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Robotic Model for Unmanned Crack and Corrosion Inspection

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***Abstract*: After prolonged usage of materials, the formation of cracks and corrosion initiates due to stress, loading condition, the environment of operation, etc. and this affects the structural integrity of structures. Periodic inspection of structures is usually planned, especially in industries where the impact of failure could be devastating, such as oil and gas pipelines, storage tanks, vessels, and airplanes, etc. which are just a few amongst others. This inspection is often aimed at detecting cracks and corrosion of internal and external components using several forms of non-destructive testing mechanism usually performed by a specialist at a high rate.**

To reduce the cost of inspection as well as downtime due to inspections and maintenance, deployments of mobile robots with fault tracking and identification purpose are steadily increasing. This paper, therefore, details the implementation of an image processing technique using MATLAB to identify defects of structural elements.

Keywords: Crack, Corrosion, Image Processing, Inspection, MATLAB, Robot.

I. INTRODUCTION

Structural failure is a significant cause of concern in industrial as, despite the best effort to curtail its impacts, it cannot be eliminated. Several catastrophic events have occurred in recent times the whole root cause all traces to structural failures such as vessel wreck, plane crashes, and tank collapse. Although extensive inspection and maintenance schedules are imposed, the effect of this with respect to cost, and downtime is sometimes unbearable due to the enormous amount of money lost per day especially in the case of extended downtime such as vessel drydocking which usually takes between thirty days to even more than one year depending on the type of vessel and maintenance scope [1].
Structural steel is present in so many industrial applications and even domestic and commercial use due to their physical and mechanical properties such as ductility, malleability, corrosion, thermal properties, etc. however steel used in applications like tanks, pipes, etc. cannot withstand corrosion and cracks due to their operating environment that tends to impact their resistance property. This makes monitoring important [2] [3]. Visual inspection is essential in accessing structural integrity, and defects such as cracks and corrosion could be detected from this type of inspection. However, a visual inspection may not be possible in some regions such as dark corners and internal points, which are not easily accessible physically. Manual inspection by inspectors is always labour intensive, stressful, and time-consuming, as such robotic platforms designed for non-destructive inspection (NDI) have been developed as seen in Liu et al. [4] and Atha and Jahanshahi [5]. Also, several other defects are commonly associated with steel structures. And early detection prevents total collapse, buckling, or fracture.

Fig. 1.Corroded storage tank surface

Different analytical and NDI methods have been employed in the inspection of cracks and corrosion, all of which are limited by cost, inspection range, and inability to detect minor pitting [6]. Also, in more robust inspections, some countries are limited by access to better equipment. Therefore, developing a low cost-efficient system for use in the inspection of structural defects can play a significant role in bridging this gap.

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II. PROBLEM DESCRIPTION

In inspecting structures such as vessel hulls, airplane fuselage, or even tanks, structures containing or carrying substances first must be emptied, and platforms are put in place to allow for close physical inspection and repairs by workers. Industrial structures commonly found in factories and large organisations are, however, massive, which makes physical inspection tedious as the platforms need to be moved continuously or rearranged as needed. Similarly, in the inspection of tanks and vessels, workers might be exposed to hazards such as working in gas chambers, dark and tight corners, etc. which makes access difficult. Also, human inspection data are often subject to some degree of error due to visual impairment, stress, and absent-minded estimation, etc. which might allow for misjudgement in accurately representing structural defects.

The presence of cracks and corrosion in structures are indicators of the state of the materials, and while cracks are caused by the concentration of stress in the material or even discontinuities, if not detected on time, the crack will gradually increase and cause damage. Although surface cracks could be relatively easy to detect, some cracks occur inside the material, which may be due to manufacturing defect, and this type of crack requires more extensive analysis for identification.

Corrosion also occurs on materials, and although there are different types of corrosion based on the area of material application and environmental conditions, pitting and rust are, however, general forms of corrosion usually found on uncoated surfaces. Pitting is mostly associated with the disintegration of paint coating, which can extend to random material penetration. Grooving mostly occurs at intersections, which are very vulnerable to holding liquid substance.

The aim of this paper is, therefore, to implement visual identification of cracks and corrosion failure on a robotic inspection platform. This is to automate the process of inspecting structures.

