

Automated Inspection of Monopole Tower using Drones and Computer Vision

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Abstract— Drones are used in a wide range of applications such as manual inspection of mobile towers, transmission lines, and Search and Rescue operations. Traditional methods of using drones for manual inspections can be time and cost consuming. Skilled labor is also required for controlling the drone. Several ‘crack detection algorithms’ have been developed for detecting cracks but there are still problems with accuracy. In this paper, we propose a computer vision algorithm under the robot operating system (ROS) platform that can detect the Region of Interest (ROI) and analyze images in real time. Drone airtime is reduced as a result of this method. This newly developed system will inspect towers and detect cracks and rusts therein. This method also considers the challenges that occur in manual methods as well as drone capabilities. This system takes the measurement of the detected cracks, and classify the types of rusts found using Deep Learning Techniques.

Keywords- drones, inspection, tower, deep learning, computer vision, robot operating system

I. INTRODUCTION

Drones are used in wide range of applications such as manual inspection of mobile tower, transmission lines, search and rescue operations[1], 3D mapping,etc. This method is time and computational cost consuming and requires skilled labor for controlling the drone. Many crack detection algorithms have been proposed and developed for detecting the cracks but it still has some problems in false detection. The proposed computer vision algorithm will overcome such issues like false detection. Apart from the computer vision algorithm, the drones have some issues like stability in outdoor, flight time, autonomous path etc. So our newly developed system will inspect the tower and detect the cracks considering the challenges possessed in manual methods as well as drone capabilities. The aim of the project is to overcome the challenges facing in manual inspection of a mobile tower. The manual inspection of the tower also brings labor safety issues as every time he has to climb up the mobile tower (up to 300 m) to check the cracks.

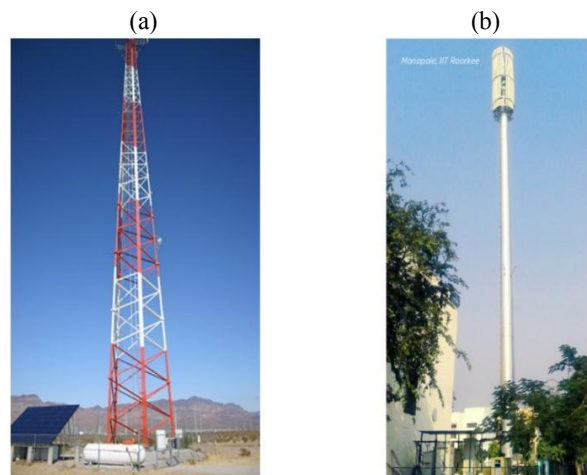


Figure 1.1. (a) Lattice Mobile Tower (b) Monopole Mobile Tower

There are two types of mobile tower existing in the market- Lattice and Monopole tower. For this research work, we are working on the monopole tower because of small tower foot print and foundation.

Our aim is to achieve an overall 90 % efficiency in detecting the cracks and send the image captured and drone parameters such as height to the controller room for future investigation. This drone-based inspection system can be used not only in mobile tower inspection but also for the inspection of transmission lines, bridges and roads etc.

Many authors have proposed and developed a computer vision algorithm for crack detection in buildings, bridges, roads etc. But the existing method would treat edges/ corner of buildings as cracks and also use drones or UAV (Unmanned Aerial Vehicle) for recording the images or video frames only and later it is post-processed for crack detection.

Manual inspection of drones is also challenging as it requires a skilled person to control the drones and another

person for checking the cracks from the videos obtained from drones. The novelty of this paper is that it automates the whole process by controlling the drone using the Robot Operating System (ROS) and detects the cracks and rusts using Deep learning algorithm. We used Global Positioning System(GPS) for the autonomous flying capability and ultrasonic displacement sensor for the height estimation.

This paper implements a computer vision algorithm and deep learning technique for detecting cracks and rusts in monopole mobile towers and to integrate it with drones using ROS. This drone-based system can replace human labors for manual inspection of towers.

