level and h(x) denotes the number of pixels in the image that have a gray level equal a definite value. Simple contrast enhancement can be achieved if we use a linear transformation which sets the minimal and maximal gray values of the image to the minimal and maximal gray value of the gray level scale respectively, the gray levels expand from '0' to '255'.The nonlinear transformation is usually performed with a γ-correction so that $\gamma > 1$ the mapping is weighted toward darker output values, and $\gamma < 1$ the mapping is weighted toward brighter output values.

Shading Correction

A decrease in the angular intensity in the projection causes low spatial frequency variations in Since the plate is of a constant thickness, we would expect to see a constant gray value for the metal part and another constant gray value for the holes, can be overcome by using linear shading correction[13].

Input image x(i,j) will be linear transformed according to

$$y(i,j) = a(i,j)\, x(i,j) + b(i,j)$$

The coefficients a(i,j) and b(i,j) are estimated by analyzing two real images r1(i,j) and r2(i,j) and the corresponding ideal images i1(i,j) and i2(i,j)

$$ik(i,j) = a(i,j)\, rk(i,j) + b(i,j) \text{ for } k = 1,2,3\ldots\ldots$$

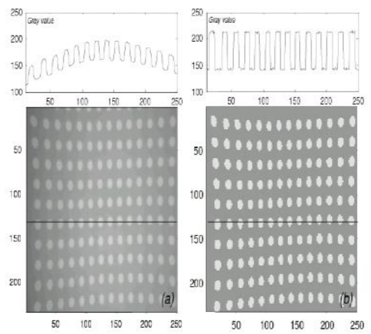
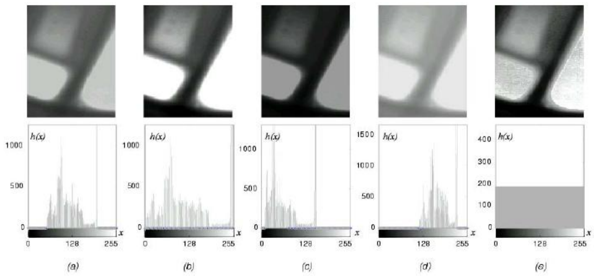


Figure: Shading Correction

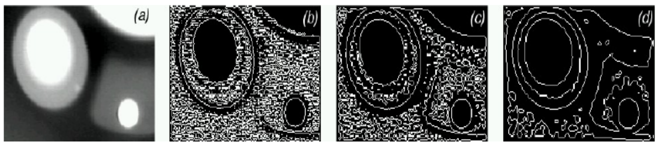
E. Restoration of blur caused by motion

Recovering detail in severely blurred images for known a-priori images exist as an analytical model, or as a-priori information in conjunction with knowledge (or assumptions) of the physical system that provided the imaging to estimate the best source image, where there given the blurred example and some a-priori knowledge. The blur caused by uniform linear motion is removed by assuming that the linear motion corresponds to an integer number of pixels and is horizontally (or vertically) aligned with sampling raster. In these examples, the details of the metal castings are not discernable in the degraded images, but are recovered in the restored image.



F. Segmentation

Image segmentation is defined as the process of subdividing an image into disjointed regions. In image processing for detecting faults in castings, such regions correspond to potential defects and the background (or regular structures). While there are many methods for segmenting images, two approaches for segmenting potential defects in images are used widely within the nondestructive testing community. The first technique is based on median filtering while the second is a region-oriented method [12]. Here the system uses a GSOM Artificial neural networks which is a mode of adaptive system which automatically detect pixels to be segmented.



G. Edge Detection and Region Finding

This approach attempts to detect the potential defects in an image in two steps: edge detection and region finding .In edge detection, the edges of the image are detected, correspond to pixels of the image in which the gray level changes significantly over a short distance. The edges are normally detected using gradient operators. In the second step, the regions demarcated by the edges are extracted. The key idea of region finding two step-based approach is that regions demarcated by the edges are extracted by the existing defects with present significant gray level changes compared to their surroundings. A Laplacian of Gaussian (LoG) kernel and a zero crossing algorithm can be used to detect the edges of the images. The LoG-operator involves a Gaussian low pass filter, which is good for the pre-smoothing of the noisy images. The LoG-kernel depends on parameter σ, which defines the width of the Gaussian function and, thus, the amount of smoothing and the edges detected using the LoG-kernel we calculate an image in which the edges of the original image are located by their zero crossing. The detected edges correspond to the maximal (or minimal) values of the gradient image.

