

Variants to Non-Linear Filter Techniques for Defect Segmentation in Digital Radiographs of Castings

M. NAVALGUND, R.VENKATACHALAM, G. SWAMY, V. MANOHARAN, GE
Global Research, Bangalore, INDIA

Abstract: The field of automated defect recognition has seen a tremendous growth in the last few decades. On one hand we have an operator with an advanced computing system (brain) but prone to fatigue, stress and succumbing to the environment. On the other hand, we have a tireless and extremely fast computer system. The casting industry uses x-ray inspection to verify the structural integrity of the parts. Wheels, Pistons, Steering Knuckles are a few examples of the parts inspected. Their reliability is very crucial towards the Quality of an automobile and hence the industry has strict standards towards quality that an ADR system must conform to. In addition, the bulk of production demands an extremely robust and efficient system that can be operated real-time. In the past few years this system has gone from a human intensive system to a totally automated computer aided system. Such a defect recognition system involves set-up time. This is the time required to tune the system to identify the defects in a particular part. The number of parameters to adjust, the data (images) required for the same and the ease of setting them, all affect the total set-up time. An extremely robust and efficient performance calls for a low percentage of false calls and a hundred percent true positive (defect detectability) rate. Hence, the tuning of the system parameters plays a very crucial role. When designing an ADR system the key things to be kept in mind other than low false calls and high true positives is a low set-up time, easy parameterization, flexibility to adapt to new parts, few or no parameters. This paper focuses on various techniques with low set-up time and high detectability rates to identify defects. The paper starts with giving a brief background of various techniques used in ADR. It also describes a simple and effective method to define the regions of interest in an image. The paper investigates the median filter, a classical filter used in defect recognition, and describes its variants in order to capture defects close to edges and bends (one of the problems in ADR systems). Techniques, based on thresholding, distance measures, statistical information, edge tracing and function design using truth tables are presented, that can be used to isolate the defects from its background and reduce the false calls. The paper concludes with results to validate the methods described.

1. Introduction:

Inspection means identification of an anomaly in a manufactured part. The goal of such a system is to divide an image into two classes, those belonging to a good or regular structure and those belonging to bad or defective regions. In the manufacture of light alloy castings, these defects are voids, cavities, shrinkages, porosities, inclusions etc. For an explanation on how these defects occur refer to [1]. Light Alloy castings, such as aluminum, are used mainly in the automotive industry for parts such as wheel rims, pistons, gearboxes, steering knuckles etc. Their proper functioning is critical to vehicle safety. Since these defects are usually not visible (not surface defects) radiography is used

in order to examine (visual or automated) the quality of a part. Inspection wherein an operator visually inspects the parts is highly subjective and is prone to error due to fatigue, stress, environmental conditions etc. Hence amplifies the importance of a Computer Aided Automated Defect Recognition (ADR) System.

A defect is identified by analyzing the gray values in an image. A defect can be broadly classified as a region in the image which is brighter\ darker (has higher\ lower intensity) than the its surrounding regions (background). When a computer “looks” (operates) at an image all the information it can draw out of it will be based on the Intensity of the pixels in the image. However, an edge/ border (Which separates two regions) will also have similar characteristics. Similarly some of the structures of the part, a hole for example, will have also a good contrast with respect to its background. Hence, the edges, regular part structures often are identified falsely as defects (False Positives). In order to reduce these false calls some kind of intelligence is fed into the system which is based on prior knowledge of the part, the characteristics of defects, noise models etc. This requires the system to be trained to the part being inspected. Due to this, it is very difficult to have a fully automated system or a generic system, hence the word computer – *aided* ADR system.

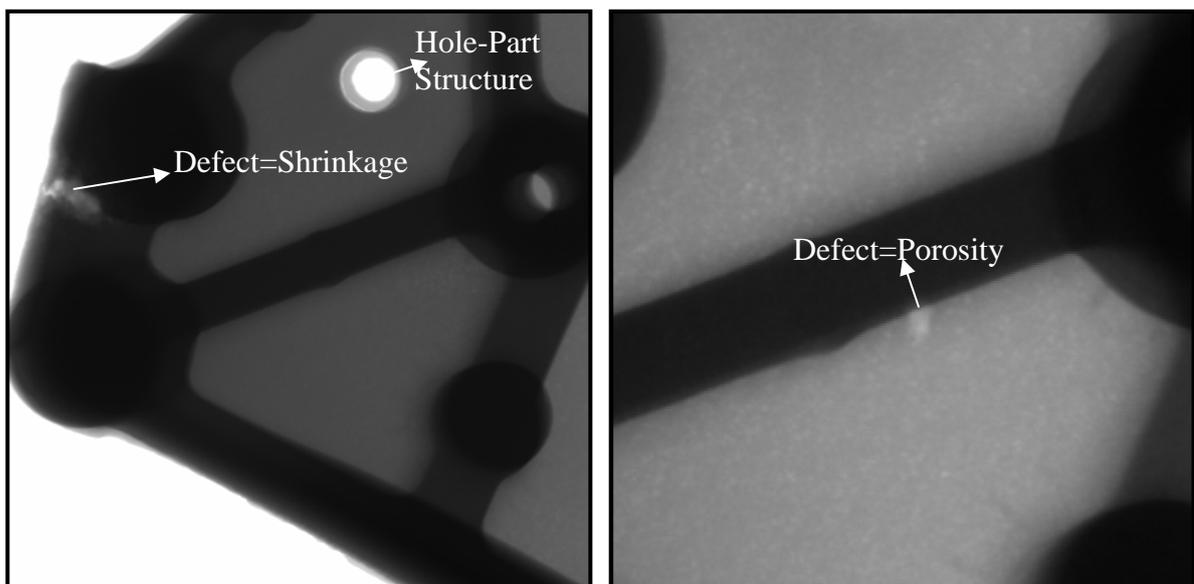


Fig 1. (a)

(b)

The current ADR systems all have a training/set-up time wherein the parameters of the system are tuned to identify defects in a particular part. The goal in the design of such a system would not be just low false positive rate and high true positive rate but also a low set-up time, flexibility to adapt to new parts and easy parameterization.

