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Localization of Autonomous Drone for Telecommunication Tower Inspection and Monitoring Using Computer Vision

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ABSTRACT

This paper provides a framework for the usage of an autonomous drone and Computer Vision as a sustainable tool for the inspection and monitoring of telecommunication towers and outdoor equipment to detect cracks, faults, and misalignment. The imagery data obtained by the drone will be real-time, authentic, and can be preprocessed for improving the performance of the system. It aims to reduce the risk and challenges faced during manual inspection of telecoms infrastructures and understanding the status of equipment during their service life to avoid downtime. The Computer Vision (CV) approach for autonomous drone inspection is scalable and effective with empirical evidence in large data gathering.

KEYWORDS : Autonomous, Telecommunication, Computer vision, telecoms infrastructures, Mobile Network Operators.

I. INTRODUCTION

The telecoms industry has been experiencing several technological advancements both in terms of services and infrastructures. Mobile network technologies rollout and upgrade have also led to the establishment of base stations and construction of towers. Generally, these infrastructures are subjected to natural forces and as such, there is a high tendency for deterioration. The state and conditions of this equipment also contribute to the quality of service and lack of effective monitoring could lead to downtime and inappropriate loss of resources. Construction and installation specifications have been developed over the years, the NCC's (Nigerian Communications Commission) technical specification for the installation of telecommunication towers and masts, covering material specifications, expected service life, painting, obstruction lighting, substructure, earthling, lightning protection, antenna mounting frames, detail superstructures for various sizes of towers up to 100 m, hot-dip galvanizing for surface protection, routine and annual tower maintenance checks and tests, among many others [1]. It is important to note that manual methods of inspection can be time-consuming, labour intensive, and error-prone in checking devices, therefore an autonomous drone using computer vision will be effective for this kind of task. Drones are used in a wide range of applications such as manual inspection of mobile towers, transmission lines, search and rescue operations, 3D mapping, etc. [2]. The proposed Autonomous drone's navigation system will be designed using Robotic Operating System (ROS) to follow an automated inspection route. The methodology for the proposed project follows an excellent data-driven approach, using advanced computer vision techniques known as object detection. Object detection is concerned with detecting instances of semantic objects of a certain class in images. At the most fundamental level, the image data gathered by the drone will be analyzed in real-time using an onboard central processor and fed into the object detection model to check the status and condition of infrastructures and equipment to detect wears, cracks, rusts, and misalignments. The proposed research focuses on the development of fully autonomous, real-time, and intelligent-based techniques for inspecting and monitoring telecommunications towers and outdoor equipment.

Analysis of the Problem: The expansion of network coverage has led to an increase in the number of base stations. The infrastructures in these stations are usually subjected to severe weather conditions which may reduce their performance or leads to failure and deterioration. Therefore, these stations require routine checks and scheduled maintenance to be carried out to eliminate downtime and ensure standard operations of infrastructures.

During inspections, accurate information is required to evaluate the status of the equipment in compliance with the NCC guidelines for technical specifications for the installation of telecommunications towers [7]. However, there are several challenges involved in the operation such as climbing of the tower, inability to check for deterioration of outdoor equipment, and low technical capabilities in analyzing tower structures. These challenges present a problem of inappropriate and irregular monitoring of telecom equipment. The research is therefore motivated by the need to: -

i. Autonomously inspect the status of base stations infrastructures
ii. Provide insight to appropriate equipment for repair or further inspection
iii. Enhance the approach of monitoring equipment by comparing them with the standard ones.
iv. Provide consistent reports and statistics of base stations that can be used by MNOs and stakeholders in the upgrade and maintenance of infrastructures.

II. LITERATURE REVIEW

Computer Vision-based on deep learning techniques has achieved great success in object detection. Object detection can provide valuable information for semantic understanding of images and videos and is related to many applications, including image classification, human behavior analysis, face recognition, and autonomous driving [3]. This technique provides useful applications especially when drones are employed in taking images, such systems are used for transmission line monitoring, rescue operations, and 3D mappings. The obtained images are processed and Region of Interest (ROI) is extracted for inspection.The interest and development of object detection models have gained popularity in recent years with rapid increase and evolvement in improving the underlying architecture of the model. A recent method adopted for object detection with very high performance is Deep Learning (DL). Object detection before Deep Learning involves several processes which start with edge detection and feature extraction using techniques like Scale-invariant feature transform (SIFT), Histogram of oriented gradients (HOG), etc. Comparison is then performed with existing object templates, usually at multi-scale levels, to detect and localize objects present in the image. The current method for automatically extracting more complex and better features from images is Convolutional Neural Networks (CNN).