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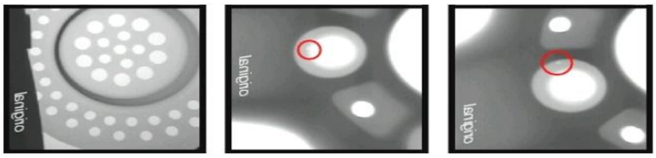
The binary edge image obtained should reproduce real flaws' closed and connected contours that demarcate regions

H. Feature extraction and selection

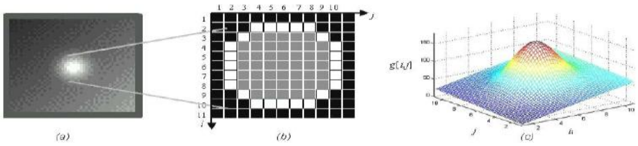
An analysis of the segmented regions, however, can improve the effectiveness of fault detection significantly by measuring certain characteristics of the segmented regions (feature extraction) can help us to distinguish the defects, although some of the extracted features are either irrelevant or are not correlated. Therefore, a feature selection must be performed. Depending on the values returned for the selected features, there classified each segmented region in one of the following two classes: 'regular structure' or 'defect'.



Feature extraction

Features that are normally used in the classification of potential defects, usually divided into two groups: geometric and gray value features. Geometric features provide information about the size and the shape of the segmented potential flaw. The extracted geometric features can be: area, perimeter, height, width, roundness, Hu invariant moments, Flusser and Suk invariant moments, Fourier descriptors, semi-minor and semi-major axis of ellipse fitted to the contour of the potential flaw, and Danielson shape factor.

The gray value features provide information on the brightness of the segmented potential flaw where the extracted features are: mean gray value, mean gradient in the boundary, mean second derivate in the region, radiographic contrasts, contrasts based on crossing line profiles, invariant moments with gray value information, local variance, mean and range of the Haralick textural features (angular second moment, contrast, correlation, sum of squares, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation and maximal correlation coefficient) based on the co-occurrence matrix in four different directions taken neighboring pixels separated by several distances, and components of the discrete Fourier transform, the Karhunen Loève transform and the discrete cosine transform taken from a window including potential flaw and neighborhood [13].



Feature selection

In feature selection, we have to decide just which features of the regions are relevant to the classification so that n extracted features are arranged in an n -vector that can be viewed as a point in an n-dimensional space. In addition, each feature can be considered as a random variable with no samples. Each variable is normalized in order to obtain a zero mean and a standard deviation equal to one.

The key idea of the feature selection is to select a subset of m features (m < n) that leads to the smallest classification error with selected m features are arranged in a new m -vector. The selection of the features can be done using Sequential Forward Selection, which selects the best single feature and then adds one feature at a time that, in combination with the selected features, maximizes classification performance so that iteration is stopped once no considerable improvement in the performance is achieved on adding a new feature. By evaluating selection performance, we ensure:

I. A small infraclass variation and
II. A large interclass variation in the space of the selected features.

For the first condition the infraclass-covariance matrix is used, and for the second the covariance matrix of each class. The best features that separate the classes 'defects' and 'regular structures' are related to the contrast

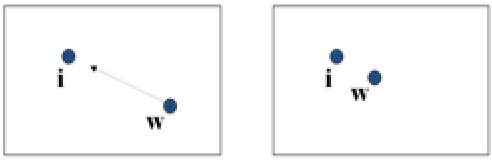
IV. GROWING SELF-ORGANIZING MAP (SOM)

A SOM or self-organizing feature map (SOFM) is a data visualization technique invented by Professor Teuvo Kohonen, which reduces the dimensions of data using self-organizing neural networks, and used to interpret large high-dimensional data sets. It is a type of artificial neural network that is trained using unsupervised learning to produce a low dimensional (typically two-dimensional), discredited representation of the input space of the training samples, called a map [14-16]. Self-organizing maps are different from other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space. It gives a low dimensional address of high dimensional datas, since most useful in higher dimensional modeling in image processing systems. The term higher dimensions can also be used to approach N number of parameters. Kohonen's SOM is also called a topology-preserving map because there is a topological structure imposed on the nodes in the network. A topological map is simply a mapping that preserves neighborhood relations. It belongs to the category of competitive learning networks. The Self-Organizing Map is based on unsupervised learning, which means that no human intervention is needed during the learning and those little needs to be known about the characteristics of the input data The SOM can be used to detect features inherent to the problem and thus has been called SOFM, the Self-Organizing Feature Map.

A SOM does not need a target output to be specified unlike many other types of network. Instead, where the node weights match the input vector, that area of the lattice is selectively optimized to more closely resemble the data for the class the input vector is a member from an initial distribution of random weights, and over much iteration, the SOM eventually settles into a map of stable zones. Each zone is effectively a feature classifier, so you can think of the graphical output as a type of feature map of the input space. Any new, previously unseen input vectors presented to the network will stimulate nodes in the zone with similar weight vectors This has the same dimension as the input vectors (n -dimensional).