2. Background:

There are two classical approaches to ADR: A Reference based Approach and a Non-Reference Based Approach. Once the Image is segmented out, the chief task is to separate out the true defects and the false calls. Different Methods to distinguish the True Positives (True Defects) from the False Negatives (False Calls) will be presented here. In a Reference based method the test image is compared with respect to an ideal defect free

image(s). Any deviation from the regular structure indicates the presence of a defect. The non-reference based methods use techniques based on capturing a contrast difference, sudden deviation in gray values. There are many methods, both Reference and Non-Reference based, which uses some form of a median filter [2]. A median filter extracts features, which are less than twice its size. The median filter based approaches are Modan filter [3,4], trained median filter [5]. Gayer et al's methods [3,6] use a frequency domain based method for identifying potential defects followed by a template matching. Kehow and Parken [3,7] segment the potential defects using adaptive thresholding and then use an expert system to reduce the false calls. Another method by Domingo Mery [3,8] and Filbert is based on detecting the sharp changes in intensity using a Log filter to detect potential defects followed by tracking the defect in different views. Since false calls will not occur when the different image sequences are analyzed they are eliminated leaving behind only the true defects. There are other methods that use Neural-Networks, Fuzzy Logic [9,10] systems, such as YXLON'S Automatic Inspector [11]. Whichever be the method the defect identification can be divided into four main steps:

1. **Pre-Processing:** Improving the quality of the acquired images through techniques such as noise reduction, contrast enhancement, shading correction etc.
2. **Segmentation:** One of the most important steps. It involves;
 - a. A quick search for Identification of possible defects.
 - b. Identification of true defects, Reducing False Calls.
3. **Classification:** Making accept or reject decision based on some statistical/geometric parameters and on knowledge of the part.

3. Segmentation:

A median filter is one of the most popular ways of defect extraction. A median filter is essentially a noise reduction filter; it reduces the variance in an image. So when the median filtered image is subtracted from the input image we get an image that captures the variance information. This difference image is binarized such that regions with variance higher than the noise variance are identified. This gives potential defect regions.

Consider Figure 2. We have a 2x2 square against a white background. If this image is median filtered with a 3x3 window. Then the Median at Pixel A would be median of (0 0 0 1 1 1 1) = 0. Similarly, the median of pixels B, C, D will also be 0. The median filter in this case has essentially removed the 2x2 object. The median image when subtracted from the original image will restore the object. This method hence can be used to extract defects using an appropriate median filter. In general defects of size N can be extracted using a median of size $\geq 2N$. However there are a few problems associated with the median filter. Consider the image shown in Fig 3. The defect lies very close to the border in the dark region. There is a large bright region around the region it lies in. When calculating the median the defect will end up having values close to the brighter region (Region -2) value. Hence when the median image is subtracted from the original image this defect region will have negative values and will not get extracted on binarization. This is one of the drawbacks of a median based filter that small defects close to the corners and bend are sometimes missed out. Another problem in general is the false detection of edges as defects. The problem in both these cases is the influence of neighboring regions during the median calculation. In order to avoid this if we could divide the image into distinct regions based on the gray value intensity then this problem of other regions influencing the median in the current region can be controlled. One way of doing this is to divide the image into regions of interest based on the its Histogram.

