CHAPTER 4: ADVANCED ADAPTIVE MEDIAN FILTER BASED NOISE REMOVAL TECHNIQUE AND SEGMENTATION METHODOLOGIES FOR THE PROCESS OF WELD DEFECT DETECTION

4.0. INTRODUCTION

Non-destructive testing (NDT) is an analysis technique used in manufacturing industry to examine the properties of a material or system without causing any damage to the internal structure. The various NDT techniques include Radiography, Ultrasonic, Visual inspection, Penetrant testing and Eddy current testing. Since NDT does not permanently alter the material under inspection, it is a highly efficient methodology that can conserve both money and time in product examination and research. The weld defects such as Lack of Penetration, Porosity, Burn Through, Slag Inclusion, Oxide Inclusion, Porosity etc., degenerate the mechanical properties of the welded structures thereby increasing the risks of fatigue, failure and disaster.

This work concentrates on the removal of salt and pepper noise using adaptive median filter where a novel enhanced Dijkstra’s three way partitioning technique is used for the purpose of sorting. This work focuses on detecting the above weld defects using segmentation techniques such as Watershed and Hough Transform. Where Hough transform based segmentation is more suitable for detecting Lack of Penetration and Lack of Fusion weld defects since they are oriented in a
straight line format. Many incidents happened throughout the world have proven the fact that weld failures have great impact on human lives and the environment. Weld defect in pipeline, railway lines and pressure vessels have caused serious explosions and disasters in many part of the world.

Identifying the defects in radiographic images by human interpreter or automated programs is a challenging task due to the presence of various noises and the highly dark nature of the industrial radiography. This work presents a new advanced fast processing Adaptive Median filter for noise removal along with Watershed segmentation and Hough Transform based segmentation. A novel improvement of the Dijkstra’s three way partitioning technique for fast sorting of pixels in less number of swaps when compared to the Bentley McIlory algorithm and the Dijkstra’s algorithm, is used for designing a fast processing adaptive median filter for noise removal. The Hough transform is a reliable technique that can be used for segmenting Lack of Penetration weld defect which is basically straight line in nature. In Hough Transform based segmentation the entire image is processed for accumulating votes in an array of accumulator. But the main limitation is its large computational complexity and the significant amount of memory that needed to be allocated while processing. In this work an enhanced method is presented to reduce the number of pixels being processed and
thereby increasing the speed of detection of Lack of Penetration weld defect. Experimental results show that the Hough Transform applied on the restricted triangular region provides an accurate segmentation of Lack of Penetration weld defect with reduced search space.

Radiographic Images are often corrupted by various types of noises like Gaussian noise, Gamma noise, Uniform noise and Impulse noise or Salt-and-Pepper noise due to the interference of the transmission channels or due to various adverse factors effecting image acquisition which degrade the quality of the image to a great extent. The abstruse image is made more perceivable by removing the noise contained in it.

The idea of the median filter is: at each pixel in a digital image, place a box around that pixel, find the median of all the intensity values in the neighbourhood of the pixel using any sorting algorithm, and then replace the original pixel's value by the median value of all pixels in the box. The box is then successively moved over every pixel in the image. The advantage of the median filter which is non-linear in nature over the mean filter is that median filter preserves the useful details of the image and works effectively for the images corrupted with unipolar and bipolar impulse noises. While performing smoothing operation median filters generally preserves the edge details of the image with very less blurring when compared to smoothing filters.
Median is the 50th percentile of data or the middle element of all the intensity values in the neighbourhood of the pixel under consideration. Median of data is a more accurate indicator than the mean of data. The median is computed in such a way that all the pixel values from the encompassing neighbourhood is sorted in increasing or decreasing order followed by substituting the pixel being considered with the computed median value. If the neighbourhood under consideration contains an even number of pixels, the mean of the two middle pixel values is made into use. The window size can be varied from low to high in Adaptive median filter. In this research work the new modified Dijkstra’s sorting algorithm is employed to sort the pixels of the whole image, so as to analyze the algorithm’s performance for higher window size of filter as in adaptive median filter.