II. RELATED WORK

The simplest and easiest method for measuring the quality of the test image is (Mean Squared Error) MSE that is, square of the difference between the error of the original and test image is calculated. Two images are compared pixel by pixel from left to right and top to bottom through a row and column. Then calculate by averaging square of the difference between the error of the original and test image. This method is faster but they are highly independent. To overcome said problems of MSE, the author introduced a MATLAB implementation of Structural Similarity Index (SSIM) [2] for quality assessment based on the degradation of structural information. They are slower in computation compared to MSE. Both the algorithms require a reference image for comparing the test image [3]. Since during inspection, the drone could take images of the tower at any angle. It will take more time while comparing every image captured with the images stored in the database.

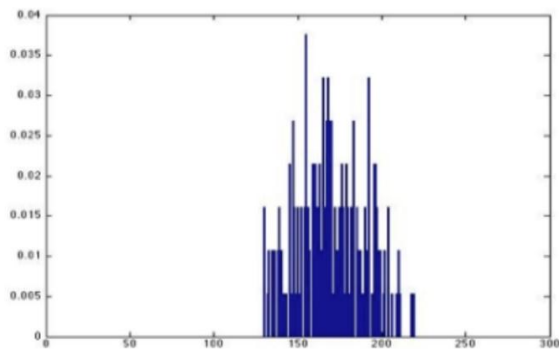


Figure 2.1. Non-cracked Images

In Computer Vision Based Crack Detection and Analysis, the author used a histogram-based classification algorithm for crack detection in concrete blocks. Fig 2.1. depicts the non-cracked images and Fig 2.2. depicts the cracked images. It is clear from those figures that the histograms having cracked images have a greater width because of the higher number of dark pixels. The Support Vector Machine (SVM) algorithm with a linear kernel function is then used for the classification purpose. The detection rate of the classifier is 76%. Histogram of Images with cracks have a larger width of histogram distribution than the Images without cracks. This is because of darker pixels (cracks) exists in the images

[4]. This method failed to detect cracks in real time and accuracy is limited to 76% only.

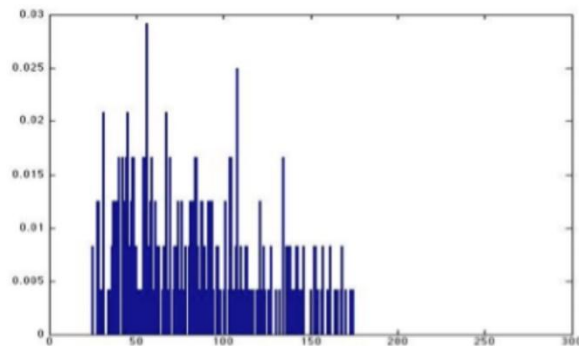


Figure 2.2. Cracked images

In Unmanned Aerial Vehicle (UAV)-powered Concrete Crack Detection based on Digital Image Processing algorithm [5]. The author implemented a UAV based system which is equipped with Raspberry Pi, camera, and ultrasonic displacement sensor, which can measure the crack image and associated distance information while UAV is flying. They used image processing strategies such as subtraction with median filter, Sauvola binarization method, image revision using eccentricity and connection of pixels, and crack decomposition and width calculation algorithm. They have the advantage of using in a large infrastructure but the problem with this method is that It will detect edges in the scene also.

