An Algorithm to Detect and Identify Defects of Industrial Pipes Using Image Processing

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***Abstract*—This paper proposes an effective algorithm for detecting and distinguishing defects in industrial pipes. In many of the industries, conventional defects detection methods are performed by experienced human inspectors who sketch defect patterns manually. However, such detection methods are much expensive and time consuming. To overcome these problems, a method has been introduced to detect defects automatically and effectively in industrial pipes based on image processing. Although, most of the image-based approaches focus on the accuracy of fault detection, the computation time is also important for practical applications. The proposed algorithm comprises of three steps. At the first step, it converts the RGB image of the pipe into a grayscale image and extracts the edges using Sobel gradient method, after which it eliminates the undesired objects based on their size. Secondly, it extracts the dimensions of the pipe. And finally this algorithm detects and identifies the defects i.e., holes and cracks on the pipe based on their characteristics. Tests on various kinds of pipes have been carried out using the algorithm, and the results show that the accuracy of identification rate is about 96% at hole detection and 93% at crack detection.**

Keywords—Defect detection; defect identification; image processing; pipe industry;

I. INTRODUCTION

Visual defect detection has drawn increasing attention in recent years since it has been an important and complicated task in the field of computer vision. It has a wide range of application areas including automatic object detection, object surveillance activity analysis and human computer interaction. In this paper, an algorithm for detecting certain manufacturing errors that may arise in case of industrial pipes is developed, which the manufacturing company can then investigate and solve. The detection and identification of defects on industrial pipes is the most important step during the post manufacture inspection. Although, it can be performed manually by experienced human inspectors but such manual inspection of industrial pipes has a number of drawbacks including high costs, laborious, low efficiency and time consuming. Therefore, an image processing based algorithm for the detection of defects is proposed. Some systems for defect detection have already been developed as commercial products. However, since long time to cope with defect detection, several techniques have been proposed using image processing [1,2]. Abdel-Qader et al. developed a method by using wavelet transform, Fourier transform, Sobel filter, and canny filter in [3]. Hutchinson et al. in [4] used a canny filter and the wavelet transform for defect detection. Another automated method has also been performed by Wu Xue-Fei, Bai Hua in [5]. It is based on image processing, a defect feature extracting method under HSV color space. They have used QFCM (Quick Fuzzy C-Mean clustering) segmentation arithmetic. Another one among the proposed methods is based on morphological operation of underground pipe defects. Shivprakash Iyer and K. Sinha [6] used smoothing using morphological operation, segmentation using edge detection. Nowadays, extensive sophisticated researches are being performed all over the world. Recently, automatic defect and contaminant inspection system has been developed for inspecting the inner surface of Heating, Ventilation and Air Conditioning (HVAC) ductwork pipeline [7]. In that paper instead of Sobel edge detection, they have used SUSAN edge detection where edges are detected by circular mask. Over there, seeded k-mean clustering approach has been used to classify features such as hole, crack and rust. But the feature extraction method used in this proposed work is different from those discussed till now. Another important application of image processing is the morphological segmentation based on edge detection captured by CCTV that is used by Tung-Ching Su et al [8]. They have used the specific method to detect defects such as multiple fractures, debris, hole, collapse, open joint and so on. But they have not distinguished between defects, rather marked them only. Most of these algorithms are designed to detect cracks for underground pipes. However, for the pipes in the industries, these algorithms may not always perform accurately to distinguish the defects i.e., holes and cracks.

This proposed algorithm is divided into three sections. In the first section, it carries out some pre-processing in the whole image including gray scale conversion, edge detection and noisy object elimination. In the next section, the pipe is extracted from the whole image and in the last one, identification method is applied. In section one, the RGB image is converted to a gray scale image and then edge detection is done using Sobel gradient method [10]. After applying Sobel gradient method [10], the resultant image may contain some noisy objects which can create erroneous results in the algorithm. To minimize their effect, these unwanted objects are eliminated according to their sizes. Then a

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bounding-box is generated to surround the pipe. In the second section, fundamental morphological operation [11] is applied to describe about region shape and connect disjoint lines. Finally some fundamental features i.e., area and perimeter are calculated for each object. Afterwards the defects such as hole and crack are distinguished based on their area to perimeter ratio.