Sorting of pixel values is the major time consuming operation in the computation of median. This novel algorithm in this work is specially suited for median filtering application. The new sorting algorithm will be much effective than the old algorithms if the number of pixel values to be sorted is very large. So this work employs the novel algorithm to sort very large number of pixels. Thus this sorting can be employed for adaptive median filter where the window size is bigger. The algorithm is implemented and tested in Java programming language for weld defect radiographic image corrupted by salt and pepper noise. Image of various
dimensions for a specific weld defect radiographic image with various noise densities are used as the test cases.

The defects in welding can lead to devastating effects. To detect the weld defects in the given image, one of the popular techniques called Hough transform is enhanced in this work. Hough transform are traditionally used to isolate geometric shapes like straight lines, ellipse, circle and parabola. This work mainly concentrates on the detection of Lack of Penetration weld defect which is basically a straight line in orientation.

4.1. PRE-PROCESSING

4.1.1. Sorting algorithms

In the field of computing, sort and search are the two basic operations which are used extensively in many applications. This motivated lot of research work in this area and led to the invention of various sorting algorithms. Among all sorting algorithms quick sort is an efficient one in terms of space and time. Though quick sort technique is highly efficient there is an Achilles heel in it. It goes quadratic for large number of values with more redundancy. Image processing generally deals with huge matrices which consist of intensity values between 0 and 255 with large repetitions where quick sort may not be effective. E.W.Dijkstra one of the pioneers in algorithms research came with a
solution to this problem. This solution has been invented originally for Dutch national flag problem. The idea of his solution was to partition the array into three parts such that left most part contains smaller values than the pivot, middle part contains the values equal to pivot and right most part contains values larger than the pivot. Other solutions to sort this type of data are: Bentley McIlroy partitioning technique and Meyer’s technique. But when compared to those methods Dijkstra’s solution is more efficient. This work put forward a novel enhancement for the Dijkstra’s sorting technique, applied in the field of image processing with reduction in number of swaps. The time consumed by the new algorithm to sort the pixels is lesser than other two algorithms.

4.1.2. Bentley-McIlroy 3-way partitioning Algorithm

The algorithm when applied for image processing application for sorting pixels can be represented as follows. Select a partitioning element or a pivot value from the pixel values. Let i and p be the pointers to the first element in the array, j and p be the pointer to the last element in array.

Repeat the below process until i and j pointers cross.

Step 1: Scan i from left to right so long as pixel value at j < pivot value.

Step 2: Scan j from right to left so long as pixel value at j > pivot value.

Step 3: Exchange pixel value at i with j.
Step 4: If pixel value at i is same as pivot value, exchange pixel at i with pixel at p and increment p.

Step 5: If pixel at j is same as pivot value, exchange pixel at j with pixel at q and decrement q.

4.1.3. Dijkstra’s Three-Way Partitioning Algorithm

The Dijkstra’s 3 way portioning algorithm for sorting pixel values works like this: Select a partitioning element or a pivot value from the pixel values. Let j and l be the pointers to the first element in the array and g be the pointer to the last element in array. Scan from left to right by incrementing j pointer.

The algorithm is as follows:

Step 1: If pixel value at j is less than the pivot value, exchange values at j and l and increment both l and j.

Step 2: If pixel value at j is greater than the pivot value exchange values at j and g and decrement g pointer.

Step 3: If pixel value at j is equal to the pivot value, increment j pointer.

Step 4: Repeat steps 1 to 3 until g crosses j pointer.
4.1.4. The New Modified Dijkstra’s Three-Way Partitioning Algorithm

The new sorting technique which is going to be discussed is an enhancement of the Dijkstra’s three way partitioning. The goal of the new technique and the original technique is same but the way in which we reach has been refined to make it much more effective in terms of number of swaps and time consumption.