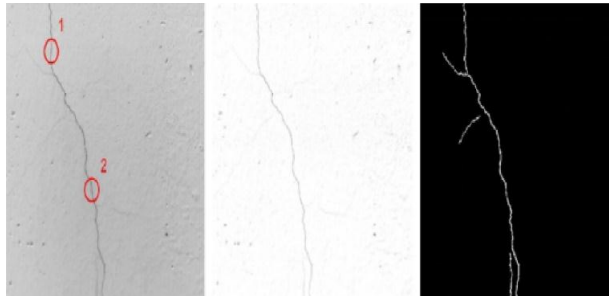


Figure 2.3. Sauvola Binarization method

In the manual inspection, the ROI of crack is identified manually and marked the region for further processing of the information such as length, area etc. This manual method of inspection requires a highly experienced and knowledgeable person. In their work [6], authors have reviewed 50 papers related to crack detection and has presented various methods to identify the crack automatically using image processing techniques. They also address the research issues which could use for future researchers. The automated crack detection can be done using some of the Non-destructive testing techniques like Infrared and thermal testing, Ultrasonic testing, Laser testing, and Radio-graphic testing are the non-destructive method used for automated crack detection [7].

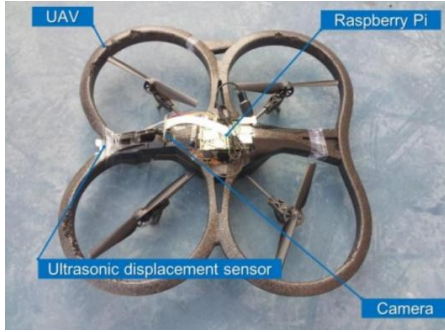


Figure 2.4. UAV-based systems for crack identification

Some authors proposed methods which use the sensor to detect cracks. Since our drone is not able to carry payload more than 50g, we have to purely depend on the camera inputs. As well those methods are time-consuming and would not detect cracks in real time. They use drones for storing the videos/images only later they analyzed the video to detect cracks. As the drone could not have much payload so for crack-detection, we had to rely fully on the image processing method. The camera megapixels influence the processing of images. This is a cheap method since we are using drones with inbuilt camera system [8].

UAV or drones were largely used in inspection of transmission lines, power plants, Search and Rescue operation. Pereira et al [9]. They have proposed a crack detection method using UAV. They used two algorithms namely Sobel filter algorithm (SOBEL) which is an edge detection algorithm and Particle filter algorithm (THRUN 2006) which used the pixel intensity and the number of pixels to detect the cracks.

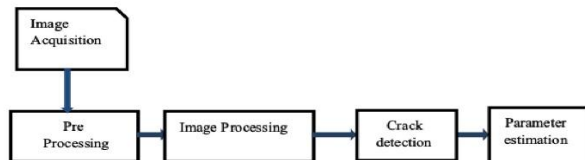


Figure 2.5. Architecture of crack detection using image processing method

The author suggests an autonomous system or a decision-making tool that can process a large amount of data to locate and classify the cracks. which can quantify, locate and classify different crack types and provide insights to the responsible person as early as possible [10].

The authors proposed rust detection using Artificial Intelligence (AI)[11]. They have compared two approaches one is detecting the rust with AI and other is using HSV (Hue, Saturation and Value) to read red rust pixels. Hue is expressed as a number from 0 to 360 degrees representing hues of red (which start at 0), yellow (starting at 60), green (starting at 120), cyan (starting at 180), blue (starting at 240) and magenta (starting at 300). Saturation is the amount of gray from zero percent to 100 percent in the color and Value (or brightness) works in conjunction with saturation and describes the brightness or intensity of the color from zero

percent to 100 percent. In HSV method, they first converted RGB image to HSV after applying the basic filter so as to reduce the influence of illumination [12]. Then they extract only red components from the image (in OpenCV, Hue range is [0,179], Saturation range is [0,255] and Value range is [0,255]) [13]. Since the range of red color in HSV around 160-180 and 0-20 for the H component, two masks were needed. After testing the authors found the best interval for the red component for reducing the false positives. The range is 0-11 and 175-180. The mask was then converted into black and white pixels and white pixels were counted. Those images having more than 0.3% of white pixels were treated as rust while those with less than 0.3% are considered as non-rust.