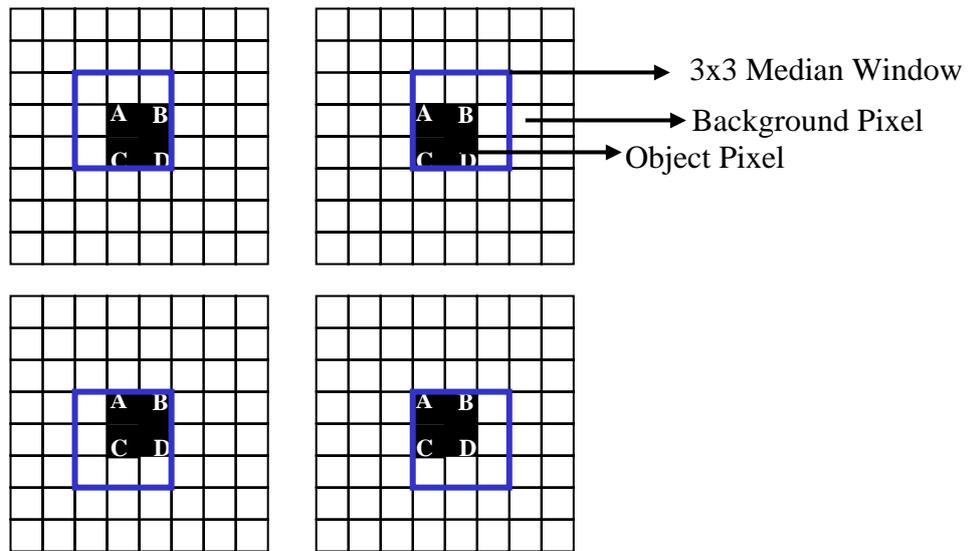


Fig 2: Median Operation

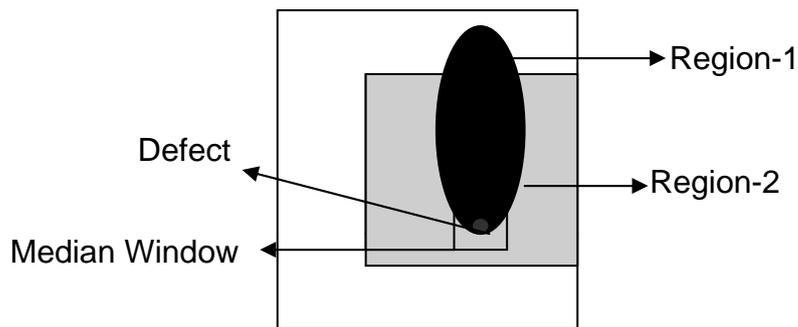


Fig 3: Defect Detection at Corners/ bends

The idea is to divide the image into sub-images based on the peaks in the histogram and then use some criterion to prevent the generation of too many regions or very small regions. These sub-images can be further divided based on their histogram.

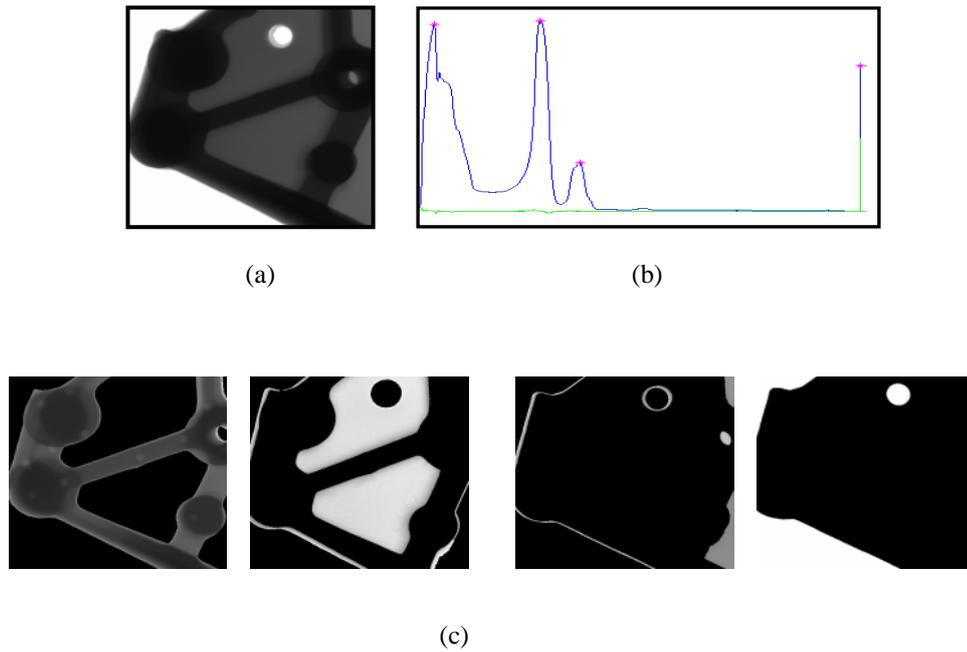


Fig 4: (a) Input Image (b) 4 Peaks Identified in the Histogram (c) Input Image Divided into Sub-Images based on the Peaks Identified

The number of levels of decomposition, the number of regions generated, the size of the regions of interest generated will affect the speed and performance of the defect extraction filter and must be kept in mind when setting the parameters if the process is not fully automated. Once these Regions of Interest are generated for one image the same masks can be used for all the images of the same part (same position), however these regions of interest will need to be correlated. One can also use the prior-information of the part such as more regions where defect identification is critical. However since one of our goals is to have the system as flexible as possible the design of such a system must use little apriori-information.

The next task is to extract defects in each region of interest. As explained earlier a Median filter can be used for the same. During median calculation at the border of the region of interest a part of the median window will lie outside the region of interest. In order to bias the median filter to operate only on the region of interest some variants of the median filter can be used.

1. Method 1: Use only those pixels (N_1 pixels) that lie inside the Region of Interest for Median Pixels. Lets say we are using a 25×25 window, 200 pixels lie in outside the ROI then the median of 425 values (non-zeros) will be used for median calculation. The drawback of this is that if the defect is big then it cannot be captured by the reduced window size.
2. Method 2: For the number of pixels lying outside the region of interest (N_2 Pixels), randomly choose pixels that lie in the current pixels vicinity and belonging to the region of interest.
3. Method 3: For the number of pixels lying outside the region of interest (N_2 Pixels), pixels are chosen from the region of Interest whose intensity distance from the current pixel is the least.