The new modification of Dijkstra’s sorting procedure is: From the pixel values select a partitioning element or a pivot value. Let j and l be the pointers to the first element in array and g be the pointer to the last element in array. Scan from left to right by incrementing j pointer. Modified Dijkstra’s 3-way partitioning algorithm is as follows:

Step 1: If pixel value at j is less than the pivot value, exchange values at j and l and increment both l and j.

Step 2: If pixel value at j is greater than the pivot value start scanning from right to left by decrementing g pointer. If the encountered value is lesser than the pivot value, exchange values at j and g, next exchange values at j and l and increment both l and j. If the encountered value is equal to the pivot value, exchange values at j and g and increment j.

Step 3: If pixel value at j is equal to the pivot value increment j pointer.

Step 4: Repeat steps 1 to 3 until the pointers j and g crosses each other.
The algorithm can be represented as below also:

while \((j \leq g)\)

    if \((a[j] < v)\)

        exchange \(a[l]\) and \(a[j]\)

        increment \(l\) and \(j\)

    else if \((a[j] > v)\)

        while \((a[g] > v \text{ and } j \leq g)\)

            decrement \(g\)

        if \((a[g] == v \text{ and } g \neq l)\)

            Exchange \(a[g]\) and \(a[j]\)

            Decrement \(g\)

            Increment \(j\)

        if \((a[g] < v)\)

            exchange \(a[g]\) and \(a[j]\)

            decrement \(g\)

            exchange \(a[l]\) and \(a[j]\)

            increment \(l\) and \(j\)

        else increment \(j\)

endloop
By this novel enhancement we assure that only the smaller values go to the left of l pointer. This makes the new technique faster than the original one with reduction in number of swaps.

This work concentrates on the removal of salt and pepper noise using adaptive median filter where a novel enhanced Dijkstra’s three way partitioning technique is used for the sorting. The implementation results shows that new enhanced sorting technique is faster and is consuming lesser number of swaps when compared to the old algorithm.

4.2. SEGMENTATION

Segmentation is the process of partitioning an image into separate objects or component parts. This work suggests Watershed segmentation for the segmentation of weld defective area for various types of defects such as Slag Inclusion, Oxide Inclusion, Porosities, Burn-Through etc., and it proposes the use of Hough Transform and Triangularly Traversed Hough Transform based segmentation which is more suitable for segmenting defects like Lack of Penetration and Lack of Fusion which follows a straight line in nature.

4.2.1. Watershed Segmentation

Watershed Segmentation based on mathematical morphology is a powerful technique used for the principle application of segmenting blob
like objects from the background. Watershed is basically applied to the gradient of the image than applying directly to the image. The low gradient region interiors correspond to catchment basins and the region edges corresponds to the high watersheds. Watershed segmentation consists of three points where the first one is a point which belongs to a regional minimum. Second point is a point at which a drop of water will fall with certainty to a single minimum. Third type of point is a point at which there are equal chances that the water will fall to more than one such minimum.

4.2.2 Traditional Hough Transform

Hough transform is designed to locate lines in an image, so it is well suited for the detection of Lack of Fusion and Lack of Penetration weld defects from radiographic weld images. The key technique used in Hough Transform based segmentation is that the image in the xy plane is converted to a more useful representation in ρθ plane. The binary pixels with the intensity value ‘1’ in the xy plane are mapped into the ρθ plane which becomes sinusoidal curves for varying range of θ values as shown in figure 4.1 and figure 4.2. Voting in the accumulator cell is conceded with respect to the number of curves that intersects in parametric space which is in turn based on the number of collinear points in the xy plane. For every point in a line the accumulator cell is incremented by one.
Though this classical technique is in use for a long time, one of the major drawbacks is that for $k$ parameters each denoted by $N$ cells, $N^k$ accumulators are required, leading to high computational complexity. To overcome the computational complexity, this work proposes an enhancement in Hough transform.