III. RELATED WORKS

Steel structures are made by combining several elements in different compositions to achieve the purpose of their end-use. While some structural application requires stiffness, strength, etc., some other application might require ductile and malleable property. The iron content in these materials, however, makes them rust-prone when exposed, which creates vulnerability to corrosion [7]. Early detection of the inset of failures means proactive maintenance to preserve the integrity of the structure by preventing further spread.

Image processing has been recently implemented in non-destructive inspections, and crack, and corrosion detection is one area where this technique can be applied. In the previous study by Sharma and Tejinder [8], image processing was used in rust detection. The steps involved obtaining relevant images of the area of interest, which can be obtained through mounted cameras on robots. The following step, however, proposed rust detection by various rust types and levels, which all emphasised different algorithms, then the area of rust is then calculated to determine the degree of rust spread, and finally, a solution is proposed in the preferred maintenance to carry out.

On the outer surface of pipes and structures, [9],[10] utilised statistic measurements of the picture pixels in quantifying pitting while [11] corrosion detection was based on the morphology of the surface such as colour, shape surface roughness, etc. Medeiros [12] also proposed a method based on describing the surface texture of the material obtained from the co-occurrence matrix and colour.

The learning-based approach has also been employed in image processing, as seen in the typical pattern recognition systems like a neural network [13] [14] [15]. Also, wavelet method was used by [16] [17]. Zhang et al [18] also used this method of packet decomposition energies as a sub-band level in corrosion identification. Tao et al. [19] studied the corrosion process of aluminium alloys with the wavelet method, where the study concluded that the values of sub-image energy reduce with prolonged exposure. Numerous studies have also been done in the identification of cracks in concrete [20] [21] asphalt [22] and pavement [17].

The algorithm employed by sharifzadeh et al [23] on the identification of holes, breaks, and rust using image processing involved thresholding of binary images and entropy study. The success rate of their method was 90.3% meanwhile Ghanta et al. [24] study was based on wavelet transformation, but the rust identification involved cross-correlation model and analysis of colour but their method was limited by the size of the rust and image size, and in the end, it was only 52% effective.

This literature shows that the method of image processing is a feasible option in identifying structural defects, which is a better alternative to the traditional manual inspection of structures. And with the increasing application of machine vision, it becomes necessary to explore other methods with practical implications. The projected technique exploits MATLAB software for analysing cracks on structures through the identification of texture using edge detection. The images are analysed through the application of thresholds and several filters to eliminate noise.

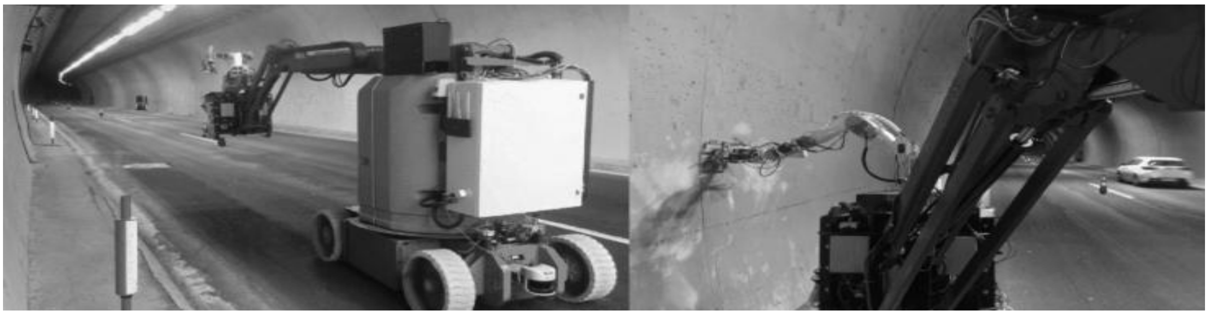


Fig. 2.Crack detection robot for tunnel inspection [25]

IV. MATERIAL AND METHODS

The project involved the initial construction of an unmanned vehicle designed to support and carry the necessary inspection equipment such as wireless cameras and sensors, then the electronic and mechanical control function of the vehicle was worked on. This included the integration of driving mechanism, tire selection, speed and power calculations, etc. the wireless control module was also installed to control all actuators on-board the vehicle.