II. Proposed Algorithm

The proposed algorithm detects the defects in the industrial pipes through image processing. It is arranged in three sections. First section is declared pre-processing, second one as extraction of pipe from background and third one is defect identification. Summary of our method is shown in below by a flowchart (Fig. 1).

A. Pre-processing

The raw data (RGB image) acquired from digital camera are pre-processed for further data analysis. It includes the gray scale conversion [9], edge detection and elimination of noisy objects present in the raw image. The different data-processing stages are depicted below.

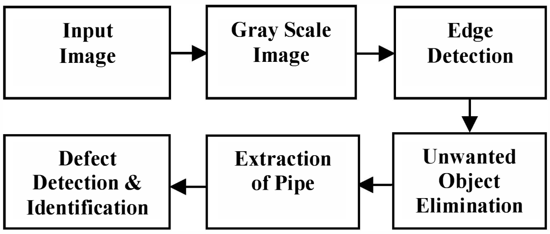

Fig. 1. The process flowchart of the proposed algorithm

1) Edge detection: At the RGB image is converted to grayscale and then Sobel gradient algorithm [10] is applied to detect the sharp changes, to preserve the defects. Sobel edge gradient preserves the boundary of objects. The gradient is a vector and the components are measured in the x and y direction. The components are found using (1) and (2).

$$\frac{\partial f(x,y)}{\partial x} = \Delta x = \frac{f(x+dx,y)-f(x,y)}{\partial x} \tag{1}$$

$$\frac{\partial f(x,y)}{\partial y} = \Delta y = \frac{f(x,y+dy)-f(x,y)}{\partial x} \tag{2}$$

Where, f is intensity function. To detect the presence of a gradient discontinuity, the change in the gradient at (x, y) is calculated and the magnitude (M) and gradient direction are found using following (3) and (4). A pixel at location (x, y) is an edge pixel according (5).

$$M = \sqrt{(\Delta x^2 + \Delta y^2)} \tag{3}$$

$$\theta = tan^{-1}(\frac{\Delta y}{\Delta x}) \tag{4}$$

$$BW(x,y) = \begin{cases} 1, & if\ M(x,y) > T_h \\ 0, & if\ M(x,y) < T_h \end{cases} \tag{5}$$

Where, Sobel gradient methods take threshold T_h automatically.

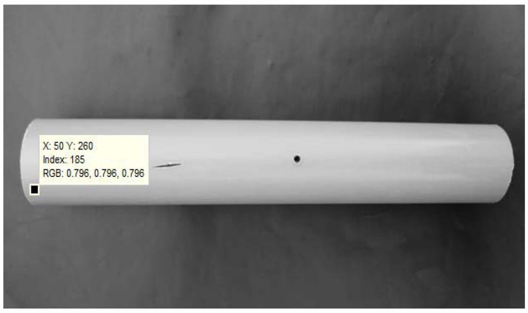

Fig. 2. Gray scale image

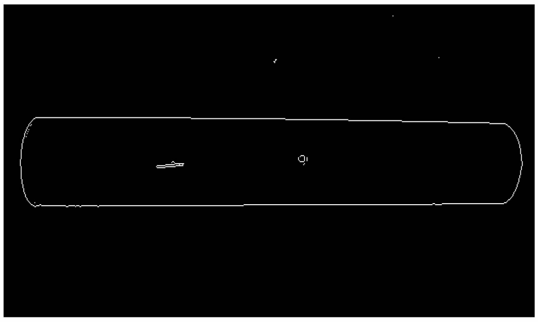

Fig. 3. Sobel gradient image. After applying Sobel gradient to the gray scale image, the resultant image contains the edges of pipe and the defects.

