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Robust Gnome Percolation Model Segmentation for Automatic Visual Quality Inspection and NDT

Sarin CR*
Department of Mechatronics Engineering
Karpagam College of Engineering
Coimbatore, India
crsarin@gmail.com

Santhosh Krishnan
Department of Mechatronics Engineering
Karpagam College of Engineering
Coimbatore, India
santhoshavsk@gmail.com

Ajai M
Department of Industrial Refrigeration & Cryogenics
TKM College of Engineering
Kollam,India
ajaitkm@gmail.com

Prof P Subramnium ME (Phd)
Professor Department of Mechatronics Engineering
Karpagam College of Engineering
Coimbatore, India
psm_leo55@yahoo.co.in

Abstract: Quality assurance is the systematic monitoring and evaluation of the various aspects of a product to maximize the probability that minimum standards of quality are being attained by the production process. 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. To achieve zero defects ("Zero PPM") output cost-effectively, manufacturers are making the commitment to move to online, automated Non Destructive Testing (NDT) methods. The proposed NDT method is to identify microscopic casting defects and cracks automatically, which may be even internal fault in nature and measure them by intelligent object detection and feature extraction tools. The paper introduces the Gnome Percolation Model based automated visual quality inspection and NDT employed using intelligent object detection and feature extraction in image processing as a tool in the automated visual inspection and NDT of finished products which have many advantages over existing methods .

Keywords: GNOME; Automatic quality inspection; NDT; Percolation Segmentation

I. INTRODUCTION

Imperfections in the industrial products may build up during manufacturing operations like smelting of the metals and castings; during pressure treatment; 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 [1]. They may turn out negatively on various properties such as electrical conductivity, magnetic permeability, strength, density, and plasticity etc[2].

Successful industries inevitably place great emphasis on managing quality control - carefully planned steps taken to ensure that the products and services offered to their customers are consistent and reliable and truly meet their customers' needs. 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 [3]. Rejected product is expensive for a firm as it has incurred the full costs of production but cannot be sold as the manufacturer does not want its name associated with substandard product. To achieve zero defects ("Zero PPM") output cost-effectively, manufacturers are making the commitment to move to online, automated Non Destructive Testing (NDT) methods [4].

Quality assurance which is a process-driven approach is the process of analyzing, verifying, documenting and archiving or determining whether products or services meet or exceed customer expectations with specific steps to help defining and attaining goals. This process considers design, development, production, and service.

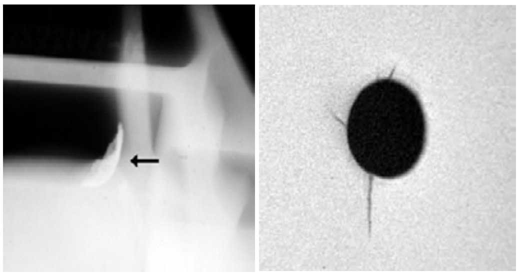

Figure 2: Internal and External Defects

Non Destructive Testing and Evaluation (NDT & E) plays a crucial role in ensuring the reliability and performance of metal components. The NDT methods are able to verify the structural integrity and compliance to the standards by examining the surface and subsurface of the objects as well as the surrounding without disturbing its structural properties and nature [5]. NDE places due emphasis on characterization of microstructures, residual stresses as well as quantitative determination of size, shape, and location of a defect or anomaly. The need for NDT has increased dramatically in recent years for various reasons such as product safety, in-line diagnostics, quality control, health monitoring, and security testing, etc. Besides the practical demands the progress in NDT has a lot to do with its interdisciplinary nature. Automatic defect recognition (ADR), especially by Real Time Radioscopy is still most popular because of its capability, flexibility, and relative cost effectiveness [6-7]. Moreover RNDE can spot out even microscopic internal defects with unsupervised operation to measure them by intelligent object detection and feature extraction tools [8]. The AVI is a quality control task to determine automatically whether a system complies with a given set of product and product safety specifications.