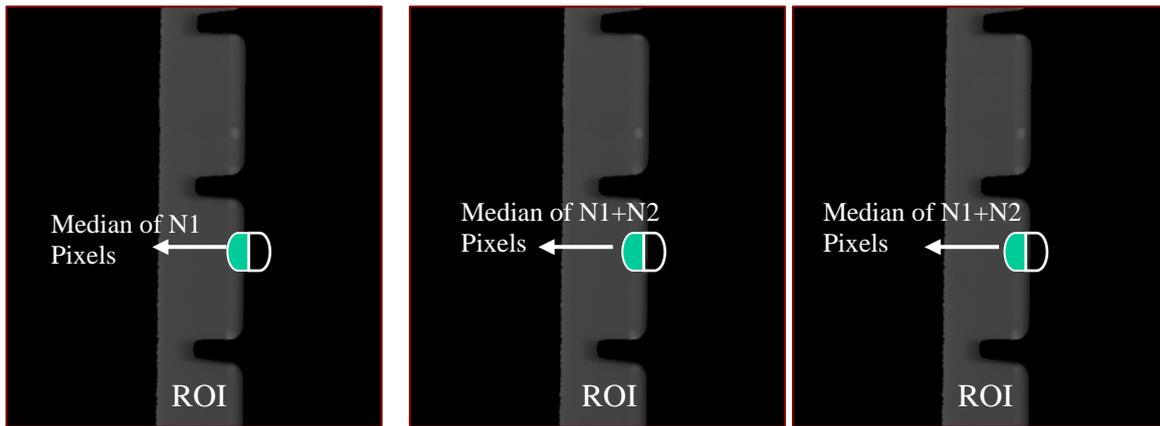


Fig 5: (a) Method-1

(b) Method-2

(c) Method-3

Once we have the Median Result for the region of interest it is binarized. Shown In Fig, 6.d is the binarized result for a particular region of interest. As seen in the figure along with the defect we also have the boundary of the region of interest coming up. The following section presents various methods to isolate the boundary and reduce false calls.

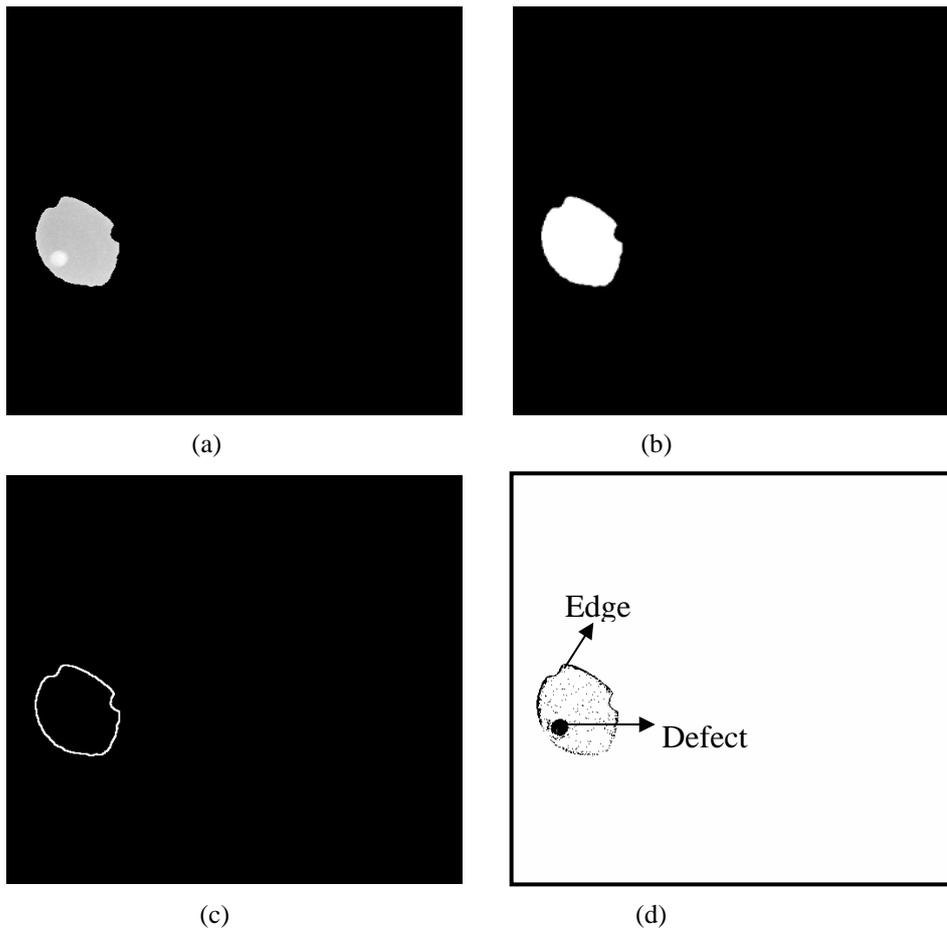


Fig 5: (a) Region Of Interest (b) Region of Interest Mask (c) Edge Of ROI (d) Binarized Median Result

3.1 Method 1- Distance Criterion

In this method for every black pixel in the binarized Median Result (Fig 7.b) (Ex. $(x1,y1)$), its distance with respect to all the white pixels a window around the corresponding pixel in the ROI edge map (Fig 7.a) is measured. The idea is that the edge information obtained from the Binary Mask of the Region of interest can be used to remove the false calls due to edges in the binarized median result. Ideally, the distance between the edge false call pixel (Fig 7.(b) $(x1,y1)$) and the corresponding edge pixel will be zero. However, the thickness of the edges is not the same and due to mis-registration and the jittering effect of the median filter, a distance threshold needs to be used. If the distance of the pixel 7.(b) $(x1,y1)$ from any white pixel in the window in fig 7.a is below the threshold then it means that the pixel lies on or very close to the region edge and hence it is deleted from the Binarized Median Result. The problem with this approach is that if the threshold is large, then some part of the defect that is close to the edge will also be removed. On the other hand, if the threshold is small then the edges are not completely removed.