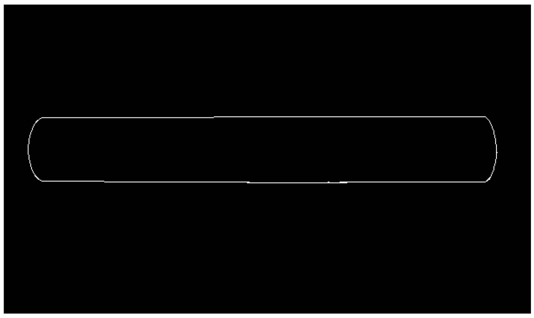

Fig. 4. Sobel gradient image of a pipe without any defect (ideal case). Ideally, Sobel gradient finds the edges only in the boundary of a pipe if the pipe has no defect.

After completion and combination of edge detection along vertical and horizontal direction, Sobel gives resultant edge detection. Fig. 3 is an example of Sobel gradient image. And Fig. 4 is the example of the ideal case. Only boundary of the object is illustrated.

B. Extraction of Pipe

Pipe extraction is an important part of this algorithm. As noises in background create problems with the defects (hole and cracks), extraction of pipe from background is necessary. This section involves running through images pixel by pixel and performing numerous calculations using this pixel and its surrounding pixels. It is consists of three steps. From resulting edge image, algorithm eliminates unwanted objects. Then, a bounding-box is created surrounding the pipe for the presence of some noises in image. And last extraction of pipe from background is done. By extracting the pipe, test image is represented in a more appropriate manner for further processing. The proposed algorithm is elaborately described below.

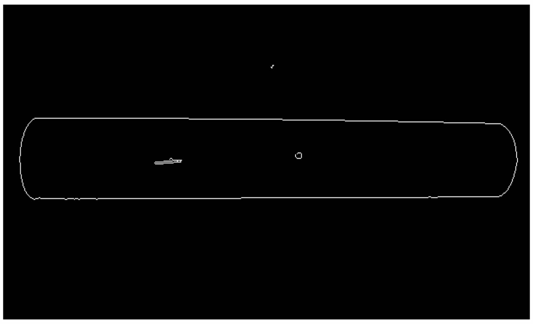

Fig. 5. Unwanted object elimination. Noisy objects are eliminated based on area.

1) Unwanted object elimination: First, defects and the boundary of objects are distinguished. Therefore, objects (some dots, some small objects and noises) remain in the foreground and background as shown in Fig. 5. The main purpose of this is to keep only the defects in the foreground. So, needless objects should be eliminated. Unwanted object elimination follows the following formulas (6).

$$BW(x,y) = \begin{cases} 1, & if\ M(x,y) \geq T_{area} \\ 0, & if\ M(x,y) < T_{area} \end{cases} \tag{6}$$

If the size of an object is very large, the optimum threshold (T_{area}) value discards the majority of the unwanted objects. Thus, algorithm removes all connected components (objects) that have fewer than T_{area} pixels. From Fig. 5, it can be seen that unwanted object is eliminated. Nevertheless, some noises still remain. Therefore extraction of pipe is necessary.

2) Bounding-box creation: Before separating pipe from background, bounding-box is created around large object according to the algorithm based on following (7),

$$B.box = \begin{cases} 1, & if\ obj.area(l) \geq obj.area(i) \\ 0, & otherwise \end{cases} \tag{7}$$

Where, *obj. area (l)* represents the largest object present in the image while *obj. area (i)* represents the other objects. It is assumed that the pipe in the image is the largest object and according to that the resultant bounding box is shown in Fig. 6.

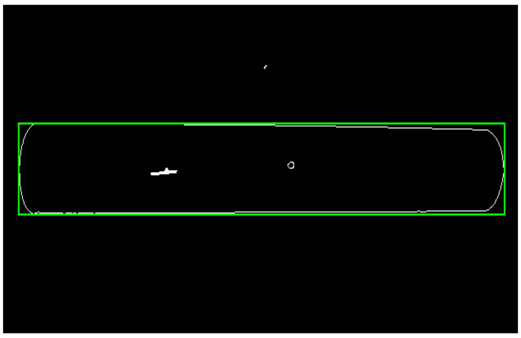

Fig. 6. Bounding-box is created around largest object. It is based on the respective size of the area of all objects present in the image.

