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REVIEW PAPER

Power Transmission Line Inspections: Methods, Challenges, Current Status and Usage of Unmanned Aerial Systems

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Abstract

Condition monitoring of power transmission lines is an essential aspect of improving transmission efficiency and ensuring an uninterrupted power supply. Wherein, efficient inspection methods play a critical role for carrying out regular inspections with less effort & cost, minimum labour engagement and ease of execution in any geographical & environmental conditions. Earlier various methods such as manual inspection, roll-on wire robotic inspection and helicopter-based inspection are preferably utilized. In the present days, Unmanned Aerial System (UAS) based inspection techniques are gradually increasing its suitability in terms of working speed, flexibility to program for difficult circumstances, accuracy in data collection and cost minimization. This paper reports a state-of-the-art study on the inspection of power transmission line systems and various methods utilized therein, along with their merits and demerits, which are explained and compared. Furthermore, a review was also carried out for the existing visual inspection systems utilized for power line inspection. In addition to that, blockchain utilities for power transmission line inspection are discussed, which illustrates next-generation data management possibilities, automating an effective inspection and providing solutions for the current challenges. Overall, the review demonstrates a concept for synergic integration of deep learning, navigation control concepts and the utilization of advanced sensors so that UAVs with advanced computation techniques can be analyzed with different aspects of implementation.

Keywords Unmanned Aerial Vehicle · Voltage Transmission Line Inspection · High Voltage Transmission Lines · Condition Monitoring · Conductor & Insulator · Deep Learning Techniques · Blockchain Technology

1 Introduction

The increasing population in the present-day warrants the demand for more power consumption that leads to the expansion of power transmission lines across developing countries. These transmission lines are often constructed in complex terrains like mountains, rivers, forests & de-populated zones, etc. The continuous exposure of power transmission lines to the climatic conditions in the field leads to material aging, malfunction of electrical equipment, breakage of conductors, overheating of insulators and discharges caused by nearby trees during heavy wind flow/storm [1, 2]. To overcome these losses, transmission engineers need to regularly inspect and conduct timely maintenance to ensure a constant power supply [3].

Inspection of power transmission lines is critical for power companies to ensure a reliable supply of electricity to a large number of consumers in key enterprises and households in a city [4, 5]. The inspection gives critical information about the line's status and allows the line engineers to prepare for essential repairs or replacements before serious damage occurs, potentially resulting in an outrage [6, 7]. Power companies are primarily interested in live line inspection methods that maintain a constant electricity supply to the consumer without de-energizing the line, which is the only way to overcome unwanted interruptions in the power supply.

The review is concerned with the inspection of high voltage power transmission lines inspection. These inspection

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methods can be broadly classified into five different methods, wherein the ways to carry optical device/inspection devices around the power transmission lines are different, i.e., (1) visual/manual inspections with or without using advanced optical devices, (2) helicopter-based aerial inspection, (3) Mobile robot-based transmission line inspection, includes the use of cable-climbing robots or automatic overhead power transmission line damage detector move on the conductor, (4) Aerial inspections using small (rotor span 1–2 m) helicopter unmanned aerial vehicle, (5) Quadrotor/drone-based airborne power line investigation.

The earlier techniques for power line inspection include visual/manual field inspections with or without using advanced optical devices. These methods are continuing without any change for decades [8]. When there is vast rain, or natural calamities like storms, earthquakes and heavy snowfall etc., a team of electrical department inspectors are inspecting the current situation of transmission lines and provide maintenance as per the requirement. The inspection process includes either walking on foot adjacent to the transmission lines or traveling around the transmission line with visual inspection devices (i.e., binoculars, high zooming capacity cameras, ultraviolet/infrared cameras & corona detection cameras) to detect the faults in power transmission lines [9]. The visual inspection methods are not always accurate because an inspection agent has to watch the power transmission lines and components with the naked eye or with the help of optical inspection devices. This process is prolonged, dangerous, expensive and a lot of time is wasted to conduct such surveys. Even though a power line inspector has excellent observation skills for visual inspection, still a lot of defects like micro-cracks and internal defects are not found with a naked eye. Also, digital devices like infrared (IR) cameras are used for data collection, but still, it is considered a manual process.

Mobile robot-based transmission line inspection is considered as an automated inspection method which involves in identifying the power transmission lines and discontinuities such as corrosion, cracks in conductors and insulators, misplaced conductor, corrosion and physical damage, etc. using cable-climbing robots. The cable-climbing robot closely inspects the conductors and presents a more descriptive status of the conductor. However, this method is considered as a slow process of investigation, designing a versatile robot and its installation to the conductor is a challenging task.

Compared to the Mobile robot-based transmission line inspection, the Unmanned Aerial Systems (UAS) enhances the inspection process more safe, inexpensive and less time consuming and eliminates the need for workers to physically access hostile environments such as radiation that leads to health issues, skin cancer, effects on brain tissues and central nervous system etc., installations that can cause injuries etc. UAS utilized for powerline inspection can be broadly classified into two types i.e., (1) helicopter (rotor span 1–2 m) or even a UAS specially made for this purpose, (2) advanced drones or commercial quadcopter equipped with a camera and other data acquisition systems. UAS can take high-resolution videos and images, capture thermal images and transfer the data in online mode at a faster rate that would take days in visual/manual inspections.

UAS applications are developed to be autonomous in terms of flying/hovering along the transmission line following the pre-determined waypoints. It is also considered to be autonomous in terms of data collection, as the existing most advanced cameras can capture images and videos and transfer them back to the Ground Control Station (GCS) with live transmission features [10–12].Though many theories have explained the existing problems such as damage to insulators, conductor corrosion, vibration damage, cracks on conductors and insulators, atmospheric contaminants, fretting between aluminum conductors near to clamps and other fittings, sparking, transmission line corona and partial discharging levels [9, 13–15] etc. The main aim of power line inspection is to determine the state of transmission lines and utilize that information in order to realize a decision for its maintenance. This process involves the health monitoring of power transmission lines and components which are shown in Fig. 1.

This literature review reports the inspection methods for the power transmission line, including the task of mapping, identifying errors in power line towers, components and transmission conductors. The potential & challenges of UAS based inspection methods over the other existing methods are discussed comprehensively, including the ways of data acquisition methods & techniques used in data processing and fault detection. The challenges of UAS based navigation for power line inspection and feasible possibilities are discussed.

1.1 Internal structure of UAS

This manuscript mainly concentrates on the UAS type of (Quadcopter) inspection for power transmission lines due to their maneuverability and their ability to lift, hover and land smoothly with precision making them useful for power transmission line inspections. As shown in Fig. 2, a generic quadcopter consists of a flight controller and receiver, Electronic Speed Controller (ESC), Brushless DC Motors (BLDC), Lithium-Ion Polymer (Li-Po) battery, Power Distribution Board (PDB), 3D gimbal, Surveillance camera, video transmission and receiving module and frame, etc.

1.2 Bibliometric analysis

To know the status of existing research on the inspection of power transmission lines and methods, we conducted a

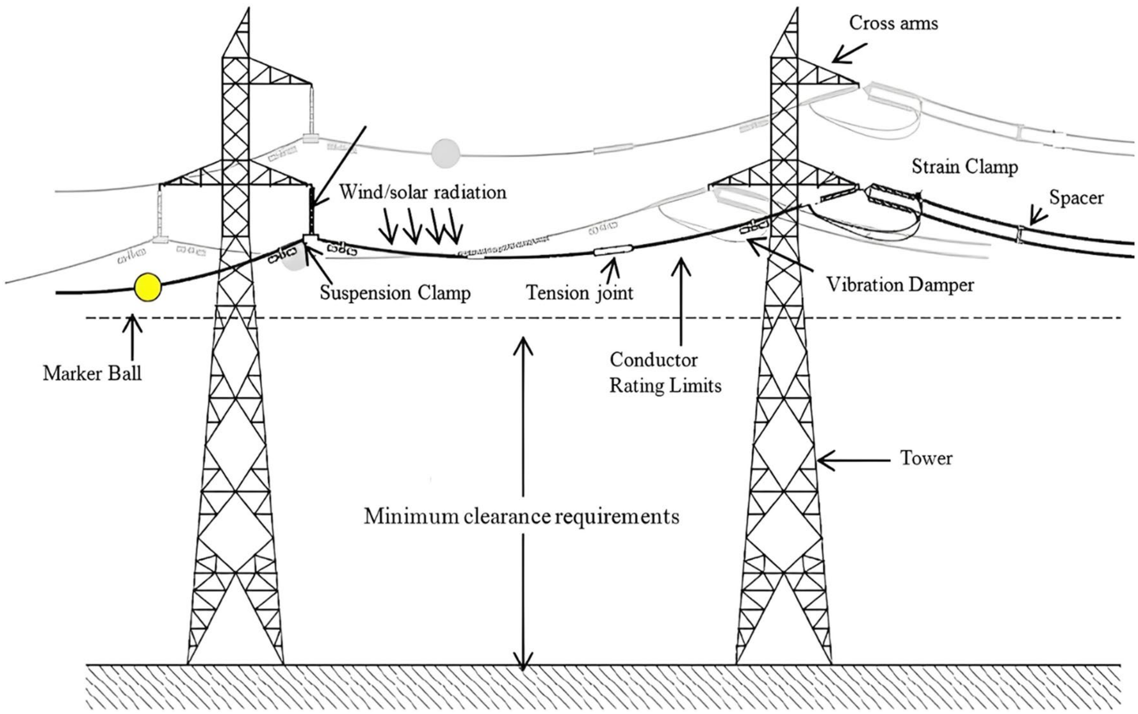


Fig. 1 Typical transmission line with components [13]