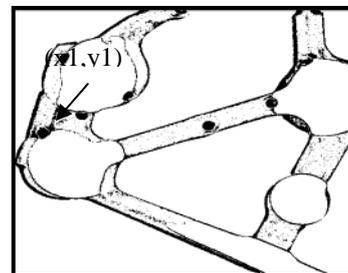
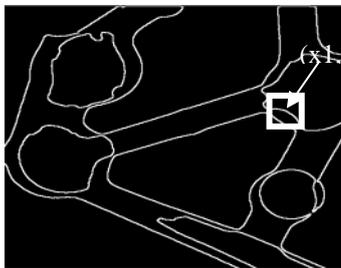


Fig 7: (a) Edge of Binary Mask of ROI

(b) Binarized Median Result

3.2 Method 2- Gray Line Profiles

From the Edge of the ROI straight lines are drawn at regular angle intervals towards the centre of the Region of Interest. The mean and standard deviation along the line profiles are measured. Seen in Fig 8 is an example. As seen in the table the lines passing through the defect (Dark Blue lines) have a high standard deviation and mean. A weighted function combining these two parameters can be used to determine a defect.

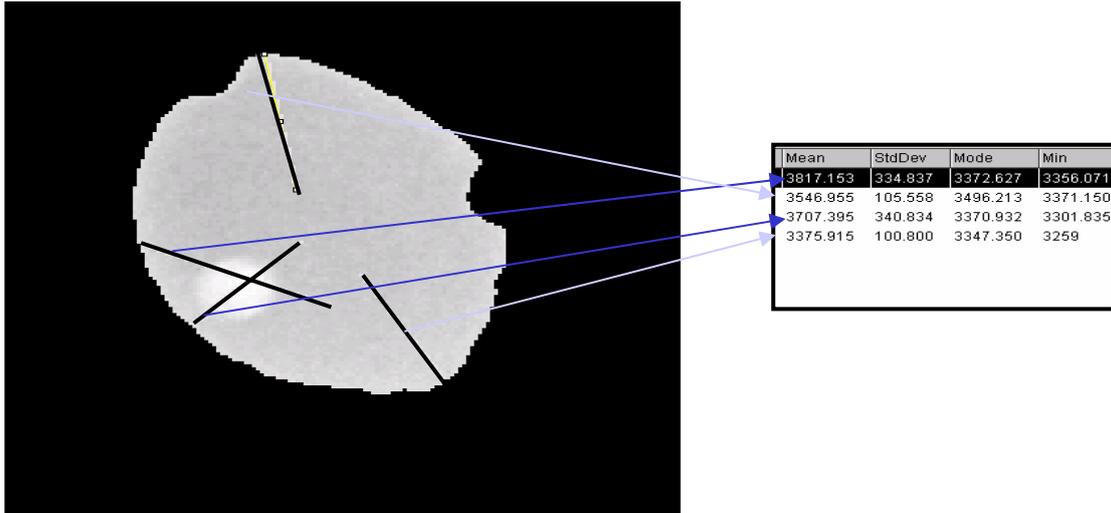


Fig 8: Mean & Std. Deviation across the lines (Black) in the Region of Interest

3.3 Method 3- Crossing Lines

This method uses the edge map information of the ROI mask. A continuous edge is traced in the ROI (green contour in Fig 9. (a)). Lines of fixed length and perpendicular to the edge contour are drawn (Blue Lines Fig 9.b. The profile along the perpendicular line in the Binarized median result is plotted Fig 9. (c). As seen from figure wherever there is a defect there is a peak of considerably large width (not spikes that correspond to noise). This peak information (location) can be used to determine if there is a defect close to the edge contour. The idea behind this method is that the perpendicular line through a defect will have a higher number of zero intensity pixels than a line, which passes through only edge/noise. Hence, the profile will show a peak when it passes through a defect. In addition, since this defect will usually not be a speck the peak will be a wide peak.