Figure 4.1: Represents 4-points in $xy$ plane

Figure 4.2: Represents the corresponding sinusoidal curves in the parametric plane
4.2.3. Triangularly Traversed Hough Transform

This work discusses about a novel method for identifying Lack of Penetration weld defect from the radiographic image, which is basically a non overlapping straight line in nature. Primarily the edges of the input image are determined using Canny edge detection with the required specific threshold value. The edge detected image comprises 0’s and 1’s where 0’s represent the background points and 1s represent the non-background points with the assumption that 1 represent white pixels and 0 represent black pixels.

Run length smearing algorithm is applied to identify the initial and final points of a line by comparing the two neighbouring pixels relative to a threshold value. If the resultant is less, those pixels are connected by converting the intermediate white pixels into black. The radiographic weld image of the welded metal plates contains two types of edges, the boundary edges and the edge of welded area. The edges containing the boundaries are excluded and the end points of the next lengthiest edge that contains the Lack of Penetration weld defect area is found out for the application of Hough transform.

The \( \rho \) value for a vertical straight line (Lack of Penetration) is traversed as a triangular region with its three vertices \((x_s, y_s), (x_e, y_e)\) and \((x_m + \frac{d}{2}, y_m)\) which can enclose the line, where these are the starting, ending and top edge points. Thus the scanning region is optimised by
reducing the search space. The constraints for \( \rho \) can be expressed as 
\[-d \leq \rho \leq d\]. Where the distance \( d \) of the line and the midpoint are given by the expressions 
\[\sqrt{(x_e - x_s)^2 + (y_e - y_s)^2}\] and \[(x_c, y_c) = \left(\frac{x_e + x_s}{2}, \frac{y_e + y_s}{2}\right)\] respectively.

The algorithm for triangular traversal is represented below:

```plaintext
for x \leftarrow (x_c \text{ to } (x_c - \frac{d}{2}))
  y_e = (y_e - m)
  y_s = (y_s + m)
  for y \leftarrow y_s \text{ to } y_e
    if a[x][y] = 1
      call(Hough-Transform based segmentation)
```

Where \( m \) is the number of pixels taken on either side of the line, which is 1\% of length of straight line.

### 4.3. RESULTS AND DISCUSSION

This work mainly concentrates on the creation of a new advanced fast processing Adaptive Median filter for noise removal and an enhanced method of segmentation using Hough Transform for a restricted triangular region. This work compares the modified Dijkstra’s algorithm
with the conventional Dijkstra’s algorithm and Bentley algorithm based on the number of swaps and execution time. The new sorting procedure is developed in Java programming language and the algorithm’s performance is analyzed. These three algorithms are implemented and tested on radiographic weld images of various dimensions. The number of swaps taken to sort the pixel values along with the time consumption is enumerated for analysis. Median filtering is generally applied for images corrupted with impulse noise. Due to the high noise density there are more repetitions of 0’s and 255’s as pixel values in the image matrix, this makes it more congenial for the application of new proposed technique. In Adaptive median filter the window size can be varied and it can be of very big size. In this analysis the new modified sorting algorithm is employed to sort the pixels of the whole image, so as to analyze its performance for higher window size of filter as in adaptive median filter. This algorithm is being implemented in Java and the results are tabulated in Table 4.1. Generally swaps and comparisons are the most time consuming operation in any sorting algorithm.

The comparison of the three techniques based on the time consumed for sorting the intensity values is depicted in the Table 4.2. From Table 4.2 it can be inferred that the newly enhanced technique is faster than the other two techniques due to the least number of swaps.
It is evident from the Figure 4.11, 4.12, 4.13 and 4.14 that the number of swaps in the new modified algorithm is very less when compared to the original Dijkstra’s algorithm and the Bentley algorithm. The new algorithm has been employed in sorting the pixel values for computing the median value in adaptive median filter. This adaptive median filter has been employed in denoising radiographic weld images of various dimensions and noises. The results of denoising the radiographic images shown in Figure 4.3 and 4.5 corrupted with salt and pepper noise are being depicted in the Figure 4.4 and Figure 4.6 respectively.