The final phase of construction involved testing vehicle mobility in real conditions. Hardware components involved DC motors, servos motors, batteries frame wireless video transmitter and receiver module, cameras, and a solar module for vehicle charging. Other peripheral sensors were also installed on the vehicle to aid in measuring other variables not mentioned in this paper, such as temperature and humidity sensors, IR transmitter, etc.

Fig. 3.Robot platform with wireless inspection camera

V. VEHICLE CONSTRUCTION

The Sub-systems of the vehicle include the power system, control system, manipulator and chassis Design

A. Power system

This provides the vehicle with the necessary electrical power needed for the manipulator, end-of-arm tooling, and other components.

B. Battery Capacity

The limit of the batteries is set to the power required for segments to keep running for the base runtime. The stacking states of every segment will vary all through a preliminary trial, for example, the Drive motor will vary between full-load, no-load cycles more than once, while the PC and sensors will have close to consistent power necessities. The total power requirement was approximately 266W due to the presence of several sensors and actuators onboard. In satisfying these requirements, the batteries must hold roughly 270Wh of usable vitality to give a thirty-minute runtime.

C. Control system

This system is made up of all the sensors, the memory unit, all of which feeds back information that manages the exact development of the controller and end-of-arm tooling. For the control system of the vehicle, Arduino mega, and other sensors such as the DTT11 temperature and humidity sensor, Ultrasonic sensor, PIR sensor, were used.

D. Machine vision system

The UGV is equipped with a wireless camera that transmits images from within a 100m radius. This allows the vehicle to inspect the surrounding and transmit images for crack analysis. The images are conveyed over a wireless receiver, which is directly linked to a monitor.

E. Manipulator

The manipulator is in the form of a robotic arm. The arm is controlled by servo motors and carries the wireless camera with a pan and tilt orientation. The robotic arm featured three degrees of freedom, spherical motion, remote drive capability, compact size, lightweight & low inertia, high accuracy & repeatability, high mechanical stiffness, and rugged & reliable design. A choice of servos coordinated the predefined holding torques of RX64 (64kgcm), and RX28 (28kgcm) were picked.

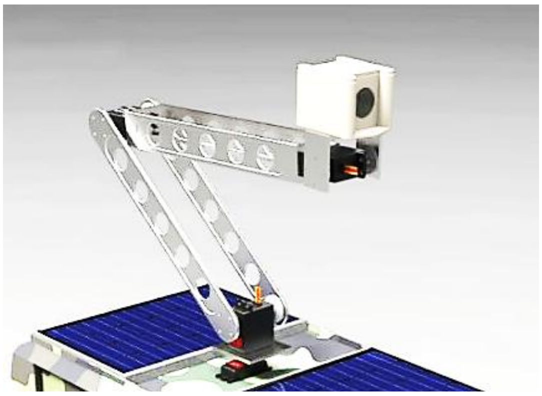


Fig. 4. Robot Arm

F. Chassis construction

The primary real structure choices were the materials and strategy for development and fixing strategies. One of the principal considerations for the chassis was weight, which was estimated as 20kg, henceforth lightweight materials were obligatory while yet keeping up an inflexible undercarriage. The materials likewise will have to be impervious to corrosion, except if completing procedures are utilized on the specific parts, where the disadvantage is future modifications will expose the material; thus, there is a requirement for resurfacing. Mild steel was picked because of its simplicity of machining, cost, and accessibility.

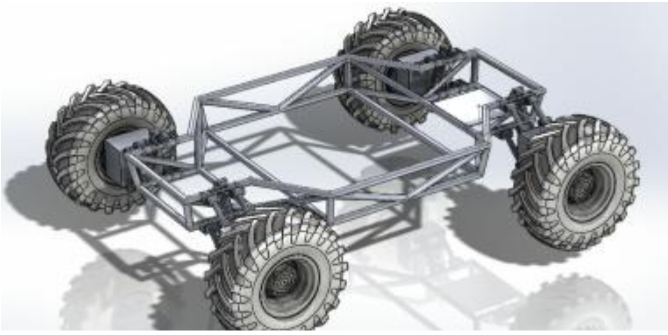


Fig. 5.Designed chassis

G. Fabricated chassis

The construction involved using mild steel angle bars to shape and formed the chassis. Welding was done for rigid joints, and bolt and nuts were used for movable joints. This technique for development usually is hard to dismantle as welded, and riveted joints must be destroyed to dismantle. Its advantage, however, is the simplicity of manufacture, which results in a rigid outcome. Regardless, the procedure is tedious and doesn't loan itself well to the modifications which are without a doubt required in a model plan.