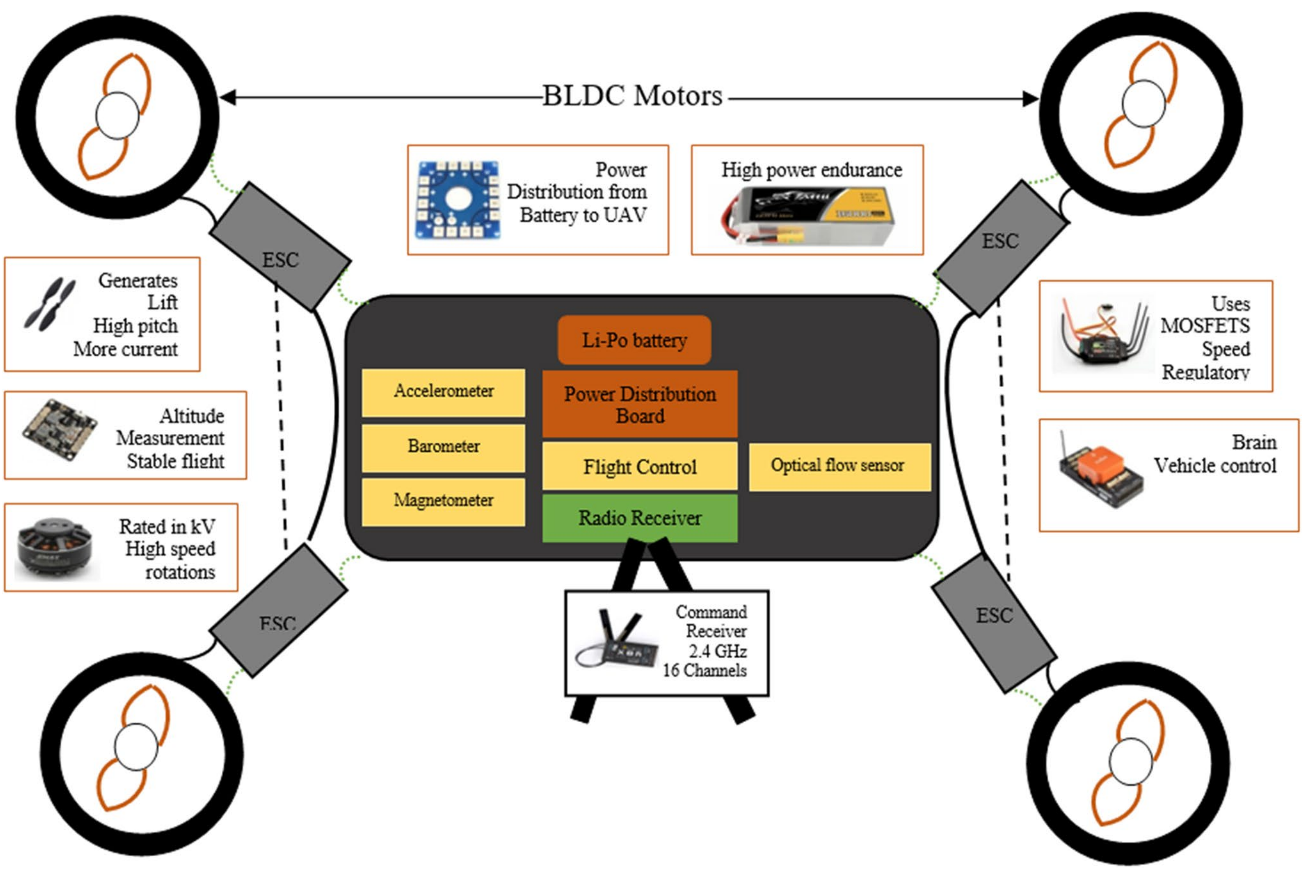


Fig. 2 UAS internal hardware

bibliometric analysis on 18 September 2021 using acknowledged databases such as web of science and google scholar. The total number of research publications indexed by the databases from 2004–2021 is shown in Fig. 3. A total number of 348 documents are found that includes 137 research articles related to power line inspection and deep learning methods. The total number of research articles was very low and stable till 2014. From 2015 onwards, articles on power transmission line inspection, methods, and UAS increased to a higher level and reached 70 publications in 2020. There are 44 articles in 2021, i.e. (18/09/2021). Before 2012, inspection methods and methodologies were published in research articles, but implementation was not done in a real-time scenario. After 2016, research articles have gradually increased on power line inspection methods, types and deep learning algorithms related to inspection. With the development of UAS and deep learning technologies, aerial inspection has recently become widely used by power companies.

2 A brief introduction and modes of inspection for power transmission lines

In this section, various methods used for power line inspections are discussed briefly and their merits and demerits are highlighted. The possible improvement with quadcopter-based navigation and inspection system was suggested by keeping in view of better control, safety in operation, cost criteria, and faster inspection.

2.1 Visual/manual inspections with or without using advanced optical devices: Foot-patrolling-based-inspection

The most widely used methodology for the inspection of conductors and insulators in the past is foot patrolling inspection. In this method, two or more technicians from the electrical department are sent to inspect the conductors by walking on them or using any ground vehicle by moving on the cable lines as shown in (Fig. 4a). To find the defects in cables and breakage of components, these technicians used binoculars, infrared cameras and ultraviolet cameras [16]. However, this methodology is tedious, time taking and sometimes dangerous to the technicians and workers. Another most prominent disadvantage of this method is that, the inspection is not possible during natural hazards like heavy rains and extreme weather conditions [17].

2.2 Helicopter based inspection

In this method, inspection is done on the insulators and conductors of power transmission lines by a team of engineers/technicians (mostly three members) by flying in the helicopter over the power transmission lines as shown in (Fig. 4b). Generally, the crew will be a pilot, an inspector and a camera technician for recording videos and capturing thermal or ultra-violet images for offline inspection [18]. In this method the pilot will fly the helicopter and the inspector will observe the growth of vegetation around the transmission lines and poles. The camera technician has to capture all the images of towers, including the cables and components like insulators, conductors, cross arms, top pads and objects around the transmission lines. Later a group of highly qualified engineers will inspect these collected videos and images for detection of broken insulators and conductors or missing top pads. However, this method is not considered more accurate and safer, as the data acquired will not be sufficient due to the fast movement of the helicopter over the transmission lines. Sometimes it might take the lives of the inspection team as they have to move very close to the transmission lines and it is also considered very expensive and requires a lot of visual inspection skills [19].

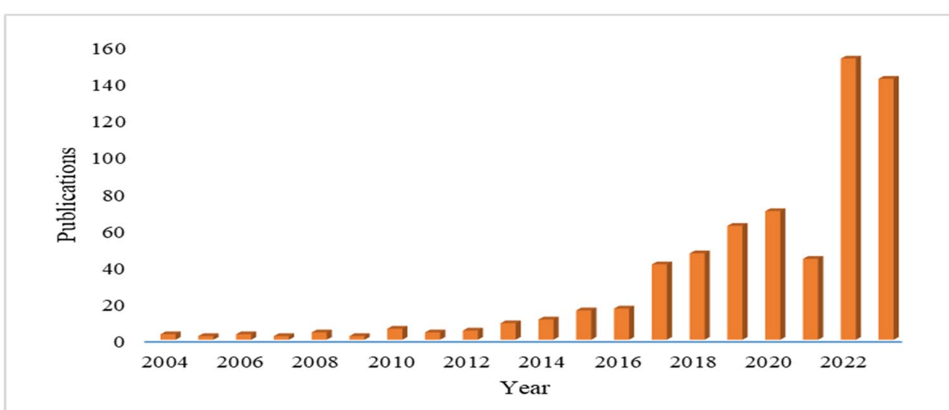
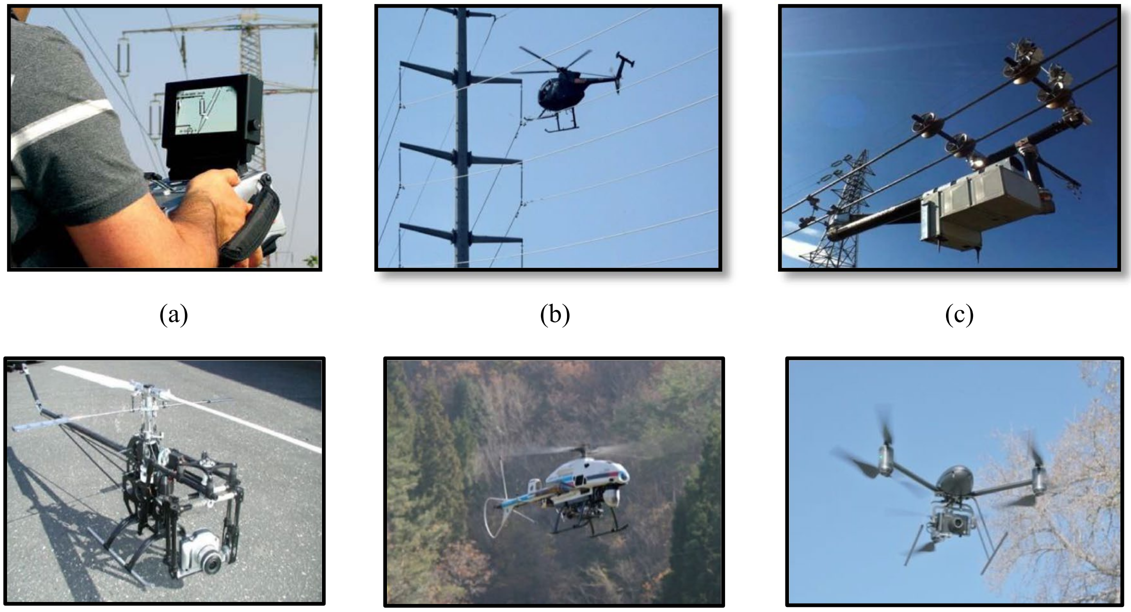