Real-time object detection can be divided into two based on the algorithm architecture, one-step object detection, and two-step object detection. One-step detection algorithms combine detection and classification steps uses the idea of regressing the boundary box prediction. It divides images into smaller grid boxes and prediction of class probabilities of x and y coordinates is performed for every bounding box. Generally, the combination of the classification and detection steps enables one-step object detection to run faster with low performance on small objects (e.g You Only Look once, YOLO and its variants). Conversely, two-step detection algorithms firstly identify bounding boxes and classify each bounding which may potentially contain objects separately. This involves using a Region Proposal Network (RPN) to obtain regions that are later fed into a Deep Learning (DL) architecture for classification (e.g anchors in Faster R-CNNs).The researcher's attention has not been focused on using this technique in inspection and monitoring of telecommunications infrastructures, rather such application is found in power transmission towers inspection. In a research conducted by [4], an algorithm and methods for improving the capabilities of UAV-based inspection systems were developed using Faster Region Convolutional Neural Network (Faster R-CNN) which is an original region proposal network sharing features with the detection network that improves both region proposal quality and object detection accuracy. This model monitors temperature anomalies along with cables, and on insulators hanging from electric towers and detects hot spots and rusted insulators from sequences of visible images. [4]. However, the drone used in this research is not autonomous and as such requires human expertise to navigate and use the system which can often lead to instability of the images obtained for analysis.

In [2] Detection of cracks formed in monopole towers and estimation of its length and breadth was carried out in real-time using a one-step detection algorithm, saving the altitude for further rectification using Unmanned Aerial Vehicle (UAV), but one of the shortcomings encountered during this research is the low performance of the computer vision model used as a result of the chosen architecture.These reviewed works show that drone (Unmanned Aerial Vehicle) and computer vision for tower and equipment inspection is currently the focus of research. None of this research however has been able to develop a fully autonomous drone inspection system using two-step object detection algorithms with impressive performance. Furthermore, research in autonomous drones with two-step object detection algorithms for monitoring and inspection of telecommunication towers and outdoor equipment has not been carried out in any literature as far as the researchers know.The research is therefore tailored towards the development of an autonomous drone that will be capable of inspecting and monitoring telecommunication towers and outdoor equipment in real-time to detect cracks, rust, deformation, misalignment, and standard checks. A monitoring web application for flight reports, image analysis, and visualization will also be developed.

III. PROPOSED SYSTEM

The architecture for the proposed research will utilize a drone with a vision-based path-finding strategy to navigate through automated inspection routes and around base stations. Navigation and pathfinding for the drone are programmed using a Robotic Operating system (ROS). The drone will use an onboard microprocessor and a high-resolution camera to inspect the region of interest (ROI) in the station equipment using computer vision techniques based on Deep Learning architectures for object detection. The onboard microprocessor which hosts the trained model can identify cracks, rusts, the state of outdoor equipment and check if the equipment meets standard specifications. The data collected by the drone for each flight time will be streamed to the cloud and later downloaded, uncompressed for further analysis and improving the performance of the detection model. Processed data is accessed by the inspection agent for making appropriate decisions. The architecture of the proposed system is as depicted in Figure 1.