VI. CRACK IDENTIFICATION

The methodology involved in image processing required image enhancement, contrast adjustment, and fractal thresholding.

The image pre-processing is initially done to suppress the unnecessary elements from the image that might interfere with the analysis while enhancing the desi features. This helps to simplify the subsequent analysis as varying light conditions and noise are filtered out. The identification algorithm is stated below.

- Original images are obtained from the robot
- Conversion of the original image to a grayscale image
- Derivation of a median filtered image using 5 x 5 median filter
- Edge detection application of image is attained
- The threshold image is established
- Final image processing
- Output result.

The non-linear method was employed in image filtering. This method considers the filtered (f*), original ($f_{org}(i,j)$)and blurred ($f_{blur}(i,j)$) pictures of the defect as shown in the equation 1 below.

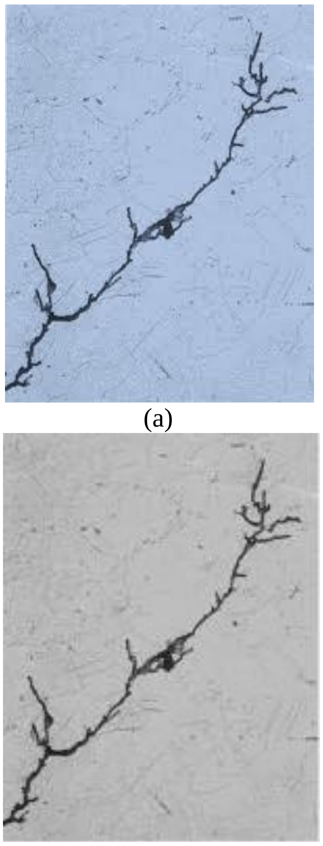
$$f^* = Z(i,j) \times [f_{org}(i,j) - f_{blur}(i,j)] + m \quad (1)$$

Where m represents the mean of the initial image. A low pass filter is applied to the original image, and the gaussian spatial filter was selected. (see equation 2)

$$H(u,v) = exp[-\frac{D^2(u,v)}{2\sigma^2}] \quad (2)$$

The blurred image can then be obtained by the expression

$$f_{blur}(i,j) = [f_{org}(i,j) \times F^{-1}[H(\vartheta_i, \vartheta_j)]] \quad (3)$$



(a)

(b)

Fig. 6.Illustration of enhanced image: (a) Original image from mounted wireless camera and (b) image after application of non-linear filter

Thresholding was implemented in the image segmentation. This is the conversion of the image into a binary form as a means of quantifying the image. The program assigns the binary digits to pixels, which is dependent on the intensity of the background. Adaptive thresholding was applied as it assigns different thresholds to regions for enhanced segmentation.

Although structural cracks have different characteristics with distinguishable curves and lines, the crack is minimum when a grayscale conversion is applied. Separation of image pixels and characterisation of cracked and non-cracked areas is essential in implementing an approach for a more efficient means of identifying cracks.

Mathematically, the fractal analysis of the images was based on the concept of the upper and lower surface. Being that f(i,j) = Up(i,j,0) = Dn(i,j,0)

The upper surface defined by

$$\mathrm{Up}(i,j,\in +1) = \max\{\mathrm{Up}(i,j,\in) + 1, \max[\mathrm{Up}(m,n,\in)]\}$$

$$Abs[(m,n) - (i,j)] \leq 1 \quad (4)$$

$$\mathrm{Dn}(i, j, \in +1) = \min\{\mathrm{Dn}(i, j, \in) + 1, \min[\mathrm{Dn}(m, n, \in)]\}$$

$$Abs[(m, n) - (i, j)] \leq 1 \tag{5}$$

The two points (m,n) and (i,j) are points in close proximity with distance less that one.

For rough surfaces, the parameter for local threshold used in image segmentation is determined by identifying an appropriate window size within the image of size M × N. a constant is subsequently derived, which can be used to set the threshold given that

$$T = \propto \times K_{min} + \beta \tag{6}$$

Where

$$0 < \propto < 1$$

The final selected values after series of experiments were s = 3, ∈ = 9, ∝ = 0.22 and β = 45

A. Noise Reduction

This step was done using the median filter technique to remove unwanted noise from the image to enable better analysis. Windows were allocated in odd numbers and sorted numerically. Sometimes though, some parts of the cracks are removed after the application of the filter.