Fig. 3 Number of publications indexed in databases based on power line inspection



(a) (b) (c)

(d) (e)

Fig. 4 Methods of power transmission line inspection (**a**) Visual/manual Inspection [22] (**b**) Pilot operated Helicopter inspection[22] (**c**) Rolling on conductor [23] (**d**) Unmanned helicopers (i) rotor span 1–2 m (ii) UAStype-1 [23] (**e**) Drone/Quad copter:UAS type-2 [24]

The automated inspection method is very close to the type of helicopter-based inspection. The noteworthy difference is that, for both data capture and data analysis, vision-based algorithms are used. These algorithms/approaches can be used in cameras to move autonomously and capture/record the data of pylons, top pads, conductors and insulators. This acquired information can be analyzed later for faults. Even though this method reduces the task of the camera person and technician in terms of time consumption, yet it is considered still expensive and has to wait for months. The process also delays due to the weather conditions such as low ceiling clouds and fog. The safety aspects of both methods (shown in Sect. 3.1 & 3.2) are considered to be dangerous as it places the aircrew and utility workers very close to the high voltage lines.

2.3 Mobile robot-based transmission line inspection includes the use of cable-climbing robots

In this method, the inspection is carried with a crawling or climbing robot on power transmission lines. This robot is assembled with GPS, sensors (telemetry, altimeter, IR etc.), visual and thermal cameras for guiding along the transmission lines, moving over the obstacles and capturing the data of transmission lines and electrical components. Due to its adjacency to the power lines, the precision of inspection is high in this process as shown in (Fig. 4c). Authors in [20] stated that, implementation of these robots is highly risky as they are not suitable for inspection of power lines due to their structure. The other biggest demerits of these robots are that it is a comparably stagnant process related to different approaches like autonomous inspection system-using rotor helicopter.

2.4 Aerial inspections using small (rotor span 1–2 m) helicopter (UAS)

In this method of inspection, UAS is equipped with multiple components like advanced sensors, vision camera, thermal camera, and global positioning system (GPS) for navigating along the power lines. These onboard components will help the UAS to guide along the power transmission lines for inspection of cables, electronic components like insulators, conductors & pylons and capture the detailed videos and images for online inspection and offline inspection on the workstation later as shown in (Fig. 4d). Due to its structure and ability to fly close to the power lines, the rate of accuracy is high in terms of detection of faults and it can replace the high-cost automated helicopter inspection. This system is also cost-effective and safe compared to the foot-patrolling and helicopter-based inspection. The total work hour is low when compared to the other inspection methods as it takes

10 min approximately for1 km distance of power transmission lines [21].When compared with a visual inspection, the Unmanned aerial systems (UAS) enhance the inspection process more safe, inexpensive and less time-consuming and eliminates the need for workers to physically access hostile environments.

2.5 Quadrotor/drone-based airborne power line investigation

To develop an autonomous quadcopter, a mathematical model has to be developed with the help of Newton's equation with a perfect Proportional Derivative (PD) control system. To achieve such a control system, a stable dynamic model has to be developed in terms of its movement (about x, y & z-axis) and simulation of such dynamic model has to be done by using Euler's angles.

To develop the mathematical models of a quadcopter, three parameters i.e. (a) Altitude and Yaw, (b) Roll and (c) Pitch plays a major role. Pitch, Roll and Yaw are defined as the axes of rotation for controlling the movement and direction of UAS in the air. It is used for ascent or descent motion depending on the tilt direction. N.J. Wilken [25] designed these models individually and later joined them together to form the overall mathematical model of the quadcopter. The developed model was simulated in the Simulink® to observe the results. Author suggested that, more attention should be given to the dynamic model to attain stability of quadcopter, which is a vital function for power transmission line inspection. The periodical inspection of transmission lines can be done with the help of quadcopters as shown in (Fig. 4e). However, the usage of UAS comes with significant challenges like auto-pilot systems and hovering. Inspection of power lines is a crucial task in this method, but the existing techniques of inspection and data comparing are not so accurate in terms of detecting towers and estimation of vegetation growth.

3 Defects and detection methods associated with power transmission line components

In this section, the detection of power transmission lines including towers, cables and components are discussed in detail. The fault analysis of various components (i.e., insulators, conductors and top-pads etc.) are also included in this section. The common defects of power line components are shown in Fig. 5.

3.1 Insulator & fitting elements and inspection methods

Insulators are affected mainly by mechanical and thermal loading, flexural strength and deformation, electrostatic displacement, concrete development, corrosion and climatic conditions. Thermal cycling is induced by temperature differences between scorching bright days and extremely chilly nights and heat generated by power dissipation arcs, which cause micro-cracks and allow water to infiltrate the material. The amount of stress applied is determined by the dielectric metal and cement fittings used to secure the line's fasteners. Cement development, which is primarily driven by periclase (MgO) hydration and sulfate-related expansion, causes circular fissures on the ceramic insulator's surface, rendering as faulty [26].

Atmospheric pollutants, such as sea or road salts, may either attack Portland cement or they may corrode the galvanizing surface if they penetrate through metal pieces. This condition is made worse by ionic motion triggered by an electric field. A review in [27] suggested a method for identifying defects in power transmission line dampers. In this method, a baseline approach was used to detect the desired component from aerial data. Then a technique of Hessian matrix and balloon force snake method is utilized for edge detection (cracks, breakage and loose connection)

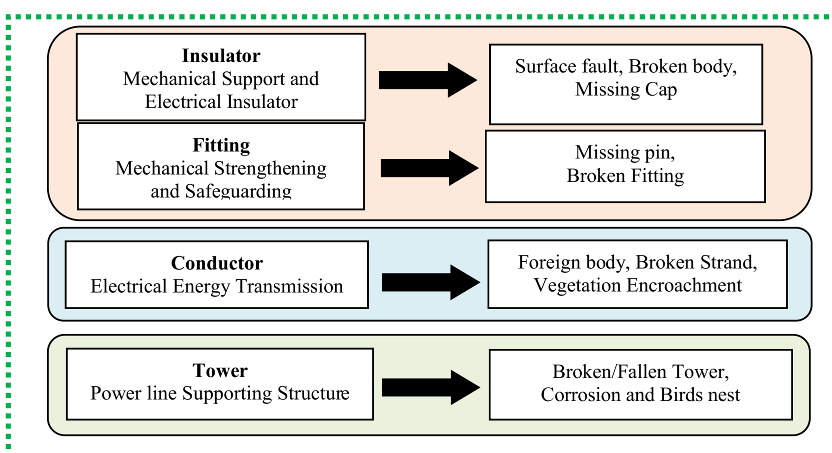


Fig. 5 Common defects of power line components

in dampers from the segmented images. Authors in [28] suggested different methods for identifying broken spacers in power lines. First, the Scanning window, Canny edge detector and Hough transform techniques are used for identifying spacers as Region of Interest (ROI). Next morphological operations are used to extract features in images. Lastly, the connected domain analysis technique is used to detect broken spacers. Vinyals et al. [29] used an algorithm known as one-shot learning, enabling a trained neural network to learn and identify electrical components and their defects. It is considered to be a promising approach for better results. In another method, the author trained a neural network with fabricated images of power lines and defects and later applied it to recognizing defects in electrical components by using unsupervised domain adaptation. Goodfellow et al. [30] proposed new possibilities for detecting unsupervised anomalies by using Generative Adversarial Networks (GANs). This methodology is used for training the data of transmission line components. For anomaly detection of defects, various parameters, such as the discrimination and the residual results, are joined and used as the irregularity score.

There are several possible causes of defects in these components, such as continuous exposure to climate, which will lead to corrosion; discharges due to vegetation encroachment; corona discharges; and improper flow of voltage, which will lead to damage to insulators and conductors. Improper maintenance will result in missing top pads and bolts on towers, cracks in insulators, conductors and HVDC lines, etc. Poor condition monitoring of these defects will lead to a breakdown of the power supply, damage to power line components, blackouts and huge losses. To overcome this, T.W. Yang et al., [31] mentioned a six-step verification process for identifying defects and faults in conductors and insulators. The author has used the UAS inspection module and the six-step process to overcome this issue. The method includes the first step is about acquiring the image of the conductor from the data system of UAS and the second step is to apply adaptive threshold segmentation to the image to extract the conductor region. In the third step, Gray Variance Normalization Method (GVN) is applied to process the images. In the fourth step, to detect the breakages of the conductor, the Square Wave Transformation (SWT) method is used, which is easy and gives accurate results. In the fifth step, a projection algorithm from the GVN method is used to detect the surface defects of the conductor. In the sixth step, the results of faults or damages are recognized by filtering the identified errors and calculating the total number of breakages. The author has conducted a series of experiments by using the same process and obtained the best results (90%-92%) in identifying the defects of conductors. The purpose of maximum likelihood estimation is also used to compute the drone to estimate position by inertial measurement unit (IMU) and visual systems. These methods gave an accuracy of 91.44% in position detection [32].