A new enhanced method in standard Hough Transform is being proposed in this work for the segmentation of Lack of Penetration Weld defect. Figure 4.7 shows the edge detected image using Canny edge detector. The experimental results depicted in Figure 4.8 and Figure 4.9 shows that ρ value varies from -250 to 250 for standard Hough Transform, while for the enhanced Hough Transform the ρ value is varying only from -150 to 150 thereby reducing the scan region. It is evident that the computational speed is higher and the space complexity of traversal in parametric plane is less for the Hough Transform applied on the restricted triangular region when compared to standard Hough Transform where Figure 4.10 shows the segmented weld image. The Figure 4.11 shows the weld radiographic image of Porosity and the corresponding watershed based segmented image is shown in the Figure
4.12, where the porosities are being segmented out properly. The Figure 4.13 and Figure 4.15 show the weld image of Lack of Fusion and Oxide Inclusion and the segmented images are shown in Figure 4.14 and 4.16 respectively.

Figure 4.3: The Radiographic Weld Image of Lack of Penetration with Salt and Pepper noise of noise density 0.2
Figure 4.4: Denoised Radiographic Weld Image with Lack of Penetration defect

Figure 4.5: Weld image of Slag Inclusion contaminated by noise
Figure 4.6: Denoised Weld image with Slag Inclusion defect

Figure 4.7: Canny edge detected weld image of Lack of Penetration applied on a pre-processed image.
Figure 4.8: The Hough peaks obtained by using Hough Transform

Figure 4.9: The Hough peaks detection using triangularly traversed Hough Transform
Figure 4.10: The segmented weld image using the triangularly traversed Hough Transform

Figure 4.11: The Radiographic Weld Image of Porosity
Figure 4.12: Segmented Weld Image of Porosity using Watershed method

Figure 4.13: The Radiographic Weld Image of Lack of Fusion weld defect

Figure 4.14: The segmented weld image of Lack of Fusion using Hough Transform
Figure 4.15: Weld Image of Oxide Inclusion defect

Figure 4.16: Segmented Weld Image of Oxide Inclusion using Watershed method
Figure 4.17: Number of swaps Vs Noise density for 75x75 image

Figure 4.18: Number of Swaps Vs Noise density for 100x67 image
Figure 4.19: Number of Swaps Vs Noise density for 221x166 image

Figure 4.20: Number of Swaps Vs Noise density for 320x240 image
Table 4.1: Number of swaps and comparisons for image with different noise densities

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<tr>
<th>Noise density</th>
<th>Image dimension</th>
<th>Number of swaps in new technique</th>
<th>Number of comparisons in new technique</th>
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Table 4.1: Number of swaps and comparisons for image with different noise densities (continued)

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Table 4.2: Execution time of algorithms

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4.4. SUMMARY

This Chapter discusses about Watershed Segmentation, Hough Transform based segmentation and image denoising based on advanced Adaptive Median filter. This work introduces a novel enhanced Dijkstra’s 3 way partitioning algorithm for the implementation of adaptive median filter for denoising radiographic weld images. It is apparent from the results and analysis that the new enhanced Dijkstra’s three way partitioning algorithm performs better than the original Dijkstra’s algorithm and the Bentley algorithm in terms of number of swaps and time consumption to sort the pixel values of a noisy radiographic weld image. This work suggests Watershed based segmentation for identifying various weld defects and at the same time proffers an enhancement in
standard way of applying Hough transform for segmentation by introducing a new methodology for reducing the area traversed in parametric space. The proposed new technique is well suited for Lack of Penetration flaw since that defect is straight line oriented. The experimental results show that radiographic images containing various weld defects such as Lack of Penetration, Lack of Fusion, Burn Through, Oxide Inclusion, Porosity etc., are being denoised and the defective regions are segmented out.