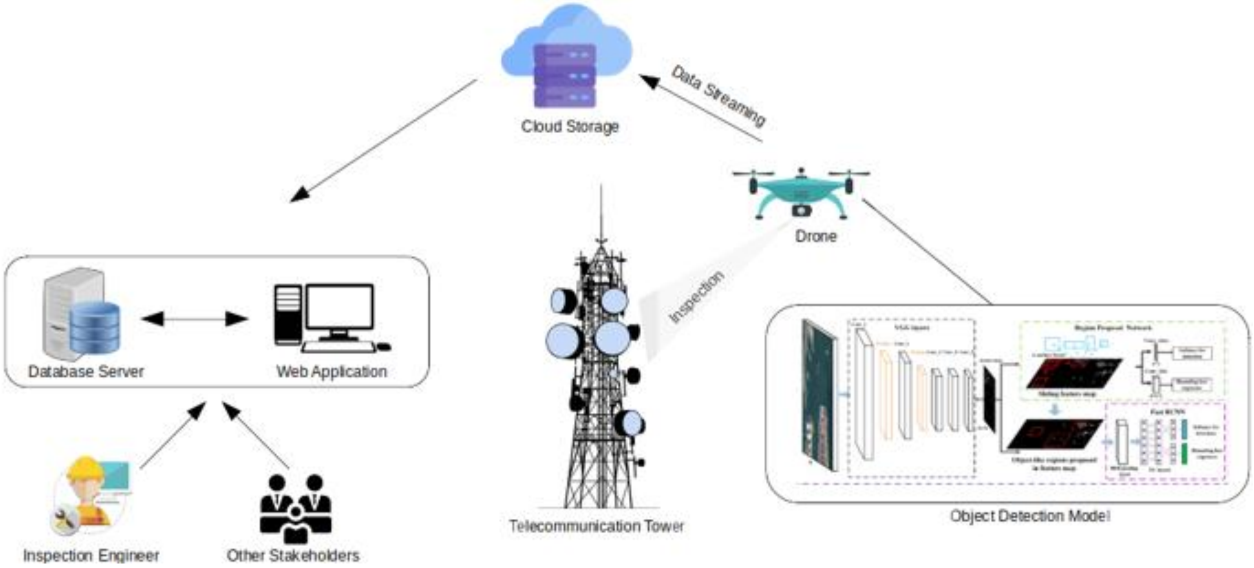

Figure 1: Architecture of the Proposed Inspection and Monitoring System

Research Methodology : The methodology for achieving the outlined research objectives will be based on advanced computer vision techniques.

Flight Path Planning and Navigation : The vision-based autonomous navigation system will be utilized by the drone. This requires real-time measurement to produce a response within a specified time, using point–line tower detection (PL-TD) that consists of transmission tower localization and PL-based visual SLAM which is an extension of the Oriented FAST and Rotated BRIEF (ORB) SLAM. Simultaneous Localization and Mapping (SLAM) shows great prospect since it can successfully perform simultaneous estimation of the state of a robot and the construction of a model (map) of the environment. The framework contains five main threads: tracking thread, local mapping thread, loop closing thread, semi-dense mapping thread, and TD thread. Visual Odometry (VO) estimates the sequential changes of sensor positions with time using sensors such as a camera to acquire relative sensor movement. The tracking thread is the visual odometry (VO) which approximates the bearing of the camera, it also determines when to add new keyframes. The local mapping thread performs PL-based local sparse nonlinear optimization (BA) to optimize the local map that is related to the newly added keyframe. The loop closing thread checks whether the loops are detected and is in charge of correcting the drift errors of trajectory estimation [5]. The entire Framework of Visual SLAM (VSLAM) will be built using Robotic Operating System (ROS) to plan the navigation path.

Computer Vision : The computer vision component of the proposed system will utilize the power of advanced object detection models. Faster Region Convolutional Neural Network (Faster R-CNN) is an original region proposal network sharing features with the detection network that improves both region proposal quality and object detection accuracy. Faster R-CNN uses two networks: a deep fully convolutional network that proposes regions (named Region Proposal Network, RPN) and another module that classifies the proposed regions (classification network) [4]. A Region Proposal Network (RPN) takes an input image, usually of any size, and outputs a set of rectangular object proposals, each with an objective score. The deep fully convolutional network is also responsible for feature extraction.

Loss Function : The loss function is responsible for estimating how well our model is learning. Training the RPN requires a binary class label to be assigned to each anchor. The anchor with the highest Intersection-over- Union (IoU) overlap with a ground-truth box is assigned a positive label. A non-positive anchor is assigned a negative label if its IoU ratio is lower than 0.3 for all ground-truth boxes. An objective function following the multi-task loss in Fast R-CNN will be minimized.

The loss function for each image taken characterized by:

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i, t_i^*). \quad (1)$$

Where:
i is the index of an anchor in a mini-batch
pi is the predicted probability of anchor a being an object.
$p * i$ which is the ground-truth label is 1 if the anchor is positive, and is 0 if the anchor is negative.
t_i is a vector representing the 4 parameterized coordinates of the predicted bounding box, and t*i is that of the ground-truth box associated with a positive anchor.
L_{cls} is the classification loss which is also the log loss over two classes (object vs. not object).
L_{reg} is the regression loss
L_{cls} and N_{reg} are normalization values.
λ is the balancing parameter for the normalization values

Monitoring Application : The monitoring application will be modeled as a responsive web application to ensure efficient storage management. The output of the real-time processed images acquired will be streamed to cloud storage alongside the original image. Further analysis to extract meaningful information from the images will be performed on the cloud. Application Programming Interface (API) is an interface responsible for defining interactions between multiple software applications. An API will be an intermediary between the web application server and the database server that stores the processed information. The web application architecture is divided into two based on the utilization of servers; Client front-end and Back-end server. The client front-end will be developed using JavaScript and its libraries. JavaScript (JS) is a scripting programming language that allows interactions and complex features on web pages. Visualization and real-time analysis will be presented in the client front-end. The Back-end server will be programmed using Node.js, a server-side JavaScript library.

IV. CONCLUSION

This presentation provides a framework for effective monitoring of telecommunication infrastructure to prevent incessant collapse and the attendant loss of lives, amenities, as well as the loss of communication. It is expected that the full implementation of this work will establish a new tool for tower inspection and monitoring which will assist stakeholders and policymakers in Communication industries to monitor Mobile Network Operators for conformity to international best standard practices and consequently assist in ameliorating disaster as a result of the collapse of Telecommunication Towers and other related infrastructures.

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