To identify the defects in power lines, image classification, object detection and segmentation pipelines are widely used [33]. For example, to identify the masts in captured images, a framework of power mast recognition can be utilized and the desired region can be selected as ROI. Secondly, a data structure of defective models can be trained for detecting the small components (top pads, conductors) and their defects (broken insulators, cracked poles, missing top pads) from the selected ROI. The recognized defective components can be trained as input to AI algorithms for identifying even small defects, like broken conductors, missing splints, missing bolts and nuts, cracked insulators and conductors, etc., as shown in (Fig. 6a-f).

3.2 Conductor defects and inspection methods

Among the most common conductor types are steel-reinforced aluminum conductors (ACSR). Corrosion of aluminum strands is the most common cause of conductor degradation. Pollutants and moisture in the form of aqueous solutions containing chloride ions infiltrate the interface between the steel and aluminum strands, damaging the steel's galvanizing protection as shown in Fig. 7. Rust of galvanizing coat reveals aluminum and steel to one another and results in iron-aluminum corrosion. Aluminum corrodes quickly as an anode and white aluminum hydroxide powder is formed. The current load capacity is decreased due to the loss of aluminum and the mechanical properties of the line [34]. Along with the corrosion, wind-induced vibration can cause significant surface defects to the conductors due to cyclic mechanical load absorption [35]. When the breeze stream passes the line, it creates vortices downstream. These vortices cause Aeolian vibrations in the conductor's diameter by creating oscillating drag and lift movements with frequencies of 10–30 Hz. Wind can also create fretting of the aluminum strand close to the clamps by causing sub-conductor vibrations in stacked conductors. The fretting reduces the tensile strength of the line and speeds up the failure process.

Corrosion Problem and detection Corrosion tests are an essential element of a wide range of methods (techniques and tools) used to assess the condition of overhead lines to devise the best approach for maintenance and renovation. A detailed "snapshot in time" is required to establish the overall condition of the line for a renovation program.

Corona problem and detection In the presence of water, corona produces nitric acid, ozone and nitrogen oxides. This corrosion shortens the life of transmission lines, components and substations because of the corrosive materials. Thus,

Fig. 6 Fitting and insulator defects, missing splint and broken conductor [36, 37]

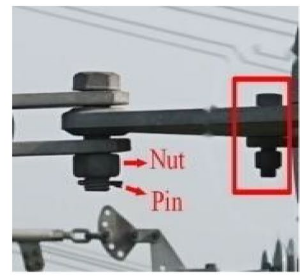
(a) Broken Insulator

(b) The visible damage of punctures along the sheath of the test insulator

(c) Insulator defect

(d) Missing Split

(e) Broken conductor



(f) Missing Pin

Fig. 7 Corroded conductor [38]

Fig. 8 Corona on Conductors [38]

a problem or defect in a component creating a local high electric field shows corona activity. Corona creates corrosive materials: Ozone, Nitrogen oxides which in presence of water vapor yield nitric acid. These corrosive materials shorten the life span of high voltage lines, components and substations. As corona is invisible to the human eye in daylight, maintenance staff utilizes a corona camera or a radio antenna to inspect suspicious regions. Figure 8 shows a case of corona condition on the conductors.

The problem with such defects always gets worse over time. The first step to overcome such defects is to detect it, which may be done using a UV inspection or a corona camera [39, 40]. Salt polluted insulators form a conductive coating when exposed to a high humidity environment, reducing the insulator's insulating properties. In severe instances, when the insulator can no longer handle the line's voltage, it leads to flashover. Most line tripping occurs before dawn or early in the morning when humidity levels are at their highest.

Ha et al. [41] used a microphone array for identifying faults (broken cables, fatigue and fracture cracking etc.) in transmission lines and to verify these defects, a Charge Couple-Device Camera (CCD) and a thermal imaging camera is used. Reddy et al. [42] used cameras mounted on UAS for capturing images of insulators at regular intervals. By using the photogrammetric method, the size of insulators is measured and an automatic classification method is used to identify the broken insulators. TLS point clouds were used by Arastounia et al. [43]to discuss about insulators, conductors, and to identify critical components such as circuit breakers, fences, and cables of electrical substations. Munawar et al. [44] & Lu et al. [45] discussed that detection of power lines is a critical task in an autonomous vision inspection system. Liu et al. [46] have also explained that the detection of lines based on monocular images will give the best results when compared to images taken from long segments [47]. Song et al. [48] presented a method for identifying HVDC cables from captured images. A Match Filter (MF) and First Order Derivative of Gaussian (FDOG) are used to detect line segments with symmetrical edges to generate an outline of the map. Secondly, morphological filters are used for extracting non-power line segments. Finally, a graph theory known as the graph-cut model is used to group the detected line segments into power lines.

Li et al. [49] combined the top-down and bottom-up line detection process in the detection of power lines with aerial images. In this process, the study has been carried by using the pulse coupled neural network filter method to remove the background images captured from the UAS camera. Lastly, the spurious linear objects are eradicated from the images using the clustering (K-means) process. The images taken from the UAS are applied with canny and steerable filters. Later circle-based search methods are used for detecting the power lines with geometric relationships. A simple process was also used by Zhu et al. [50] in power line detection. In this process a double-sided filter was used to enhance the clustered background in the images, later straight lines are detected using the random transform method and finally, to identify the power lines, a parallel line restriction approach is used.

3.3 Detection of Towers and its faults

The objective of the tower detection is to identify the type of tower, its position, and defects in a single image. Many approaches and algorithms are proposed to seamlessly perform this difficult task. In the detection of towers, top corners are the critical points of a tower instead of detecting the lines. Castellucci et al. [51] implemented a novel method to detect the edges and identify the top corners of towers, but it is observed that most of the results derived are limited to only specified parameters. However, in real-time, the towers are classified into various parameters depending on the color, shape, size, appearance, and material (e.g., wood, steel, ceramic, etc.) as shown in (Fig. 9a-d).

To identify the towers, including all parameters, many researchers have proposed different computer vision techniques and algorithms to overcome the problem. To solve the difficulty in identification and classification, a two-feed forward MLP neural network has been presented by [52]. In the first stage, the background of the tower is identified, and the second stage is trained for detecting multiple transmission towers.

Remarks The information provided in Table 1 includes, detection of power line components, features of images used in presented methods, type of component for inspection, techniques of image preprocessing, type of predictor for input data, concise information of data and performance of approach/methods used.

Color model In few studies power line components are detected by using a color model. In this, images are converted to HSI and acquired image intensity by converting the aerial images from RGB to HSI color space to locate the possible area on power line components.

The results obtained are displayed in the bounding boxes (Fig. 6). Recently, computer vision techniques like SVM [57] ROI, deep learning [58] are used to label and detect the location of towers. For best results, multiple classifiers are required to train on different parameters and backgrounds. Another promising research is to extend the system for autonomous detection of towers and faults with the exact classification by fusing the information from various sensors (LIDAR, thermal and infrared cameras).

(a) 115 kV Wood H-frame (b) Ceramic insulator on Pole-tower (c) 115 kV Steel lattice (d) 230 kV with improved appearance

Fig. 9 Four different types of towers varying in the background, size, shape and lighting conditions for power line [51]

Table 1 Summary of the state of artwork related to power line component detection

Features	Methods	Component	Image preprocessing	Component Detection
Color [52]	Color model	Insulator	RGB to HSI morphological filter	- The insulators are detected using a morphological filter and the Optical Entropic Threshold (OET)
	Color model	Tower	RGB to HSI RGB to YCbCr	- The 3-layer classified ANN features are used for the detection of types of towers based on HSI &YCbCr color features by extracting from aerial images
	Color model	Insulator	RGB to Lab K-means cluster	- K-means is used to transform RGB images to Lab color space to generate the appropriate cluster
Texture [53]	HM-LA	Fitting	RGB to Gray	- A texture feature is used for the detection of faulty power line components with repetitive geometric structures
	RI-LDP + SVM	Insulator	-	- Rotation Invariant LDP (RI-LDP) is used to detect the orientation of insulators
	Harr + AdaBoost	Fitting	RGB to Gray Smoothing filter	- The AdaBoost classifier is used to identify the classes of dampers through the sliding window of original images
Shape [54]	PLineD	Conductor	RGB to Gra	- Edge drawing (ED) is used for the detection of transmission conductors. First, straight-line segments are collected by ED and hand-craft rules with different steps are used to identify lines
	Canny	Tower	RGB to Gray Gaussian filter	- An edge detector called canny is used for tower detection. At first, contours are extracted and then images are separated into 10 X 10-pixel boxes. Finally, straight lines are employed to identify the towers and remove the false box
	MLP	Fitting	-	- For segment extraction in fittings and dampers, a multi-level perception with three levels (low-level, middle-level, and high-level) is applied
Deep [55, 56]	FCNs	Conductor	-	- To identify transmission conductor from aerial photos, fully convolutional networks are used
	Faster R-CNN	Insulator	Augmentation Resize	- The insulators in the aerial images are cropped as the main part and then resized to 500 X 500 resolutions. Next insulators are employed to Faster R-CNN for detection of insulators
	CNN + SW	Insulator	Augmentation Resize	- For insulator detection, a six-stage convolutional neural network is integrated with a sliding window
	YOLOv2	Insulator	RGB to Gray Resize	- Adaptive morphology is used in YOLOv2 for the identification of insulators
	YOLOv3	Tower	Augmentation Resize	- YOLOv3 models are trained with various pixel sizes like 288 X 288, 352 X 352, 480 X 480 and 544 X 544 for training and detection of towers