II. CONVENTIONAL STRATEGIES

Computer aided radiographic NDT is still not an approved method for higher quality and microscopic radiologic applications because there are some considerable disadvantages like safety precautions that are required for the safe use of radiation, access to both sides of the specimen are required, orientation of the sample is critical, and determining flaw depth is impossible without additional angled exposures. Due to the possibility of digital manipulation to the captured image, the inherent geometric unsharpness with Parts that are rough, irregular in shape, very small or thin, or not homogeneous are difficult to inspect and resultant lower spatial resolution as compared to film (radiographic) images, SNR (signal vs. noise) issues, sensitivity to scattered radiation, and the general lack of procedural consensus among primes and OEMs.

Digitized radiographic images are often corrupted by non-uniform illumination, contain noise, and have low contrast levels. Imaging plates (IPs) are expensive and can be damaged if the system being used requires manual handling of the IPs. Theoretically, IPs may be reused thousands of times, but constant use will always result in damage to the IP and image artifacts, eventually to the point of necessary replacement [9]. More over conventional Radiographic methods shows less reliability for some materials like polymers, ceramics as a major share of energy absorbed by object or by distributed pollutants. This can be eliminated by compensation factor added during feature extraction.

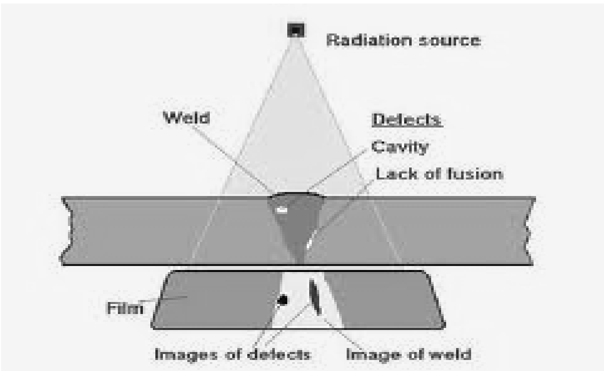

Figure 2: Radiographic Non Destructive Testing

These undesirable factors caused the research of automated defect detection of weld radiograph to focus on pre-processing and defect segmentation and to improve the image quality so that a better visibility of the defects on the image can be produced. The development of CR has brought X-ray imaging to a new era of digital filming as well as inspection. The interpreter no longer needs to place the radiographic film on an illuminator and vary the intensity of the light source. The inspection is done by viewing the computed radiograph in a computer monitor and using an intelligent imaging algorithm to adjust the pixel properties to expose the defects. More defects can be exposed using the features in the advanced image processing system such as image enlargement, cropping, enhancement, measurement, etc [10]. Nevertheless, the required knowledge and experience of NDT interpreters is regardless of digitized or computed radiographs as shown in Fig 2. This paper proposes an idea of using intelligent detection and feature extraction using Improved GNOME -Percolation algorithm a tool in the automated visual inspection and NDT of finished products.

III. AUTOMATIC DEFECT RECOGNITION

In general, automatic defect interpretation of radiographs consists of five stages as shown in Fig 3, i.e., image digitization, pre-processing, defect segmentation, feature extraction and defect classification

The principle aspects of an automated inspection unit are shown typically, it comprises the following five steps (Mery et al, 2001):

a. A manipulator for handling the test piece,
b. An source, which irradiates the test piece with a conical beam to generate an image of the test piece,
c. An image intensifier which transforms the invisible image into a visible one,
d. A CCD camera which records the visible image and
e. A computer to process the digital image processing of the image and then classifies the test piece accepting or rejecting it.

The more common way of acquisition is through scanners, which works with light transmission – usually called transparency adapters [6][11].Computed ADR systems utilize rays in a single plane (scan plane) by directing fan beams from a source through the object to linear detectors leading to a higher rate of data acquisition, by translating the source-detector pair across the extent of the object in the scan plane, and then repeating the procedure from a number of angular orientations. The rotation of object permits reconstruction of a complete image which allows larger objects to be scanned and smaller objects to be moved closer to the source into a narrower section of the fan beam, leading to increased resolution through enhanced utilization of detectors to image smaller subsections of the object in any one view.