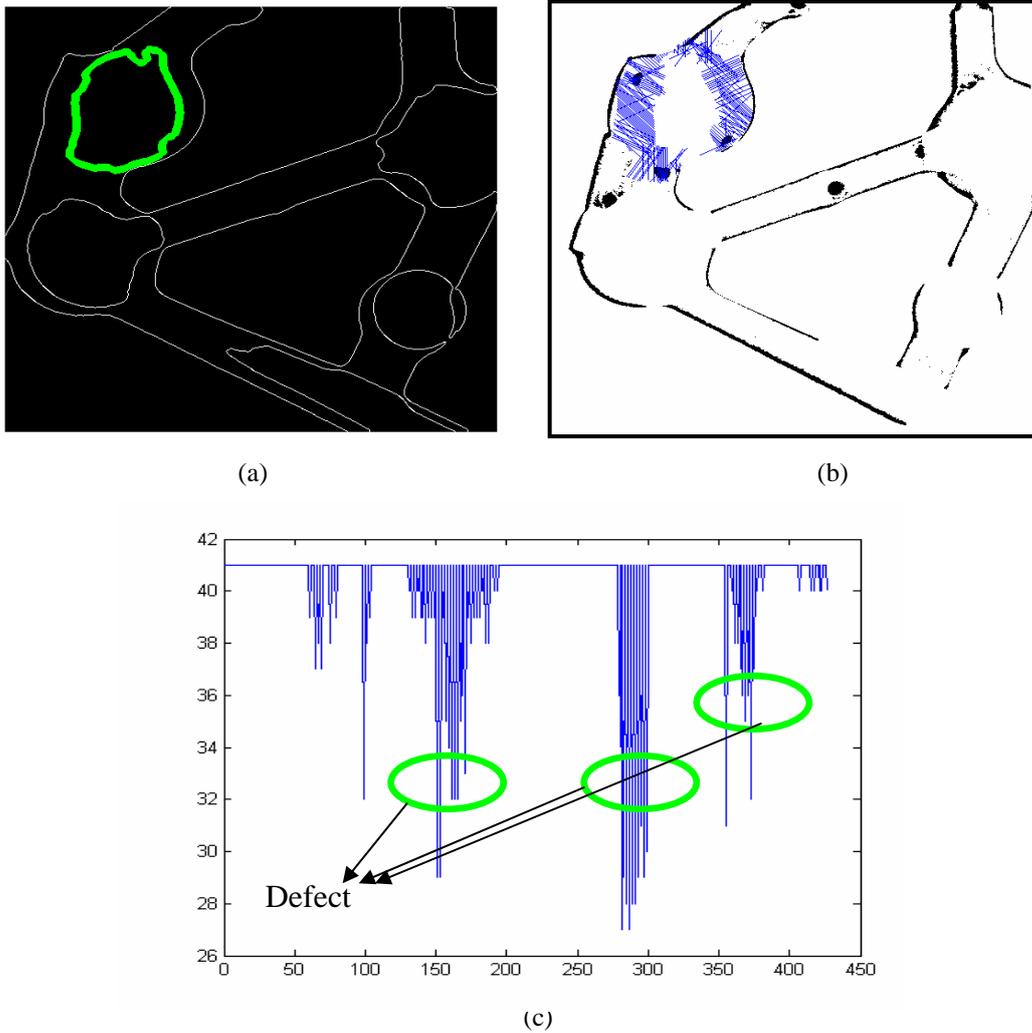
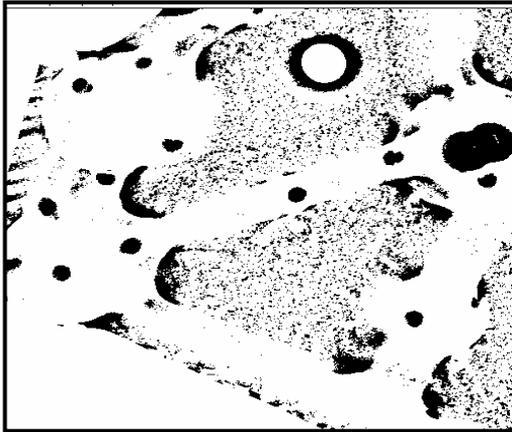


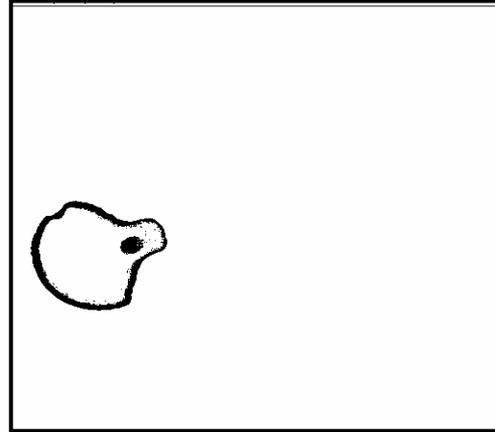
Fig 9: (a) Traced Edge on Edge Image (b) Perpendicular lines for Every traced Edge pixel on the Binarized Median Result (c) Profile along each Perpendicular line

3.4 Method 4: OR – Circular Median

This method is based on the truth tables used in hardware design. In reference based methods the test image (defective image) is compared with defect free images (reference/golden images). The idea there is that features belonging to the part will be present in both the reference and the test image whereas a defective feature will be present only in the test image and some sort of a comparison will be able to identify this anomaly. In this method too we are doing a sort of comparison but rather than comparing two images here we are comparing the same image at different scales. The entire image is first median filtered and then binarized. This result (Fig. 10.a) will have all the defects but a lot of false calls too. For a comparison, we now median filter the region of interest and then binarize it. This result will have the defects in that region of interest and the edge of the region of interest. In order to remove the edges we now compare this result with the previous result. The table in (Fig 10.c) summarizes the comparison strategy, which comes out to be a simple bitwise ‘OR’ operation. Thus, we are able to remove the ROI edges. This is the first step. However sometimes a part of the ROI edge might be present in both the binarized results. In order to remove these we have another comparison, step 2. The edge of the region of interest is dilated (Fig 11.a) and this image is compared with the previous comparison result (Fig 10.d). Table (11.e) shows this design.



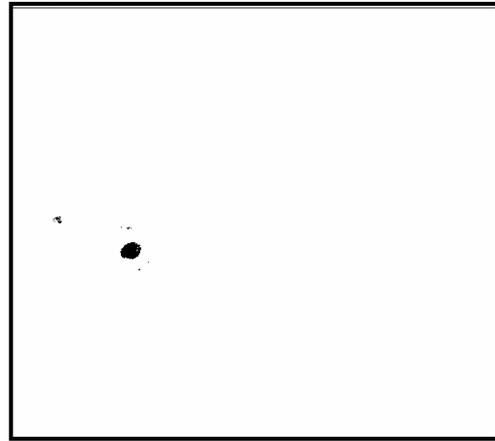
(a)



(b)

Fig (a)	Fig (b)	Desired Output (F)
0	0	0 (Defect)
0	1	1(False Call)
1	0	1 (Edge / False Call)
1	1	1 (N/A)

(c)



(d)

Fig 10: (a) Binarized Median of Test Image (b) Binarized Median of Region of Interest
(c) Truth Table (d) Truth Table