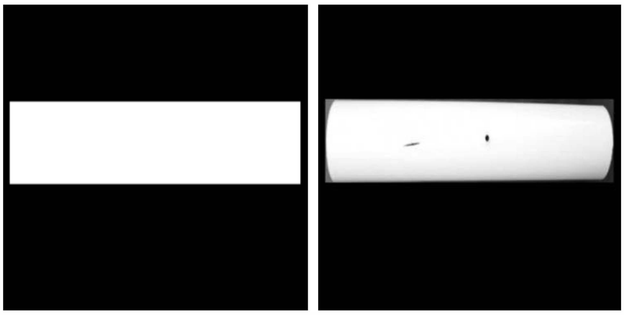

Fig. 7. (a) Image containing the foreground pixels (b) Image after extraction of pipe. This is extracted by multiplying intensity image of HSV with foreground image.

3) Separation of pipe: After creation of bounding-box around target object, algorithm turns all the pixels inside the bounding-box into white pixels. This is declared as foreground image. This is illustrated in (8).

$$Foreground(x,y) = \begin{cases} 1, topleft\ (x,y) \leq obj.area(x,y) \geq bottomrigt(x,y) \\ 0, otherwise \end{cases} \tag{8}$$

Where, *Foreground(x, y)* means the position of all white pixels and if all points of *obj.area(x, y)* lay between *topleft(x, y)* and *bottomright(x, y)* our algorithm turns all pixels to white.

Then only the intensity of the test image is taken. The intensity component is found using (9).

$$I = \frac{(R+G+B)}{3} \tag{9}$$

Where, *I* is the intensity of the image, *R, G* and *B* are the individual components of the image respectively.

Later, the image containing the foreground pixels (Fig. 7(a)) and the intensity image are multiplied. Thus the pipe is separated from the background (Fig. 7(b)).

C. *Defect Identification*

At this stage, the remaining objects are regarded as the candidates of the hole and the crack after Sobel gradient method. Before detecting the defects, morphological operation is applied on Sobel gradient image. Narrow breaks must be eliminated unless algorithm returns unexpected result. Defect is identified using the following features.

1) Mathematical morphology: Dilation and erosion methods are performed to connect the disjoint lines. As the area is expanded using dilation shown in Fig. 8(a), erosion is used for recovering original size of object and thereby removes discontinuity of bright pixels. From Fig. 9(b), it can be seen that disjoint lines are joined. Then, the hole and crack candidates are separated and their information is used to track and classify defects.

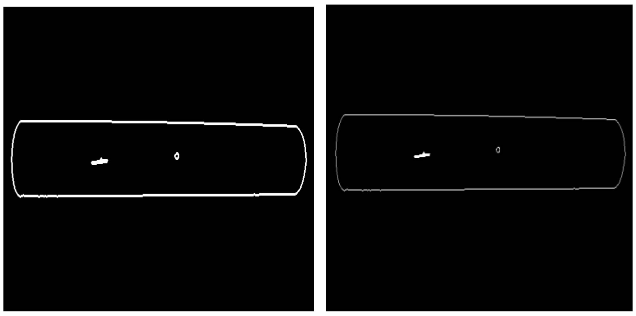

Fig. 8. (a) Image after dilation (b) Result of erosion of dilated image. Erosion removes outer layer of object pixels. Thus, discontinuity is removed.

Fig. 9. (a) Defects before dilation and erosion (b) Image after removing discontinuity of bright pixels using dilation and erosion.

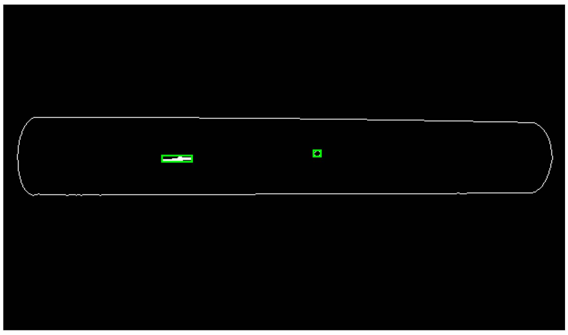

Fig. 10. Defects are detected based on their area. These are represented by a minimum bounding rectangle that tightly bounds the defects.