A neighborhood relation connects the neurons to adjacent neurons.

This dictates the topology, or the structure, of the map. Usually, the neurons are connected to each other via rectangular or hexagonal topology.



Before learning *After learning*

The growing self-organizing map (GSOM) is a variation of the popular self-organizing map (SOM). It was developed to address the issue of identifying a suitable size of the SOM, which is usually concerned with vectorial items [17-18].

To deal with algorisms implemented as programs, which are hardly represented by vectors, a new version of GSOM is proposed here. This novel algorithm incorporates randomness into the self-organizing process to produce higher quality clusters within few epochs and utilizing smaller neighborhood sizes resulting in a significant reduction in overall processing time.

Growing self-organizing map (GSOM) is an extension of SOM . GSOM is a dynamic SOM, which overcomes the weakness of a static map structure of SOM. Both SOM and GSOM are used for clustering high-dimensional data. This is achieved by projecting the high-dimensional data onto a two- or three-dimensional feature map with lattice structure where every point of interest in the lattice represents a neuron or a node in the map. The mapping preserves the data topology, so that similar samples can be found close to each other on the 2D/3D feature map.

Like most artificial neural networks, GSOMs operate in two modes: training and mapping. Training builds the map using input examples. It is a competitive process, also called vector quantization. Mapping automatically classifies a new input vector. It provides a topology-preserving mapping from the high dimensional space to map units. Map units, or neurons, usually form a two-dimensional lattice and thus the mapping is a mapping from high dimensional space onto a plane. The property of topology preserving means that the mapping preserves the relative distance between the points. Points that are near each other in the input space are mapped to nearby map units in the GSOM. The GSOM can thus serve as a cluster-analyzing tool of high-dimensional data. In addition to that, the GSOM has the capability to generalize. Generalization capability means that the network can recognize or characterize inputs it has never encountered before. A new input is assimilated with the map unit it is mapped to

The GSOM training consists of three phases: initialization phase, growing phase, and smoothing phase.

The initialization is crucial to achieve a quality-clustering result. The following parameters are determined in this phase:

I. The map topology (either rectangular or hexagonal);
II. The number of nodes which is the resolution of the map;
III. The weight vector initialization of nodes;
IV. The width/height (or aspect) ratio of the map.

V. MOTIVATION TO PROPOSED WORK

One major problem with SOMs is getting the right data. Unfortunately, you need a value for each dimension of each member of samples in order to generate a map. Sometimes this simply is not possible and often it is very difficult to acquire all of this data so this is a limiting feature to the use of SOMs often referred to as missing data.

Another problem is that every SOM is different and finds different similarities among the sample vectors. SOMs organize sample data so that in the final product, the samples are usually surrounded by similar samples; however, similar samples are not always near each other. If you have many shades of purple, not always will you get one big group with all the purples in that cluster, sometimes the clusters will be split and there will be two groups of purple. Using colors, we could tell that those two groups in reality are similar and that they just was split, but with most data, those two clusters will look totally unrelated. Therefore, many maps need to be constructed in order to get one final good map.

Moreover, it is a time consuming algorithm because as the no. of neurons affects the performance of the algorithm and as the number increases the computation increases, which results in increasing computational time. The basic performance of the SOM considerable depends on the initialization of parameters. It takes more iteration to obtain required optimized output for wrong initialization.

Many of the above problems can be eliminated by using an improved SOM algorithm, which is derived to select a particular random variable by intelligent decision-making and uses Mahalanobis distance based on correlations between variables by which different patterns can be identified and analyzed. It gauges similarity of an unknown sample set to a known one. It differs from Euclidean distance in that it takes into account the correlations of the data set and is scale-invariant. In other words, it is a multivariate effect size. Thus instead of using a common mode of operation for a number of operations, they uses an advanced system of algorithm which will adapt to a new value in each iteration of operation.

VI. RELATED WORKS

There are implemented many improved versions of SOM algorithm in order to obtain better performance and fast operation. Many of these systems are capable of overcoming many drawbacks of conventional SOM algorithms, which helped to reduce complexity and increased the performance. Odin Taylor, John Tait and John Maclntyre(2006) added the improvements and modifications to Conventional Self Organizing Map algorithm in order to increase its throughput to handle high dimensional data at a speed suitable for Network Intrusion Detection purposes. Stefano Zanero(2003) proposed a new system of improved SOM algorithm to obtain a network-based, anomaly based intrusion detection system, which uses unsupervised learning algorithms.