In the deep learning approach, they have chosen caffe framework [14] and used an existing model called bvlc_reference_caffenet which is based on the AlexNet model to find time as their dataset is very limited. In fine-tuning, we use an already trained network and adjusted it using the new data as input. This technique provides several advantages. First of all, it allows the reuse of previously trained networks, saving a lot of time. Furthermore, since the bvlc_reference_caffenet has been already pre-trained with 1 Million images, the network has prior knowledge of the correct weight parameters for the initial layers. We could thus reuse that information and avoid over-fitting problems. The last layer of the model was also modified to reflect the rust requirements.

They found that deep learning models work better in real case scenario and also suggest that OpenCV model can be used to remove the false positive before passing the image to deep learning method. Also, the OpenCV based algorithm may also be useful for the classification of images where the Deep Learning algorithm has low confidence. Deep learning model has higher accuracy. A better result can be achieved with more data-sets and if two models combined together overall accuracy is improved.

III. RESEARCH OBJECTIVES AND APPROACH

A. Research Gap

Since our tower structure is complex so already existing crack detection cannot be used as they classify the edges of the tower as cracks. So we need to come up with an efficient algorithm. Manual inspection of the tower is risky and it needs a lot of labor work. Safety is the primary issue and in post-disaster scenarios, we can use this automated drone system for inspection.

B. Research Objective and Methodology

- To implement an efficient crack detection algorithm.
- To implement a technique for rust detection and classification.

Parrot Bebop package is used for operating the drones. OpenCV is used for image processing and later integrate it with ROS. For crack detection, Haar cascade classifier is used. Unlike cracks, rust is difficult to detect with standard computer vision techniques.

IV. METHODOLOGY

A. System Design

The proposed system is shown in the figures 4.1 and 4.2.



Figure 4.1. Crack detection system

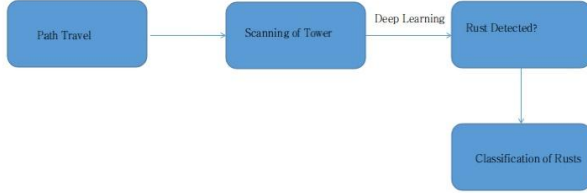


Figure 4.2. Rust detection system

B. Experimental Setup and Procedures Adopted

The drone or UAV is programmed to autonomously move around the tower and scan the whole tower in 360 degrees. UAV was used to capture the images/video of the mobile tower. Then it is processed for rust detection and crack detection. If any rust/crack is detected we will save the coordinates of the rust/crack in the database along with the height of the UAV obtained from the displacement sensor. We are able to detect cracks in real time in mobile towers.

C. Techniques Developed or Used

We have used deep learning technique for rust classification with the help of TensorFlow framework [3]. It is an Open source machine learning library used in deep learning. The advantage is that we don't need of extracting features manually as raw pixels of the image were used. In their work [15], they consider only red rust. They could only classify whether the input is rust or non-rust. So we are extending their works by considering other rusts such as black, brown, and yellow rusts and this will give the user the insights of the inspection carried out. For classification of rusts, we use retraining method which allows us to use an already trained model called Inception V3 model for classifying our rusts.

For measuring the cracks, normal corner detection is slightly modified and Haar cascade classifier is proposed for detecting the cracks in mobile towers.

V. RESULTS AND DISCUSSIONS

A. Implementation

UAV or drone is used to capture image/video of the tower. The drones will capture the 360-degree view of the tower. Haar Classifier is implemented for crack detection, once the crack /ROI is detected we will apply grab cut algorithm to extract the region of crack only by removing the

background. Then we will apply the modified corner detection algorithm to calculate the length and width of the cracks obtained in mobile towers. Note that we will also store the height of drone from the ground to save the location of the affected region as for future inspection, it would help the user to make insights of the decision made by our system. For every detection, we will save the drone height and the crack coordinates to a database this will help in a future inspection. A simple python script can be written to command the UAV to check the previously stored location of the tower. A modified corner detection method is able to locate the coordinates of the cracks. From Fig 5.2 we can calculate the length and breadth of the crack by $X_{max} - X_{min}$ and $Y_{max} - Y_{min}$. For detecting rust, deep learning models were used to check whether the image frame has rust or not. Based on the confidence rate, this method is used to classify the rusts. If possible OpenCV inbuilt libraries can be used for calculating the area of the affected region as we know the color of the rust that has affected the region.