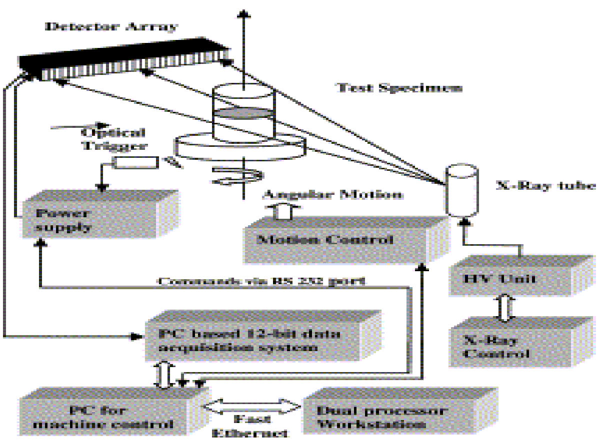

Figure 3: Radiographic Non Destructive Testing

Most modern scanners are fourth-generation devices, consisting of a fixed complete ring of detectors and a single X-ray source that rotates around the object being scanned. The system is enabled with direct acquisition of the image for the advanced image processing systems which can be enhanced, analyzed and extracted the feature.

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. Programmable controller (PLC) may also control the manipulator for positioning the test piece

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.

IV. DIGITAL IMAGE PROCESSING

In general terms, imaging technique directly measures the absorption and transmission properties of a component under investigation to capture the live images by applying a wide range of algorithms, together with sophisticated computer software system, to recognize the fault and its dimensions and features using intelligent image processing technique including image segmentation, feature classification, image interpretation, and pattern recognition can be implemented efficiently, automatically or semi-automatically with certain interactive manipulations by the operator [10-14]. The AI algorithm classifies the image obtained from ITC to ‘Area with defects’ and ‘Background’.

A. Image Formation:

Modern CT systems now employ more sophisticated scintillation crystal materials and solid-state photo detector diodes for image acquisition and the output from each photodiode is a current proportional to the light striking the diode which can be directly converted to a voltage by a low-noise transimpedance amplifier (TIA), or integrated over time using a capacitor or active integrator op-amp circuit to produce a voltage output. The signals from these capacitors are multiplexed using FET switches in the diode-array detector. The signals are then routed to the digital acquisition system (DAS) which amplifies and converts the signals to a digital format using high-resolution analog-to-digital converters (ADCs).

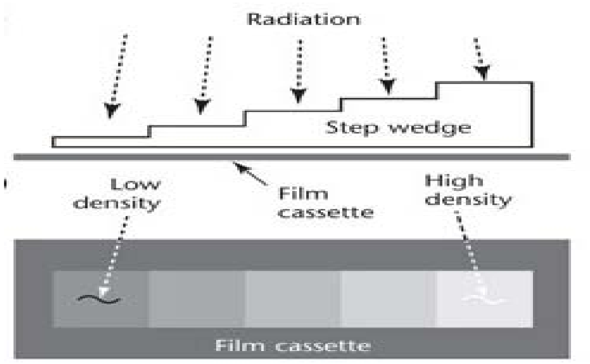

Figure 4: Differential absorption

A defect in the material modifies the expected radiation received by the sensor as noted in Figure 4. 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 as shown in Figure 5.

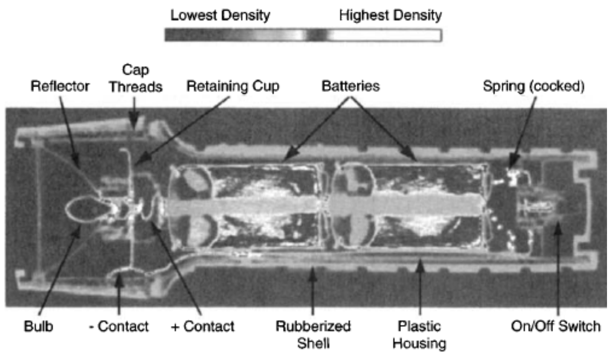

Figure 5: Differential absorption in a specimen.