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Y. Han and Y. H. Song(2003). Used a improved self-organizing map for partial discharge diagnosis of large turbo generators. J. Z. Lei and A. Ghorbani proposed one of the advanced systems for Network intrusion detection using an improved competitive learning neural network in 2004. H. Moradkhani, K. Hsu, H. V. Gupta, and S. Sorooshian increased the performance by a new mode of SOM algorithm for analysis of stream flow forecasting using self-organizing radial basis function artificial neural networks. Most of the above methods use reduction of iteration rather than intelligent weight selection

VII. IMPROVED GSOM ALGORITHM

The GSOM process is as follows:

A. Initialization phase:

1. Assume output nodes are connected in an array (usually 1 or 2 dimensional).Assume that the network is fully connected - all nodes in input layer are connected to all nodes in output layer.
2. Initialize the weight vectors of the starting nodes with random numbers between 0 and 1.
3. Calculate the growth threshold (GT) for the given data set of dimension D according to the spread factor (SF) using the formula

GT= -Dln(SF)

B. Growing Phase:

1. Let W0 be the initial input.
2. Determine the weight vector that is closest to the input vector using Mahalanobis distance criterion. This step can be summarized as:
3. αk and X1 which is an initial approximation of Xk; where The maximum number of iterations J
4. For i = 1, 2, …… to J do
5. Compute Vi that corresponds to the largest eigenvalue li of matrix Δf(Xi, Xk);
6. If li < Xi" then break (converged); Else continue
7. Let the search direction be ci = vi viT > i 5 − Xi;
8. For selected cases with ci>0 is defined as
9. Xi= $\left\{\begin{array}{ll} (C-1)hi & \text{if intercept is included} \\ C\ hi & \text{Otherwise} \end{array}\right.$
10. For unselected cases with ci>0
11. Xi = $\left\{\begin{array}{ll} (C+1)hi & \text{if intercept is included} \\ C\ hi & \text{Otherwise} \end{array}\right.$
12. Set Xi+1 = Xi + αpi. Here α is found by line search;
13. Repeat iteration for each Xk = Xi. To maximum J limit
14. The weight vector adaptation is applied only to the neighborhood of the winner and the winner itself.
15. The nearest neighbor, which is closest to the selected neighbor, is taken.
16. Initialize the winner with corrected value for freed loop

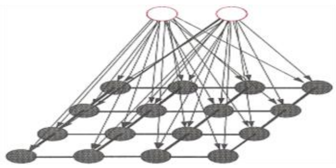
$$\Delta w_{ij} = \Delta w_{ij} + \prod \Delta w_{ij}$$

Determine the "winning" output node i, where Wi is the weight vector connecting the inputs to output node i. Note: the above equation is equivalent to Wi x >= wk x only if the weights are normalized.

17. Initialize the new node weight vectors to match the neighboring node weights.
18. Initialize the learning rate (LR) to its starting value.
19. Repeat steps 2 – 9until all inputs have been presented and node growth is reduced to a minimum level.

C. Smoothing phase.

1. Reduce learning rate and fix a small starting neighborhood.
2. Find winner and adapt the weights of the winner and neighbors in the same way as in growing phase



VIII. CLASSIFICATION

Once the proper features are selected, a classifier can be designed which typically assigns a feature vector to one of the two classes: 'regular structure' or 'defect', that are assigned ‘0’ and ‘1’, respectively. In statistical pattern recognition, classification is performed using the concept of similarity: patterns that are similar are assigned to the same class though this approach is very simple, a good metric defining the similarity must be established. Using a representative sample, we can make a supervised classification finding a discriminate function that provides us information on how similar a feature vector is to the feature vector of a class [19].

IX. CONCLUSION

The importance of quality control and nondestructive inspection are known-well for industrial applications because of safety, very high cost and complexity of manufacturing technology as well as time-cost. One of the biggest difficulties in NDT of these structures are time-cost and high quality control requirements which are achieved in an improved by using the GSOM based automated visual quality inspection and NDT technique. The developed high-efficient automated scanning imaging technique realizes a fast NDT for the metallic structures, which gives an advanced radiographic scan imaging technique by employing a novel radiographic matrix up to 20 transducer (SITC) elements, and is developed to provide a multiple channels scanning for even large-scale complex structures. The method was tested on a set of radiographic images with known defects and was able to detect all defects. Each transducer (SITC) element in the matrix can independently and self-adapted to follow the structures to be tested during automated scanning with the help of preprogrammed reliable control system. The scanning area is extended up to 6000mm in width, and unlimited in length. The practical and industrial applications have demonstrated the powerful ability and flexibility as well as high-efficiency in the NDT of large-scale metallic structures. The inspection efficiency is increased up to 15-20 times compare conventional radiographic scanning technique.

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