Fig 5.4, 5.5, 5.6 are the real footage from the drones. Its an real time crack detection system. Here the cracks in the tower are used as testing dataset. We have able to detect it correctly. Two different types of cracks were successfully detected. After detection, we will apply grab-cut algorithm to remove the background then using modified corner detection method to extract the coordinates of cracks to estimate the length and breadth of the cracks obtained.

B. Results and Observations

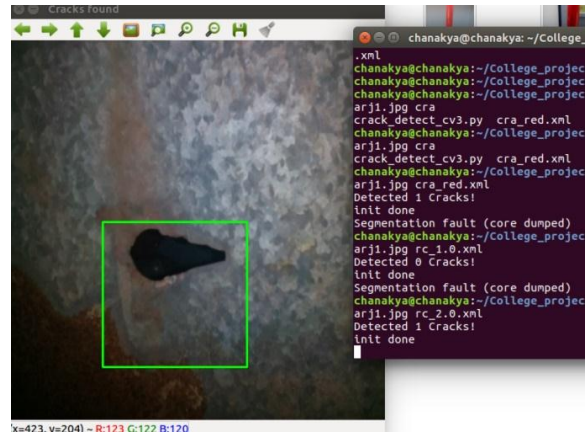


Figure 5.1. Crack detection using haar cascade

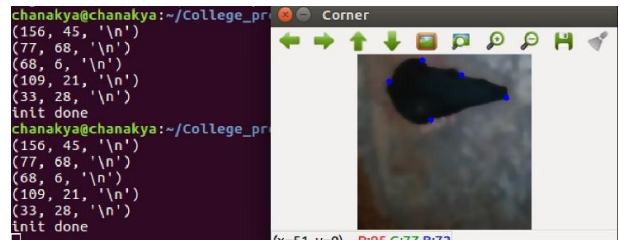


Figure 5.2. Crack measurement



Figure 5.3. Example 2 for Crack Detection using Haar Cascade

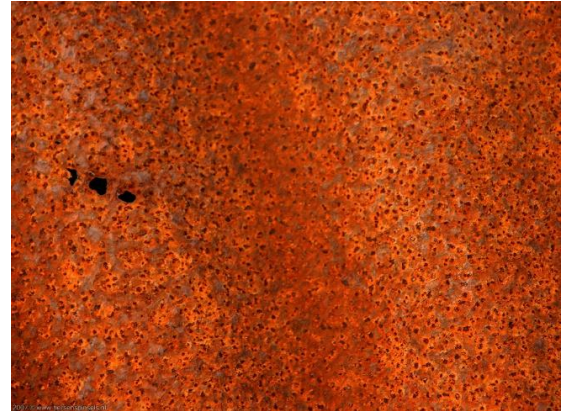


Figure 5.8. Red Rusts

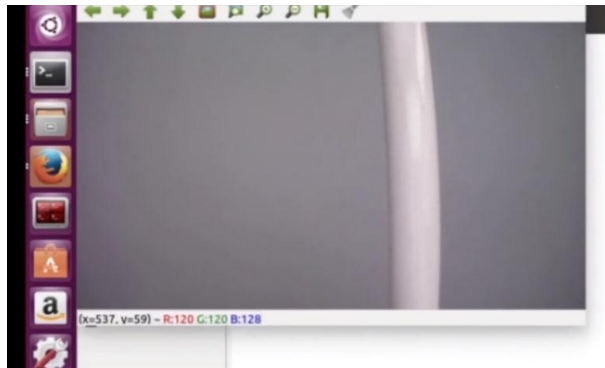


Figure 5.4. Crack Detection using drones (Stage 1)