3.4 Fault identification and diagnosis

From the literature review, it has been observed that the topic of fault identification and diagnosis has attained less research interest compared to component identification. The main reasons are: i) datasets or data base of faulty components are not available; ii) from component to component, a variety of defects are seen; iii) in the images, the same defect can be seen in multiple forms, which makes the defect identification process harder. Because of the aforementioned factors, there is a severe shortage of fault data, making training AI algorithms difficult. The typical procedure followed for fault identification and diagnosis is comprised of two stages: i) Identifying the component and ii) Detecting the fault. In the first stage, Region of Interest (ROI) is used to detect the component and crop it out of the background so that it may be investigated further. Then, in ROI, a defect prediction approach is used to discover faults. Some researchers have eliminated the first stage as they consider the component the principal part of the image. The literature review concerning the identification of the component and fault detection/identification is shown in Tables 1 and 2 respectively.

Remarks The information provided in Table 2 includes the information related to the concepts of fault identification and diagnosis, type of fault, suggested method, the technique used in the identification of components, methodology used in detecting defects, features of data techniques, brief information, and performance of metrics used.

The abbreviations used in Tables 1 and 2: Fully Convolutional Network (FCN), You Only Look Once (YOLO), Support Vector Machine (SVM), Hue, Saturation, Intensity

Table 2 Summary of the state of artwork related to fault identification

Fault	Method	Detection	Identification	Detection of defects
Corrosion of tower [59]	DELM-LRF	-	DELM-LRF	- The corrosion on transmission towers is identified by LRF and DELM. At first, LRF is used to extract features on the surface of the tower and the extracted features are classified into corrosion levels using DELM
	CMDELM-LRF	-	CMDELM-LRF	- The deep features are collected from visible images and applied multi-modal imaging to detect the damage on the tower
Broken strand of conductor [20, 60]	CT	Gestal	Rules	-—Cross Template and handcraft rules are used to recognize the broken strand, spacers and dampers installed at conductors
	CED-IFR	CED	IFR	- A Canny edge detector was used to extract the segments of the conductor from aerial images. Then IFR is used to detect the broken strand in the conductors
	GVN-SWT	GVN	SWT	- The aerial images are converted to gray color space by using GVN. Then conductors are extracted by adaptive threshold segmentation. Thus, broken strands are identified by using a Z-shaped waveform from SWT
The surface fault of insulator [22, 61]	M-PDF	OAD-BSPK	AlexNet	- Insulators are detected from aerial images by using OAD-BSPK and the detected region is given as input to pre-trained AlexNet to extract features. Finally, a trained SVM is used to identify the faults on the surface of insulators
	IULBP	-	IULBP + Rules	- An improved IULBP is used for feature extraction in insulators. Then GrabCut is used to find the faults on the surface of insulators
	CGL-EGL	CGL	EGL	- The region of insulators is detected by Canny edge detection and GrabCut segmentation. Then EGL is used to find individual caps. Finally Local Outlier Factor is used to find the faulty caps on surface of insulators
	M-SA	F-PISA	Color model	- Insulators are detected by F-PISA and a particular region is extracted by color determination in Lab color space. Then a fault diagnosis scheme is used to detect the surface faults on insulator
Vegetation encroachment [62]	CNN-SM	-	CNN-SM	- The height of trees is calculated using a binocular camera mounted on a fixed-wing UAV, and the vegetation around conductors is detected using an 8-layer CNN-SM
	PCNN	-	PCNN	- A PCNN and morphological operation is used to detect vegetation by multiplying the horizontal distance between conductors and trees by height
Missing cap insulator [16, 24]	M-YOLO + AM	M-YOLO	Adaptive morphology	- YOLOv2 is used to detect the insulators on power lines and adaptive morphology is used to highlight the missing cap on the insulator. Later GrabCut is used to display the faulty region on the insulator
	Up-Net + CNN	Up-Net	CNN	- In this Up-Net is used to determine the segment of insulators and a 10-layer CNN is used to identify the missing cap of insulators

Table 2 (continued)

Fault	Method	Detection	Identification	Detection of defects
Missing pin of fitting [63, 64]	HM-LA	Haar + AdaBoost	HT + LSD	- As per And or Graph (AoG), the fitting is represented as a combination of several parts like pin and nut. To detect these parts, Haar + AdaBoost classifiers are used. Later Hough transform is used to highlight the missing pin of the fitting
	CNN	ACF + AdaBoost	CNN	- ACF + AdaBoost classifiers are used to locate the fitting region. The features of the fitting region are then extracted using an 8-layer CNN and divided into three types: normal fitting, fitting with a missing pin, and background fitting

(HSI), Luma, blue-difference, red-difference (YCbCr), Local Directional Pattern (LDP), Deep Extreme Learning Machine (DELM), Local Receptive Field (LRF), Improved Free Man Rule (IFR), Circular Gradient Location and Orientation Histogram like (CGL), Elliptical Gradient Location and Orientation Histogram like (EGL), Pulse Coupled Neural Network (PCNN), Orientation Angle Detection and Binary Shape Prior Knowledge (OAD-BSPK), Faster Pixel-wise Image Saliency Aggregating (F-PISA), Aggregate Channel Features (ACF), Convolutional Neural Network for Stereo Matching (CNN-SM), Hough Transform (HT).

The most feasible methods for the inspection and monitoring of overhead power transmission lines with algorithms/methods are listed in Table 3. It summarizes the most used methods and data collected through different software or algorithms applied for different applications in the inspection of power lines [65]. Many types of research are going on to present a combination of deep learning and RGB-D (Red, Green, Blue) data for helping the UAS to identify the location and details of obstacles/defective components.

In the present literature, researchers have considered a diagnosis of faults as a classification task or detection of the object. In practice, different forms of faults lead to difficulties in developing a robust algorithm. It would be better if faults are identified from the aspect of irregular images. The topic of defect analysis excluding the step of power

Table 3 A summary of feasible software/algorithm used for power line inspection

Ref. no	Vision-based data analysis software	Thermal Image Inspection	Offline inspection (Visual/manual inspection)	Software/Algorithm
[2]	✗	✓	✗	(Electrical Transmission detection)
[7]	✓	✗	✗	✗
[66]	✗	✓	✓	(ImageNet)
[10]	✓	✗	✗	(Computer Vision, MATLAB toolbox)
[11]	✓	✓	✓	(Image Processing, MATLAB toolbox)
[12]	✓	✓	✓	(Canny Edge Detector, HOG, Computer Vision, MATLAB)
[67]	✓	✗	✓	(Edge Detector, Mapping)
[14]	✗	✗	✓	(HOG, MLP ROI & MATLAB)
[68]	✓	✗	✓	(Segmentation, Graph cut)
[61]	✗	✓	✓	(Image processing, MATLAB)
[69, 70]	✗	✗	✓	(Machine learning, Computer Vision & MATLAB)
[17]	✓	✓	✗	(Multivariate regression analysis
[21]	✓	✓	✓	(HOG, CBS)
[22]	✗	✓	✓	(Image processing, HOG & MATLAB)
[71, 72]	✗	✗	✓	(Local to Global power line detection)
[73]	✓	✗	✓	(PCNN, HOG)
[51]	✓	✗	✗	(MATLAB, HOG)
[53]	✓	✗	✗	(Gray Variance Normalization, Square Wave Transformation)

transmission lines and components deserves future research. Nevertheless, implementation of these results in the practical application of UAS is highly welcomed as the present research is mostly evaluated and limited to the laboratory only. The standard assessment guideline, along with methods and the open data sets will support the research in the entire field of inspection and data analysis.

Most of the researchers have concentrated on developing a system either for inspection or navigation. These improved systems worked to some extent in the specified/developed tasks, but they have many limitations in terms of accuracy and ability to function efficiently in the specified tasks. It is also observed that the developed systems are not yet fully integrated with UAS for the inspection of power transmission lines.

4 Important issues related to power line inspection using UAS

This section describes two important aspects i.e., (1) hardware or ways to acquire power line inspection data; (2) an overview of control methods for UAS collision-free movement during the inspections.

4.1 Hardware/ways to acquire power line inspection data

After going through various literature reviews on data acquisition methods and automatic inspection of power line systems covered by [36, 74], a summary is written based on different ways of data sources for power line inspection including their advantages/disadvantages and the process of implementation in the UAS. The identification of transmission line components is considered as a prerequisite for further inspection. It is not only important for fault identification but can also be used for UAS navigation. In traditional methods, the acquisition of images is carried by foot patrolling inspectors and crew members traveling in helicopters with binoculars and cameras to record the data in a logbook. Later advanced methods of an inspection like UAS are using automatic video surveillance cameras for image acquisition and detection of faults. An innovative research method like Remote Terminal Unit (RTU), as well as Surface Vehicular Patrolling (SVP) is suggested for the data acquisition.