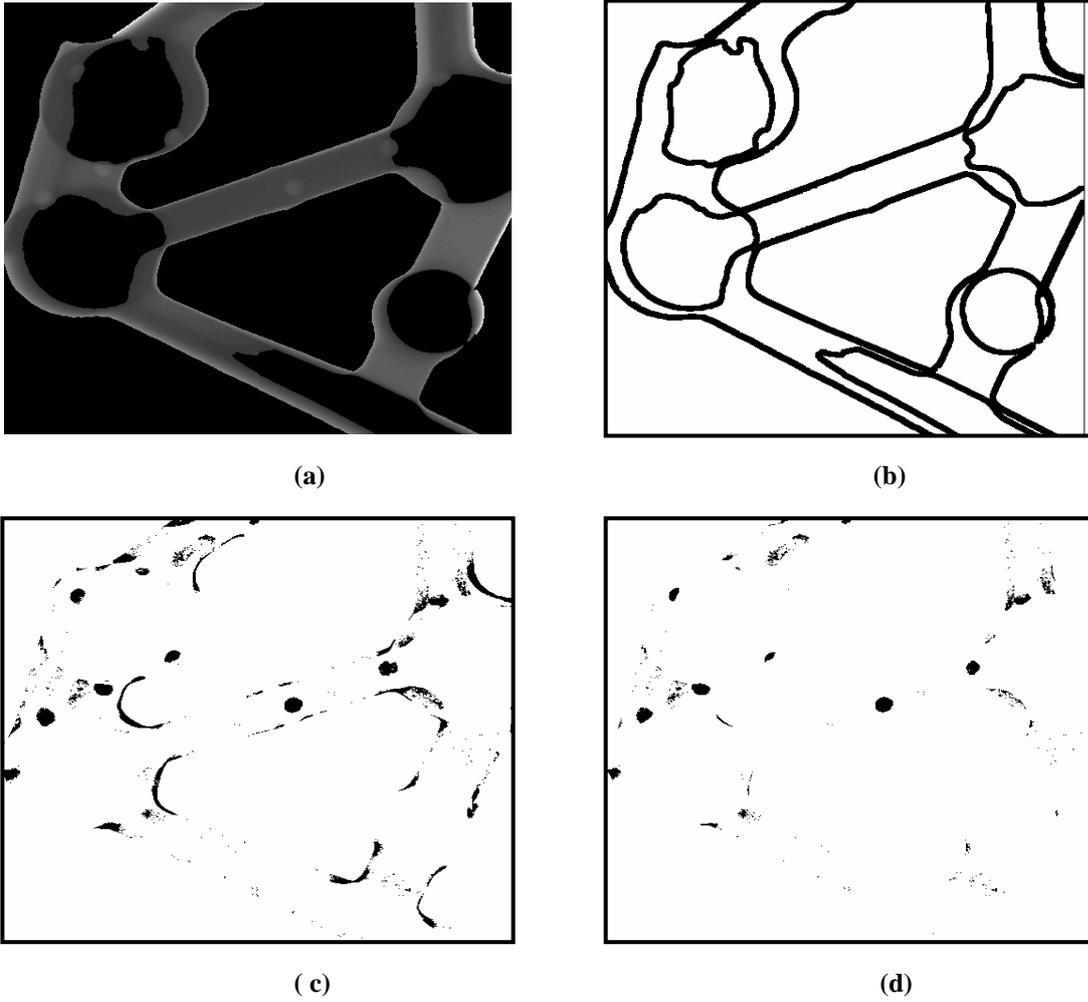


Fig (a) (Pixel Intensity)	Fig (b) (Pixel Intensity)	Desired Output (Pixel Intensity)
0	0	1 (Edge)
0	1	1(False Call)
1	0	0 (Defect)
1	1	1 (N/A)

(e)

Fig 11: (a) Region of Interest (b) Edge of Region of Interest (c) Result of step 1
 (d) Result of step 2 (e) Truth Table - Design for step 2

4. Classification:

The next step after defect extraction is to make the accept/ reject decision. In order to make this decision certain rules are framed such as clubbing of small regions, which are close together, removal of isolated very small regions, merging of a small region with a neighboring large region etc. Removal of regions with poor curvature. These rules also

require input about the part such as which is region of the part is very critical and which is significantly less important so that different thresholds for the classification rules to be set. For example, a small defect in a critical part might warrant the rejection of the part. A relatively big defect on the other hand in a lesser critical region might be acceptable. The classification module is designed based on these accept-reject rules/ criteria.

5. Results & Conclusion:

In this section, we present a few results based on the segmentation methods presented here. It must be noted that these results are before the classification stage. The advantages of these methods is that they do not require reference images as in database approaches, there are fewer number of parameters to adjust, they are simple methods and the parameterization is simple requiring less operator knowledge and time. These advantages make it a flexible system reducing the set-up time and at the same time giving a high defect detectability rate. Figure 12 illustrates the results (before using any classification rules) from using methods described section 3 of this paper.