B. Preprocessing:

After digitizing the films, it is common practice to adopt a preprocessing step for the images with the special purpose of correct the shading effect, restore blur deformation of images, seeking mainly the attenuation by elimination of noise and contrast improvement.

a. 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 ($10 \leq n \leq 16$).

b. 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. Brightness preserving Bi Histogram Equalization (BBHE) first decomposes an input image into two sub images based on the mean of the input image. One of the sub image is set of samples less than or equal to the mean whereas the second one is the set of samples greater than the mean. Then the BBHE equalizes the sub images independently based on their respective histograms with the constraint that the samples in the former set are mapped into the range from the minimum gray level to the input mean and the samples in the latter set are mapped into the range from the mean to the maximum gray level 6. It means first sub image is equalized over the range up to the mean and the other sub image is equalized over the range. Thus, the resulting equalized sub images are bounded by each other around the input mean, which has an effect of preserving mean brightness and improved contrast as shown in Figure. The enhanced image intensity of image is

Output(x, y) = (Input(x, y) - B) / (W - B)

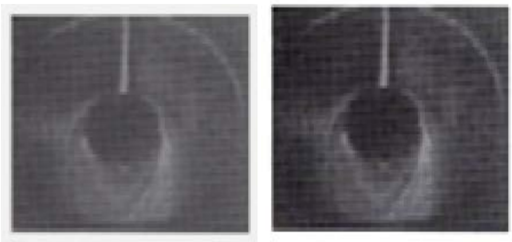

Figure 6: BBHE Contrast Enhancement

c. Shading Correction:

Even under the best of imaging conditions, the illumination across a field of cells isn't quite uniform. This is due to imperfections (i.e. slight misalignments, mars, dust, and additional physical properties) contributed by each optical element (bulb, filters, mirrors, objectives) within a light path. 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 as shown in Figure 7.

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)

for k = 1,2,3…….

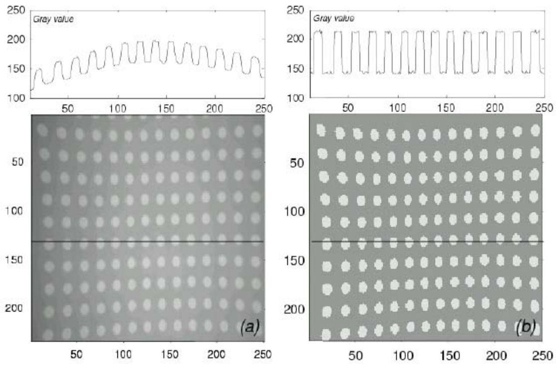

Figure 7: Shading Correction

d. Restoration of blur due to motion:

The main aim in image sharpening is to highlight fine detail in the image, or to enhance detail that has been blurred (perhaps due to noise or other effects, such as motion). With image sharpening, we want to enhance the high-frequency components; this implies a spatial filter shape that has a high positive component at the centre.

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.

e. Edge preserving smoothing:

Neighborhood averaging or Gaussian smoothing will tend to blur edges because the high frequencies in the image are attenuated. An alternative approach is to use median filtering. Here we set the grey level to be the median of the pixel values in the neighborhood of that pixel. The median *m* of a set of values is such that half the values in the set are less than *m* and half are greater. The outcome of median filtering is that pixels with outlying values are forced to become more like their neighbors, but at the same time edges are preserved. Of course, median filters are non-linear. Median filtering is in fact a morphological operation. When we erode an image, pixel values are replaced with the smallest value in the neighborhood. Dilating an image corresponds to replacing pixel values with the largest value in the neighborhood. Figure:8 shows how median filtering replaces pixels with the median value in the neighborhood. It is the rank of the value of the pixel used in the neighborhood that determines the type of morphological operation.

C. Segmentation:

Image segmentation is the process of subdividing an image into disjointed regions correspond to potential defects and the background (or regular structures) which attempts to detect the potential defects in an image in two steps by 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 as shown in Figure 8. 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. The binary edge image obtained should reproduce real flaws' closed and connected contours that demarcate regions

a. *Gnome Sorted Percolation Algorithm:*

Several techniques for crack detection have been developed recently. The most obvious solution is the use of standard intelligent image processing methods or combinations of it. Gnome sort, proposed by Hamid Sarbazi-Azad in 2000 [14] then later on described by Dick Grune and named "Gnome sort"[15], is a sorting algorithm where moving an element to its proper place is accomplished by a series of swaps. The running time is $O(n^2)$, but tends towards O(n) if the list is initially almost sorted with an he average runtime is O(n2).The algorithm always finds the first place where two adjacent pixel elements are in the wrong order, and swaps them. It takes advantage of the fact that performing a swap can introduce a new out-of-order adjacent pair only right before or after the two swapped elements. It does not assume that elements forward of the current position are sorted, so it only needs to check the position directly before the swapped elements.