2) Defect detection: Algorithm works in a way such that every object inside the pipe is detected, rather than objects which has large area. This is shown in Fig.10. Defects are detected based on following (10).

$$B.box(i) = \begin{cases} 1, & obj(i).Area \leq obj(l).area \\ 0, & otherwise \end{cases} \tag{10}$$

Where *obj (i).area*= every defect into large bounding-box and *obj (l).area*= area of large bounding-box.

3) Defect classification: To extract defect feature in input image, algorithm calculates area, perimeter and later derives ratio of area to perimeter. Since algorithm creates bounding-box based on corresponding defects and then according to feature, thus identify. This is shown in (11).

$$r_{ap} = \frac{Obj(i).Area}{Obj(i).Perimeter} \tag{11}$$

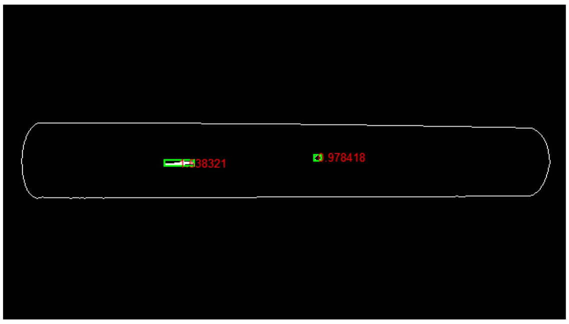

Fig. 11. Output of proposed algorithm. One small crack and a small hole are identified accurately according to their area to perimeter ratio. These are represented by a minimum bounding rectangle that tightly bounds the defects.

Where *Obj (i).Area* and *Obj (i).Perimeter* are number of pixels in the region and distance between each adjoining pair of pixels around the border of the region respectively.

In case of a hole, the perimeter and area are closely similar to each other. So this feature can be defined as $r_{ap} < 1.10$ and $r_{ap} > 0.80$.

In case of a crack, the perimeter is fairly less or greater than area. Thus, this feature can be defined as $r_{ap} > 1.10$ and $r_{ap} < 0.80$. Fig. 11 shows the final output of the proposed algorithm.

III. Experimental Result

The proposed algorithm is tested on various images of pipes which contain defects including hole and cracks. The main objective is to detect the defects effectively and distinguish them according to their characteristics. In the experiments, the value of T_{area} is assigned as 4. This implies that the objects whose area is less than 4 pixels are eliminated. For instance, in fig. 3 small objects have appeared along with holes in the background. Therefore, if area of smaller objects in pixel is less than 4, the algorithm discards those small objects. Then, the morphological dilation and erosion are performed to eliminate the discontinuity of white pixels shown in fig.8 with six-pixels-diameter flat disk shaped structuring element. The area by perimeter ratio (r_{ap}) decides the defects whether it is a hole or a crack. If the value of r_{ap} is within the limit of 0.8 and 1.1 then this algorithm identifies the defects as *hole*. On the other hand, if the value of r_{ap} exceeds the limit of 0.8 to 1.1, this algorithm identifies it as a *crack*. The algorithm has been tested on many images containing holes (30) and cracks (45). According to the features, defects are detected and identified and bounded by green bounding boxes. Fig. 12 and 13 show the experimental results with input RGB images and corresponding detected defects bounded by rectangular bounding-box. In both images, cracks and holes are identified correctly. The ratio of area by perimeter (r_{ap}) for crack is found 1.43 and 1.5247. This algorithm also identifies the holes correctly as the value of r_{ap} for holes is found within the limit (i.e., 0.84 and 0.92).