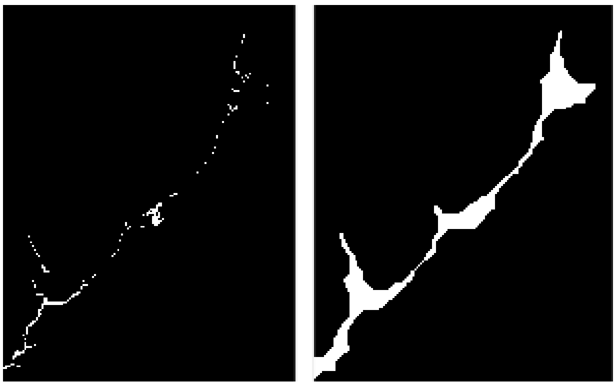


Fig. 7.(a) After threshold application (b) image after application of median filter

B. Break Points

Discontinuities in crack might occur due to image processing like the application of thresholding's and noise reductions. A breakpoint procedure is, therefore, employed. This process is achieved by identification pixels of cracks and breakpoints and then connecting them. The breakpoints are identified from a transverse pixel in the horizontal route afterward, subsequent pixels and cracks are identified and connected. The process iterates and the resulting image is crosschecked in both the X and Y-axis.

VII. RESULT AND DISCUSSION

The classification of cracks was obtained using MATLAB, and a noise-free image is obtained after several layers of image processing. Several samples of cracks on different structural materials such as steels, super alloys, mild steels, and even cement were tested and analysed. The resulting output image showed an estimate of the crack length, which is obtained by specifying the approximate area of the original image. (See figure 8 below)

Fig. 8.Final output showing crack length

In images with transverse cracks, fractal thresholding method is applied, and image discontinuities are filled by using the closing operation. This method helps in better noise reduction than the median filter option. While for longitudinal cracks, discontinuities are filled after the application of closing operation.

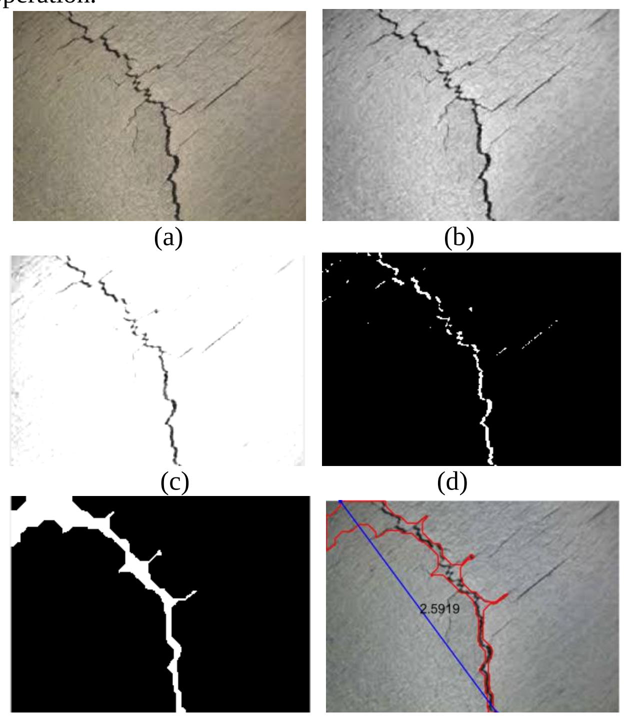


Fig. 9. (a) Control image (b) grayscale image (c) enhanced image (d) segmented image with 0.89 threshold (e) image after noise reduction (f) final output

VIII. CONCLUSION

The detection algorithm for crack identification was introduced in this study using the MATLAB image processing method. The initial step involved the image pre-processing, thresholding, and enhancement, and subsequent noise reduction and crack continuity was done.

The test results showed that this strategy could be utilized for several structures like walls, concrete, flat plates, etc. However, trials on polished stainless-steel materials yielded negative results due to light reflection when exposed.

Subsequent research could focus on the modification of the crack continuity algorithm and classification of crack types and forms.

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