Hessian driven Percolation algorithm 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 [16]. The percolation algorithm described in works can be used for even complex images which are based on the physical model of liquid permeation, are started from each pixel. Depending on the shape of the percolated region, the pixel is considered as a crack pixel or not [17].

Basically the simple percolation process consists of the described syntax:

a) Initialize the Gnome operator i=1 and the latest iterative variable k to 0
b) If the Gnome operator value is less then the maximum gray level value n, following conditions are executed.
c) The starting pixel P_s is added to the set of percolated pixels P
d) The threshold t is set to the value

$$t = \max\left(\int_{p\in Dp}^{\infty} max\ I(p), t\right) + w,$$

Where w is a parameter to accelerate the percolation depends on ray absorption cp-efficient

e) Each pixel p neighboring P is added P to if $I(P) \le t$
f) The circularity Fc is defined by

$$Fc = {4 \times |P|}/{\pi(diam\ P)^2}$$

g) Gnome operator is redefined by the value of k and k is assigned to zero If the P exceed the preceder, P> P(n-1)
h) Pixel values are interchanged and k redefined by the value of Gnome operator and i is assigned to zero if, P< P (n-1).
i) Gnome operator is increased in each step by one for all values n less than i else decreased by one.
j) Iteration on k is implemented until p reaches boundary of M×M window with centre P if the circularity Fc of P *is* close to 0, p is considered as a crack pixel.

The Improved percolation algorithm described in the previous section can be used immediately for the detection of cracks low resolution images but not for complex images. While steps 1–4 can be directly applied to complex images, the circularity Fc computed in step 5 has no obvious generalization to complex images. An extension of the percolation algorithm to complex images with improved computation time is proposed in this section. Employing the sheet filter as conventional system introduces more complexity. Implying Laplace smoothing can improve the performance of system increasing.

Sum of smoothing signals consisting of equidistant points is the moving average [18-19]. An array of raw (noisy) data $[y_1, y_2, \ldots, y_N]$ can be converted to a new array of smoothed data. The "smoothed point" $(y_k)_s$ is the average of an odd number of consecutive 2n+1 (n=1, 2, 3, ..) points of the raw data $y_{k-n}, y_{k-n+1}, \ldots, y_{k-1}, y_k, y_{k+1}, \ldots, y_{k+n-1}, y_{k+n}$, i.e.

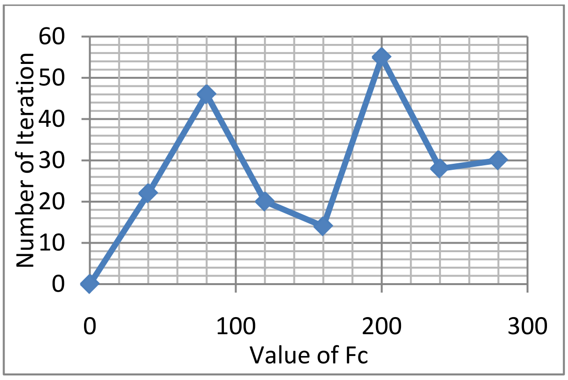

Figure 8: Smoothing with respect to Fc

Let H be the result obtained from by S choosing an appropriate threshold after smoothing.

Fc is determined by = $|P \cap H|/P$

The computation of the circularity of the percolated region is replaced by the computation of we check if the percentage of pixels in which H is contained in is close to 1.Furthermore we use H to improve the speed of the calculation. This is achieved by starting the percolation process only at pixels contained in $(|P \cap H|)\ /\ P$ as shown in Figure 8. Note that if we considered the starting pixel of the percolation process as a crack pixel only if is close to 1, then the result of the percolation algorithm would be a subset of thus it reference matrix. . Figure 9 shows the iterative segmentation for varying value of P and H.

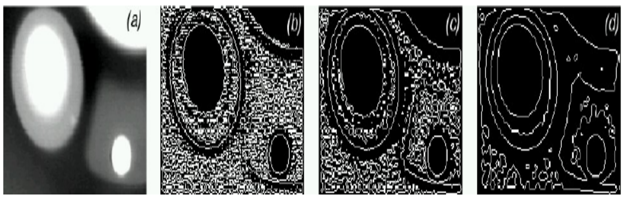

Figure 9: Selective Segmentation

b. *Feature Extraction and Detection:*

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'.