This algorithm successfully identifies the majority defects. In some images, this algorithm could not identify cracks with

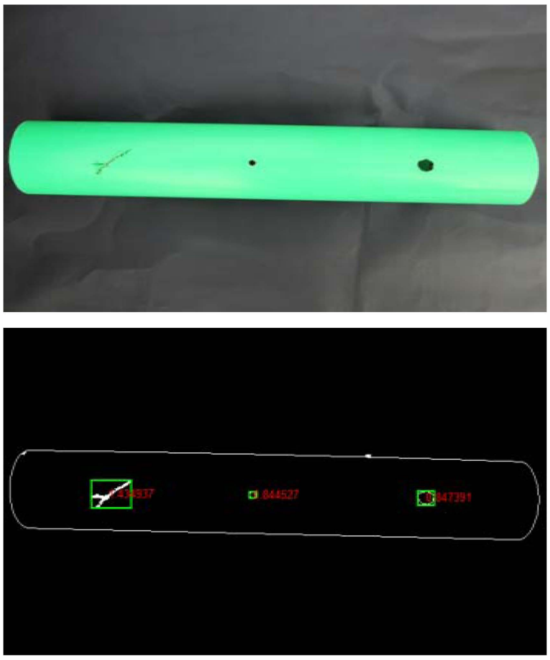

Fig. 12. (a) Input RGB image. In this image there are three defects include two hole and one crack. (b) Output of the proposed algorithm. All the defects are identified correctly according to their area to perimeter ratio and tightly bounded by minimum rectangle.

disjoint lines. As a result, instead of considering it as a single defect, this algorithm may identify it as multiple defects (Fig. 14). The holes are identified correctly as there is no discontinuity in the holes. The values of r_{ap} for two different holes are 0.95 and 0.91 respectively. However, due to the presence of discontinuities in the crack, this algorithm shows more than one values of r_{ap}.

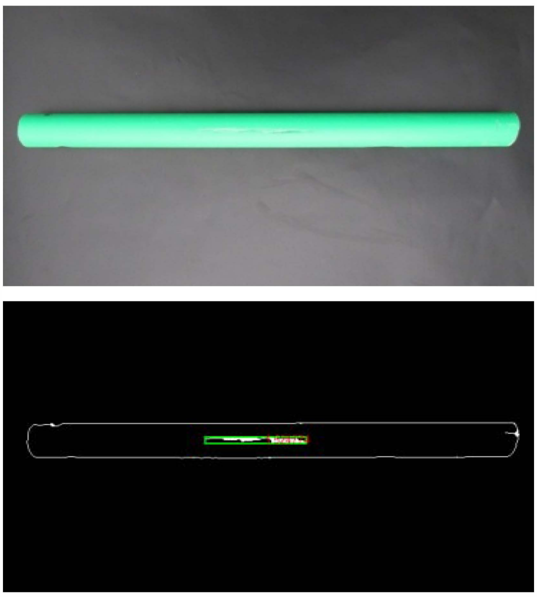

Fig. 13. Input RGB image. (a) In this image there is one defect which includes one big crack. (b) Output of proposed algorithm. This is identified accurately according to its area-perimeter ratio.

Fig. 14. Input RGB image. In this image there are two holes and one big crack. (b) Output of proposed algorithm. The holes are identified accurately but the crack is not identified correctly due to the presence of discontinuity.

TABLE I. ACCURACY RATE OF PROPOSED METHOD

Data Sets	**No of Defects**	**Detected Defects**	**Percentage of Accuracy** $(\frac{N_d}{N_t} \times 100)$
Hole	30	29	96%
Crack	45	42	93%

IV. CONCLUSIONS

In this paper, an image processing based algorithm for detecting defects (crack and hole) in industrial pipes, simply from the images of the pipes, is proposed. This algorithm identifies the defects based on the detected edges of the defects and distinguishes according to their size and shape. Experimental results demonstrate the algorithm as effective for dealing with the industrial pipe images. Based on experimental results, it can be concluded that the proposed method can segment and identify defects effectively and accurately. However, the proposed algorithm may have a few limitations in the forms that it may not successfully detect the defects if they are too closely attached to the boundary of the pipe, or if there is a crack that is discontinuous. In the future, there are plans to work on methods to detect other types of defects such as imperfection in diameter, defects in the border lines.

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