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chanakya@chanakya: ~/Documents/EY_project
chanakya:~/Documents/EY_project$ python label.py 1.jpg
W tensorflow/core/framework/op_def_util.cc:332] Op BatchNormWithGlobalNormalizat
ion is deprecated. It will cease to work in GraphDef version 9. Use tf.nn.batch_
normalization().
black_rust (score = 0.03863)
red_rust (score = 0.95965)
yellow_rust (score = 0.00159)
brown_rust (score = 0.00013)
chanakya:~/Documents/EY_project$

```

Figure 5.9. Confidence rate for red rust

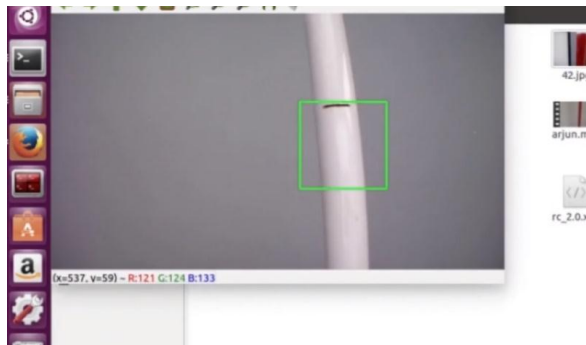


Figure 5.5. Crack Detection using using drones (Stage 2)



Figure 5.10. Brown Rusts

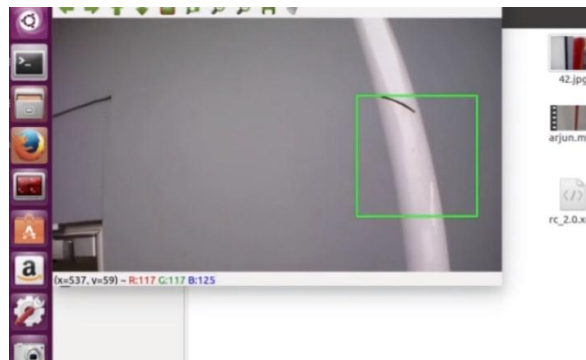


Figure 5.6. Crack Detection using using drones (Stage 3)

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chanakya@chanakya: ~/Documents/EY_project
chanakya:~/Documents/EY_project$ python label.py 1.jpg
W tensorflow/core/framework/op_def_util.cc:332] Op BatchNormWithGlobalNormalizat
ion is deprecated. It will cease to work in GraphDef version 9. Use tf.nn.batch_
normalization().
black_rust (score = 0.03863)
red_rust (score = 0.95965)
yellow_rust (score = 0.00159)
brown_rust (score = 0.00013)
chanakya:~/Documents/EY_project$ python label.py 2.jpg
W tensorflow/core/framework/op_def_util.cc:332] Op BatchNormWithGlobalNormalizat
ion is deprecated. It will cease to work in GraphDef version 9. Use tf.nn.batch_
normalization().
black_rust (score = 0.00014)
red_rust (score = 0.01350)
yellow_rust (score = 0.00037)
brown_rust (score = 0.98599)
chanakya:~/Documents/EY_project$

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Figure 5.11. Confidence rate for Brown rust

VI. CONCLUSION AND FUTURE SCOPE

A. Conclusion

In this paper, we applied a novel approach to successfully detect the cracks formed in monopole towers and was also able to estimate its length and breadth. Our novelty lies in the real time detection of cracks and saving the altitude for further rectification. Also, edge identification allowed for greater distinction. We were also able to successfully detect black, brown, red and yellow rust using tensorflow. We were able to achieve all this with 90% accuracy.

B. Future Scope

In further works, we are exploring ways by which autonomous navigation can be achieved with the help of Visual SLAM algorithm's, rather than depending on GPS. We also intend to achieve faster detection time as well as increasing our accuracy. Measuring the depth of cracks using image processing technique can also improve the performance of our system. There is still scope for improvement in this.

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