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 Danielsson 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 as shown in Figure 10.

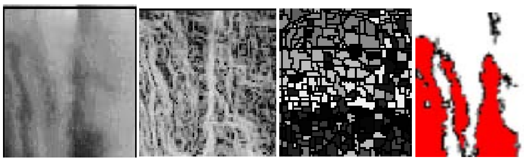

Figure 10: Segmentation and Flaw Detection

V. RESULTS AND DISCUSSIONS

A substantial amount of work has done both in real-time and in simulation applications to check the reliability and performance characteristics of the system. It was found that even microscopic particle can be monitored by using intelligent system design and that the monitoring can produce useful Information. Testing procedures, developed have been applied to a wide variety of testing samples successfully. The developed methodology with specialized flaw recognition algorithm for radiographic NDT & E has shown higher reliability, accuracy and optimized number of iteration for operation. The radiation absorption factor makes the algorithm to control the radiation level and to improve corresponding variations in detecting features. Moreover distributed selection of staring pixel instead of random selection makes the system to execute the recognition process within no time. . The image preprocessing systems for image enhancement has improved the process by better image representation as shown in Figure 11 and easy processing for defect detection and classification.

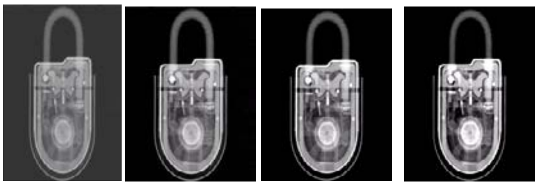

Figure 11 : Preprocessing

The image segmentation method using GNOME sorted percolation model has shown advanced defect recognition with less iteration and optimized operation as shown in figure 12.

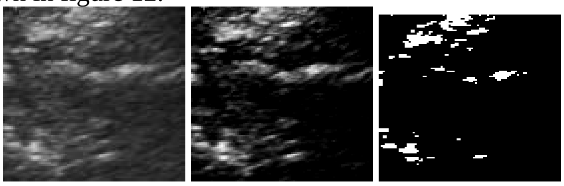

Figure 12: Flaw detection and feature extraction

The advanced image restoration and sharpening method implied multithresholding and image corner sharpening to have better representation of image for human interface.

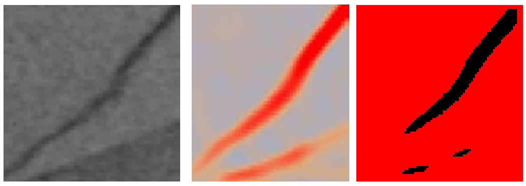

Figure 12: Sharpening and enhancement of defects.

The performance comparison of conventional percolation system with improved model has shown considerable reduction iteration before to get the most varying neighboring pixel is shown in Figure 12.

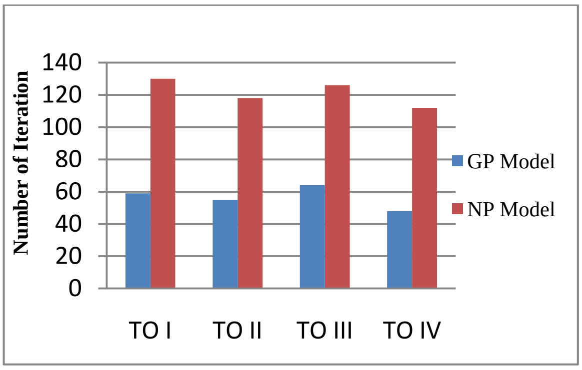

Figure 12: Sharpening and enhancement of defects.

VI. 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 advanced Hessian-Driven Percolation based automated visual quality inspection and NDT technique. The defects examined include porosity, linear indication, lack of fusion, lack of penetration, and undercut, from computed radiography (CR) images of the metallic blocks. An initial analysis shows that it is difficult to use the sheet filter method detect the defects in complex images. Thee improved algorithm detected both circular (porosity) and line-shaped (linear indication. 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 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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