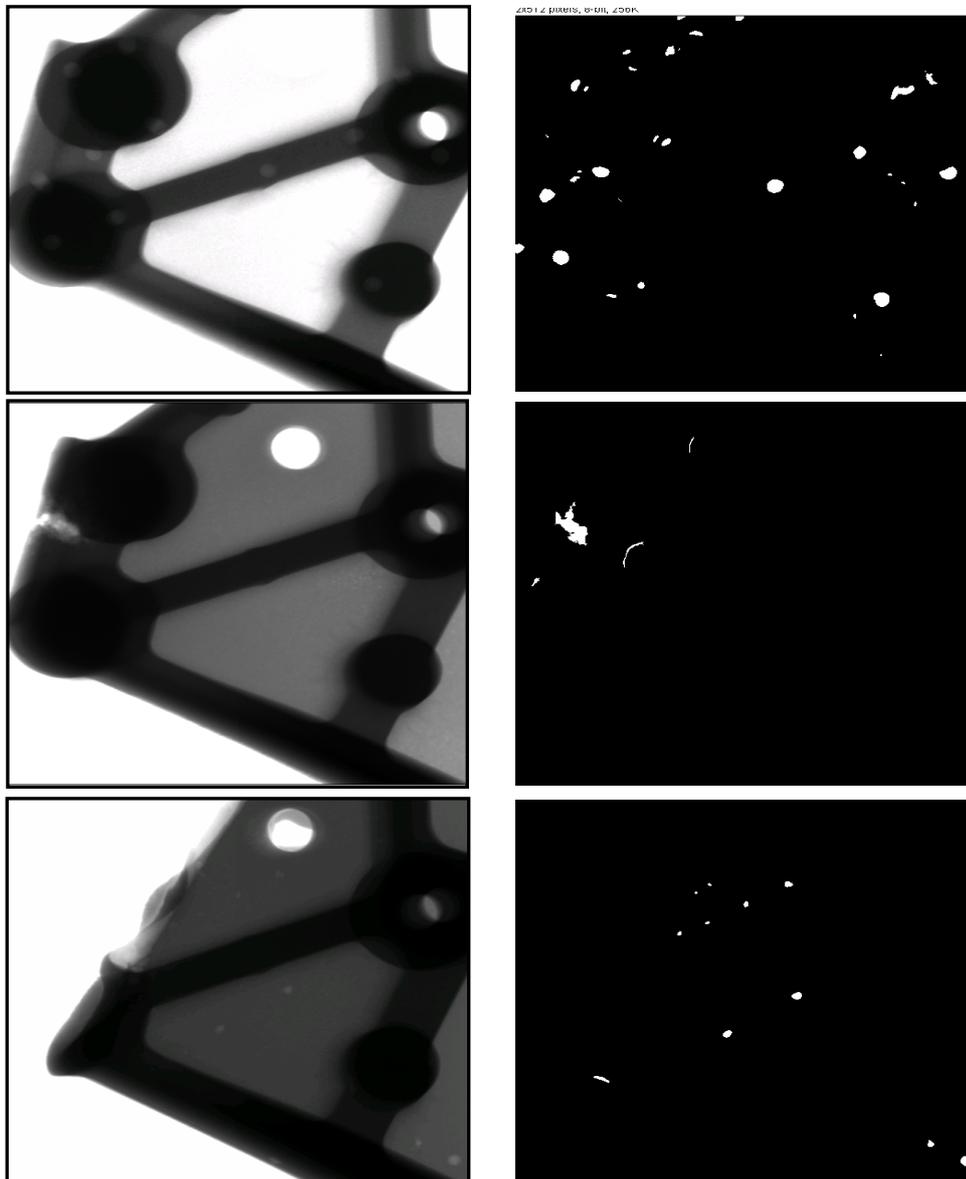


Fig 12. (a) Input Image

(b) Results

Reference:

- [1] Nondestructive Testing Handbook, Radiographic Testing. Bossi, Richard H., Iddings, Frank A., Wheeler, George C, Moore, Patrick O. Publisher: ASNT, Third Edition: Volume 4, 2002, ISBN: 1-57117-045-6
- [2] Image Processing for Fault Detection in Aluminum Castings. D. Mery, D. Filbert, Th. Jaeger. Chapter on " Digital Image Processing in X-Ray Testing ", Chapter 2, , Ed. C.S. MacKenzie and G.E. Totten, CRC Press, Taylor and Francis, Florida, 2005. ISBN 0-8247-5843-9.
- [3] A Review of Methods for Automated Recognition of Casting Defects; D. Mery, T. Jaeger, D. Filbert, May 2002
- [4] Computer Aided Detection of Castings. D. Filbert, R. Klatte, W. Heinrich, M. Purschke. IEEE-IAS Annual Meeting, 1087-1095, Atlanta USA, 1987
- [5] A Third Generation Automatic Defect Recognition System. H. Herold, K. Bavendiek, R. Grigat. 16th World Conference on Nondestructive Testing, Palais des Congrès, Montréal, Canada, August 30 2004
- [6] Automatic Recognition of Welding Defects in Real-Time Radiography. A. Gayer, A. Saya, A. Shiloh. NDT International 23(4), 131-136, 1990
- [7] An Intelligent Knowledge based Approach for the Automated Radiographic Inspection of Castings. A. Kehoe, G.A. Parker. NDT&E International, 25(1), 23-36, 1992
- [8] Automated Flaw Detection in Castings from Digital Radioscopic Image Sequences. D. Mery. Verlag Dr. Koster, Berlin, 2001 (Phd Thesis)
- [9] Automated Defect Detection in Al Castings & welds using Neuro-Fuzzy Classifiers S. Hernández, D. Saez, D. Mery, D. R. da Silva, MHS. Siqueira. 16th World Conference on Non-Destructive Testing (WCNDT 2004), Montreal, Aug 30 2004
- [10] The Research of Defect Recognition for Radiographic weld Image Based on Fuzzy Neural Networks. Zhang Xiao-Guang; Xu Jian-Jian; Li Yu. Intelligent Control and Automation, 2004. WCICA 2004. Fifth World Congress on Volume 3, 15-19 June 2004 Page(s):2661 - 2665 Vol.3
- [11] Fully Automatic Inspection of Aluminum Wheels. G. Theis, T. Kahrs. 8th European Conference on Non-Destructive Testing (ECNDT 2002), Barcelona, 17 June 2002