4.1.1 Inspection with ultraviolet images

Ultraviolet inspection plays a vital role in the field of power line inspection. In order to detect the presence of corona in power line components, a UV camera can be used. Most of the corona energy comes from a wavelength range of 300 to 400 nm (nm) [75, 76].The ultraviolet images are obtained in two ways as ultraviolet-induced fluorescence photography or reflected ultraviolet photos[77, 78].

4.1.2 Inspection with thermal images

Thermal images are captured with thermal imaging cameras or infrared cameras like FLIR. Thermal imaging camera's work on the principle of infrared radiation as visible light so that an average human can see beyond the red shortwave length [79]. Thermal imaging depends on the temperature of the object that emits radiation. The components operating at higher temperatures (hotspots) can be identified because they emit energy in the long-wavelength infrared spectrum. These cameras are mostly useful in power line inspections for the detection of a change in temperature and faults in electronic components like insulators, conductors and pylons.

4.1.3 Aerial images

In this method, images are generally captured with the help of a fixed-wing aircraft [80]. This method is used for obtaining detailed images of electronic components like conductors, insulators, transformers, cross arms, top pads and surrounding areas. Capturing aerial photos is very useful in the inspection of power transmission lines, especially in recognizing the vegetation, mapping and monitoring of faults in electronic components.

4.1.4 Synthetic aperture radar images

Synthetic aperture images (SAR) are collected by using active imaging sensors. This method is useful in creating two or three-dimensional models of landscapes or objects. SAR's are mounted on the top of aircraft or UAS for collecting the images. The main advantage of this method is that it can capture high-resolution images irrespective of day, night and weather conditions [81]. SAR's are very useful in power line inspections for control of vegetation and mapping, and they are capable of creating 4-D images and mapping.

4.1.5 Mapping of data with land-based methods

Mapping of data is collected with the help of land-based vehicles like cars, boats, all-terrain cars and human beings. To obtain the data, data collection sensors with a mobile mapping system (MMS)and data collecting modules like scanners, cameras, GPS, sensors and Inertial Measurement Unit (IMU) are mounted on the top of these vehicles or the back of a human being. The most common methods used for land-based mobile mapping data are point clouds and images [82, 83]. This method has been beneficial in mapping the GPS data of electronic components like conductors, pylons and hanging components.

4.2 Overview of control methods for UAS collision-free movement during the inspections

The power transmission line inspection using UAS brings up many challenges, i.e., path planning [84], navigation, control—hovering & stability of UAS, etc. Among these, one of the core problems is the navigation of UAS without colliding with the obstacles or power transmission lines [85]. According to S. Huang et al. [86], navigation is generally divided into two categories: 1) navigation using Global Path Planning (GPP) scheme, and 2) navigation using Local Collision Avoidance Schemes (LCAS). In the former one, a set of waypoints are generated from starting position to the ending position for avoiding obstacles and precisely moving along the power transmission lines. In local collision avoidance schemes, a waypoint is given as a local goal assignment to avoid the obstacles.

Presently with the help of control algorithms, conventional sensors and pre-located information of obstacle, UAS can perform autonomous missions along the determined flight path [87]. However, there are multiple obstacles on the overhead power transmission lines, which can affect the flight performance of UAS and its cognitive ability [88]. According to [89] different sensors, such as infrared range finders, LIDAR, radar, and ultrasonic are mostly equipped in UAS to identify the obstacles and overcome the collision of a vehicle with HVDC lines. However, due to the limitations of senor functions like a range of sensing, light sensitivity and resolution provide very less information to the UAS vehicles. Minaeian et al. [90] has used monocular cameras on UAS for image processing and to evaluate the environment around HDVC lines in RGB space. But in outdoor applications, light-sensitive and time-consuming features restrict their performance. Therefore, insufficient knowledge on ambient properties will lead to failure of UAS flight path and obstacle collision avoidance. Recently the development in the integration of sensors and processing methods, RGB-D cameras are widely suggested for its average cost and multifunctional use in robots and UAS systems. This type of cameras will have specifications, such as insensitivity to light, lightweight and high accuracy with great potential for obstacle detection.

Apart from three channels of RGB information, RGB-D cameras have an extra feature of distance information to capture the data of obstacles color, position and profile simultaneously. However, the process of extracting the data from these features remained unsuccessful yet. In recent years algorithms of deep learning, such as convolutional neural networks (CNN) and object detection have been proposed for path planning and obstacle detection & avoidance [91, 92]. Redmon et al. [93] have proposed to use YOLO for high performance in classification accuracy and object detection. From this point of view, it is understood that combining the techniques of deep learning algorithms and RGB-D camera will give better results in the detection of an obstacle. Many researchers have focused on improving the algorithm of object detection by using RGB-D cameras. For example, Depth Recurrent Convolution Neural Network (DRCNN) and Single Stream Recurrent Convolution Neural Network (SSRCNN) to detect the objects such as conductors, insulators, top pads and pylons etc. on power transmission lines [94, 95].

Zhang. X et al. [96] have combined all these methods for path planning of unmanned wing helicopter and control of obstacle collision. These existing techniques are finally clubbed into different categories. In recent years, algorithms of deep learning such as Convolutional neural networks (CNN) and object detection has been proposed for path planning [97] and obstacle detection & amp; avoidance. In brief explanation, the Geometric guidance method generates an avoidance control method based on conflict geometry. In the conflict resolution method trajectories of UAS vehicles are considered to avoid the obstacles and hover in a free path [98, 99]. Mohanta et al. [100] has proposed a collision avoidance algorithm with a significant result. Xi Dai et al. [101] proposed a CNN-based learning scheme for avoiding obstacles in unknown and unstructured environments. An architecture of obstacle avoidance with two steps end-to-end algorithm is designed, with a monocular camera pointing forward is used in UAS. In the first step, a CNN model is used for

Table 4 Summary of completed/ongoing research on power line inspections around the world

Manufacturer	Maximum speed	Transmission range & Endurance	Weight	Commercial availability
Fixed-wing aircraft (Sichuan Electric Power Corp.) [58]	70 km/h	50 min. using 16,000 mAh Li-Po battery	3 kg Max. take-off	✗
X650 Pro (XAIRCRAFT PTY Ltd.) [62]	-	20 min. using 5800 mAh 4S Li-Po battery	1.8 kg	✓
mdMAPPER 1000 (Microdrones) [103]	-	40 min	5.8 kg take-off	✓
SkyRanger R60 (Aeryon Labs, Canada) [104]	70 km/h	42 min	4.5 kg	✓
UAV (Hexrotor) [105]	30 km/h	25 min	6 kg Max. take-off	✗
Smartcopter UAH (ARCAA & CSIRO, Australia)	1.0 m/s	2 km, 55 min. range using two-stroke gas engines	12.3 kg take-off	✗
Quadrotor UAV (CAS) [106]	17 m/s	3.5 km, 40 min	2.7 kg take-off	✓
TQuad1000 (Poison Aviation Co. Ltd.) [106]	-	60 min. using 22.2v, 22,000 mAh batteries	2 kg Max. Payload	✗
Mavic 2 (SZ DJI Technology Co. Ltd.) [107]	72 km/h	31 min. using 3850 mAh Li-Po battery, 4 km	0.91 kg take-off	✓

prediction, using three effective operations such as channel split, group convolution and depth convolution. In the second step, the movement of UAS is mapped with a control mechanism in order to change the yaw angle of UAS and counter an obstacle. While hovering the UAS should analyze the conditions to avoid any obstacles. The reason for this is, sensors like, LIDAR, Telemetry and GPS always have velocity and position errors. It would be wise to consider the defects of these sensors for collision avoidance. In practical maintaining, a safe distance will improve collision avoidance. Ram prasad padhy et al. [102] has proposed a DNN based algorithm for localization of UAS in corridor environments to navigate safely without any collisions. In this process the deep models were trained to predict the input commands of flight. This deep learning network is mainly trained for multiple tasks such as, prediction of translation and rotational deviation of the UAS with respect to central bisector line.

5 Inspection using UAS: potential, limitations and challenges

5.1 Growth in Drone potential

Drone or quadcopter application utilization for power line inspection has a high potential to include safety, speed, efficiency and cost-effectiveness into the inspection services. So far, many researchers across the globe have worked to develop an effective UAV for inspection of power transmission lines. Some important discoveries are shown in Table 4. The smart guard is an industrial robot equipped with a Li-Po battery, visible light and thermal camera, image processing module and four wheels for moving around the substation for analysis of transmission lines and electrical components such as pylons, switches, conductors and insulators within the substation. As of 2016, China's power utility firms have installed approximately 300 smart guards.

A British multinational electric and gas utility company, the National Grid, has signed a licensing agreement to use the LineScout robot as reported in 2014. Also, Japan Kansai Electric Company and Japanese Electric Power Systems Inc. have adopted the Expliner robot for power line inspection. However, it is noticed that Hydro Quebec Electric Company, Canada, has equipped with Line-Ranger and Line-Drone which can be considered as the most advanced robots in terms of speed, stability, portability, obstacle avoidance and onboard technologies for the usage of power line inspections.

5.2 Limitations of current research and solutions of data analysis system for power line inspection

From the literature review, it can be clearly understood that several attempts are done in the past for automating

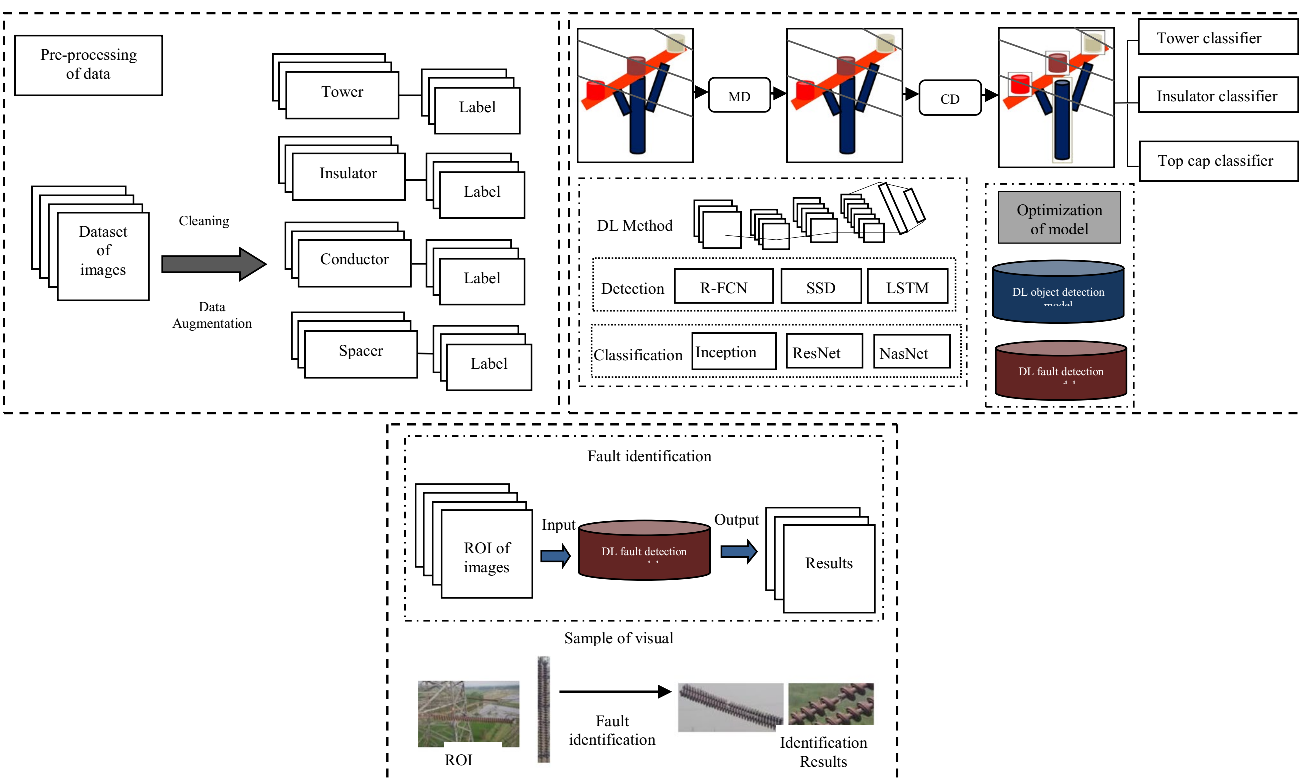


Fig. 10 A general framework of blockchain utilization for UAV based power line inspections

the power line inspection system, but the autonomous UAV was completely unsuccessful or limited to only a set of tasks. Those specific task-related approaches resulted in enormous restrictions in terms of precision and inability to respond to defined input. Detection of a wide range of faults with different classes is also not achieved. It is also noted that there are mainly four problems in the present inspection methods related to power lines. i) Data cleaning, quality and Data labeling. (As mentioned by [36] an individual human spends approximately 60 min tagging the captured pictures), ii) Disproportion of data class and Data insufficiency (In the practical world, different components have different defects and frequency. In some cases, there are no datasets available such as, tower collapse and vegetation which leads to class imbalance and a poor model for inspection), iii) Intra-class variations and iv) Multiple data sources. Therefore, a lot of time and effort is needed for attaining a completely autonomous UAV system for inspection of every minor defect (i.e., detection of broken poles, damaged insulators and cracks in conductors etc.).

To address these problems, an intelligent analysis of inspection system should be considered. Some potential approaches are defined as (i) Supervised Object Detection (SOD) uses image-level for labeling and training the images, which plays an important role in relieving human involvement of data labeling. The technician only needs to tag the object in the picture without caring about its location, which drives the process of labeling with double speed-reducing labor work, cost and time.

(ii) Autonomous image generation is promising research to address the issues of data variation imbalance and data insufficiency, intra-class variations. In this method, rare data is generated by copying or transforming. In copying, the target object is extracted by segmentation network (e.g., U-Net, Deep Lab and Mask R-CNN) [63, 73] and paste the region of object in the background image. An example of this method is also explained in [24, 108]. (iii) Multiple object detection can be used to fuse the data from different data sources to detect multiple objects in varying backgrounds, if available. A few researchers have tried using this method for fusing visible and thermal images for the detection of insulators and defects on power line components [17]. However, this method is considered to be in its early stage for using in power line inspections. (iv) Embedded application is also needed to meet the limitations of existing data analysis. At present, some embedded devices (on-board UAV) such as Raspberry Pi, NVIDIA Jetson can complete image acquisition and processing tasks (e.g., DCNN) but failed in tackling the high-performance analysis. The diagram of these systems can be seen in Fig. 10. Thus, it is a challenging task on how to achieve precise data analysis for overhead transmission line inspection with small memory and less computing time in practical engineering and application. In order to tackle the detection of power line components and fault identification, we propose a multiple component detection and classification pipeline. In this system, the pipeline works as follows: At first, the dataset of images is sent as input to the mast detector for detection of power masts and these detected power masts are cropped and used for (CD) to detect the power line components. Finally, the detected power line components are cropped and the input images are passed through fault detection models to detect potential faults such as missing caps on insulators, conductor and insulator breakage, transmission tower damage, and missing top-pads.

Images from various sensors can be used to detect multiple types of power line faults. For example, optical images are useful for detecting visual faults, whereas thermal and ultraviolet images are useful for detecting faults that are invisible to the human eye, such as equipment bad connections and corona discharges. As a result, combining images from multiple sensors can help inspection systems detect a wider range of faults. In addition to this, image channel fusion can enhance inspection performance because image channels such as optical and thermal images typically provide complementary visual information that deep learning models can use.

5.3 Challenges

The limited power of the onboard battery is one of the key challenges of UAV, reducing the inspection distance. However, stability issues remained in UAV and cause difficulty in data acquisition.

As UAS will be working around the energized extra HVDC lines, the onboard electronics will suffer electromagnetic interference and might get damaged. Hence, research is necessary on the shielding of electromagnetic interferences, which would be a great research point.

The consequences of external disruption were not taken into account by the current UAS in power line inspections (e.g., wind). As a result, it will be excellent research subject to devise dynamic models representing the robot-line coupled system for stability analysis and control of the UAS under the influence of wind.

The present UAS are transmitter operated which leads to a lack of improper identifying and sensing units of power transmission line components. So, designing artificial intelligent algorithms and methods will improve the level of autonomous inspections in power lines. Hence, a promising research point.

Utilization of geo tagging along with GPS waypoints for the access of location of defective electrical components,

Table 5 Inspection method vs performance, advancement and cost criteria matrix representing a comparative study of all the inspection methods

Performance, advancements, and cost criteria	Inspection methods				
	Visual/manual inspections	Helicopter based	Rolling on Wire (ROW)	Unmanned Helicopter	Quadcopter based inspection
Efficiency	Efficiency of this method is very low in terms of data collection and accuracy of predictions	Efficiency of this method is low in terms of cost, safety and risk	Medium (ROW was only able to capture Anomalies in proximity range)	Medium (Anomalies are captured at very fast maneuvering rate)	Quadcopter based inspection enables companies to develop more accurate and effective maintenance and repair plans, high accuracy and quality of data, cost effective, increased safety and improve maintenance & repair
Installation Cost, Asset Cost	High (depends on number of manual labor)	High	High	High	Low (Reduced by 60–70% of the total cost compared to traditional methods)
Safety	Low (chances of Electrocution)	Low (chances of Electrocution and collision)	Medium (Power line components will get damage while maneuvering of ROW)	Medium (Unmanned helicopter is maneuvered manually)	High (Autonomous coordinated movement is executed)
Inspection Quality	Low (Data acquisition is done manually by binoculars and scaffolding)	Low (Data acquisition is done manually by operators in helicopter at fast maneuvering rate)	Medium (Data acquisition is carried by ROW, but limited to specific angle and axis)	Medium (Data acquisition is carried Unmanned helicopter with non-stability mode)	High (Data acquisition is carried by Autonomous Quadcopter with HD cameras and Tarot T-3D Gimbal stabilizer)
Inference time	Tedious and slow (Overhead power transmission lines are constructed in 100's of miles)	High (A helicopter can move at a faster rate for inspection of transmission assets but the inspection cost is very high)	High (The maneuvering speed of ROW is very slow and impossible to continuously move on the conductor)	Medium (The maneuvering control of this copter is operated manually by a technician)	High (maneuvering of quadcopter is done autonomously by loading waypoints and the inspection time is increased to 80% faster compared to existing methods)
Accessibility Range	Low (technicians cannot reach to all the assets of transmission lines)	Low (Due to the fast-maneuvering rate, capturing of small defects is impossible)	Medium (Due to its physical structure, it cannot access all the sides of transmission components)	Medium (Due to its instability and manual capturing of components)	High (Quadcopter can access the remote locations of transmission lines and can hover in loiter mode)
Training Requirement	In Large interval training required (In this case manual observations and identification is carried)	Yes (The dataset collected by cabin crew will be sluggish and limited)	Yes (The live video feed is projected to ground control station and anomalies are observed manually	Yes (The dataset collected by Unmanned helicopter will mostly end up with distortions and blurriness	Yes (The HD dataset collected by quadcopter will be trained for DL algorithms)
Recall	Low (Due to manual predictions)	Low (Due to improper data acquisition system)	Low (Due to irregular maneuvering system)	Low (Due to improper data collection)	High (Due to HD data acquisition system, the DL algorithm is trained very well and number of predictions with respect to anomalies are very high)
Technical Advancements	Foot Patrolling based inspection with Binoculars, Handheld Infrared and U.V. cameras are used in this time frame	Helicopter mode of inspection with cabin crew carrying HD cameras, thermal and infrared cameras is used in this time frame	ROW mode of inspection is used with onboard cameras and UV sensors	Unmanned helicopter is used with onboard cameras, sensors and controllers	Autonomous Quadcopter is used with onboard visual and thermal cameras, advanced controllers, GPS devices and sensors

segmentation, classification of different forms of errors and their working conditions.

Huge data size has to be reduced and collected for farther use of different stack holders.

Improved DL techniques integration with UAV's application and Collective use of many UAV's together.

Installment of high-resolution cameras & advanced sensors, refined data storage and security issues.

5.4 Inspection methods vs performance, advancements and cost criteria matrix

The traditional methods, viz., visual inspection, infrared inspection, ultrasonic inspection, and helicopter-based inspection, are still readily used in most parts of the world for the inspection of power transmission lines and towers. Many inspection performance measures, i.e., time consumption, inspection quality, incurred cost, safety issues, accessibility range, computational and technical advancements etc. are taken into consideration for comparing the inspection methods. An Inspection method vs performance, advancements and cost criteria matrix are presented for comparing all the inspection methods in terms of its performance criteria, associated advancements, and costs (Table 5).

Efficiency- quickly, ease to execute and accurately inspection saving time and cost; Installation cost or Asset cost- investment required to install the inspection assets; Safety- associated risk of accidents and injuries; Inspection Quality- accurate and reliable results; Inference time-time taken capturing data and generating detected results; Accessibility range- access these locations hard-to-reach locations for all components; Training requirement- Necessity of training to operate/execute the; Recall- Proportion of true positive predictions to the total number of actual defects, indicating how well the DL algorithm can detect all defects; Technical Advancements- Upgradation of inspection method in terms of technical data capturing systems, used sensors, techniques of fault representation, assessment and storage etc.

Above matrix summarizes that there is no one-method-fits for all inspections of multiple components and their faults on overhead power transmission lines. Each method has its strengths and limitations and the selection of the most appropriate method depends on various factors, including the type of power line, its location and the available inspection resources.

6 Blockchain utilities in UAV-based power transmission line inspection

Future is looking towards a self-regulating automatic UAV based power transmission line inspection system, using the swarm of UAV's and AI along with advanced vision systems. A combination of navigation approaches, including beam exposure-based, Global Positioning System waypoint-based, and power line disclosure-based methods, coupled with UAV autopilot can help overcome current challenges in developing such an inspection system. Moreover, the challenges like handling huge data size, storge of refined data, data transparency among the distributed stakeholders, collective use of UAVs and advanced data management, the blockchain technology has demonstrated innovative solutions in different sectors [109–111].

Data-dependent services are often vulnerable to being hacked. Thus, security issues are always a big concern for such businesses. In addition, distributed access to the stored data, effective management of large data set and local intelligence capability are much-needed features to power line inspection framework, which encourages blockchain technology implementation. Inspection of a standalone (wire between tower to tower) wire segment can't be useful until and unless engineers can predict the overall health of the conductor (source transformer to user transformers wire). Power industries are looking forward to a scheme that can be helpful in terms of automating drone-based inspections, security-proof programming, data storage infrastructure and data transparency to stakeholders. Blockchain technology brings up three main features to this scheme, i.e., Security, Trust, Storage & Distributed use [109–113]. The blockchain based scheme for the power transmission line inspection can be divided into two folds, i.e., (1) Blockchain-based conceptual framework for power line inspections, (2) Parallel-plane navigation concept which helps in automating vibration-free navigation of drones.

6.1 Blockchain utilization for UAV-based power line inspection: a general framework

The Blockchain-based conceptual framework has four main entities, i.e., Blockchain, Inter Planetary File System (IPFS), Unmanned Arial System (including the video camera, infrared camera and other smart devices) & GCS (Ground Control System), and data user (source end personal, user end personal, recommending engineer, repairing engineers and different drones) as shown in Fig. 11.

(I) Blockchain Blockchain is a programming cum informatic application model used for decentralized data storage, data visibility, incapsulated and encryption algorithm/intelligence [114], peer-to-peer transmission and other technologies. Blockchain is utilized to store the inspection data collected by drones or other means in this application. As well as the encrypted algorithm/intelligence also evaluates the status of the line segment, keeps updated the wire health and identifies the defects. Only authorized entities are allowed to modify the record. The data stored on the blockchain cannot be arbitrarily modified. But it can have visibility to all stakeholders.

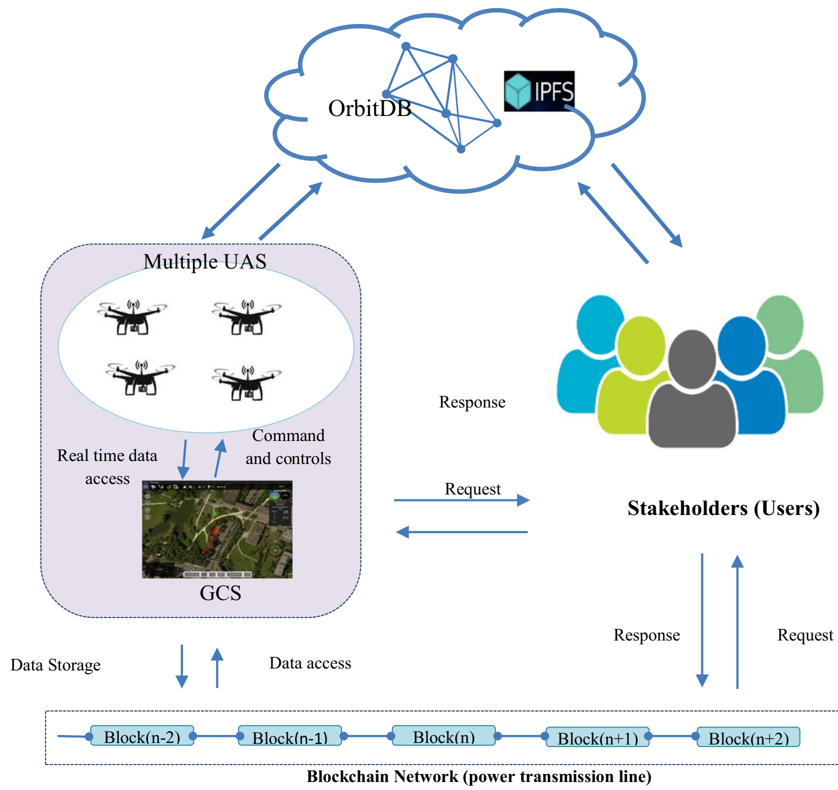


Fig. 11 An illustration of a DL based model for power line inspection and solution to data analysis system. (MD is Mast Detector and CD is Component Detector)

(II) Inter Planetary File System (IPFS) The Inter Planetary File System is a decentralized storage protocol. It is defined as an off-chain database. The off-chain database is used in order to store UAV data (mission information, flight status details, sensor data) that is too large to be stored in the blockchain efficiently. In fact, OrbitDB is a distributed peer-to-peer database performing with IPFS. The latter generates the hash of the data saved into OrbitDB and stores it as an immutable transaction in the blockchain [110].

(III) Unmanned Aerial System & GCS UAS are pilotless aircraft that can operate autonomously via the onboard computer or can be remotely controlled by a pilot at the Ground Control Station (GCS). UAS use onboard sensors to collect different types of data such as UAS speed, battery level, altitude, RGB images, thermal images. Depending on the system requirements, specific sensors can be applied. The collected data can be preprocessed or kept intact at the UAS before being sent to GCS. GCS is responsible for receiving data from UAS and sending out commands to control UAS, including uploading new mission commands and updating controlling parameters. Unmanned Aerial System & GCS are mainly responsible for uploading the inspection data to the blockchain and IPFS [115–117].

(IV) Data Users All stakeholders can be the data user, i.e., the drones, engineers managing the transmission load to the lines, maintenance engineers, research engineers, third-party users, etc. DU first needs to make a request to the base stations/GCS. If the smart system device affirms that their attributes meet the access policies, the system smart device will return a token for them to search for the stored records.

Wire segment details and inspected recorded data of the wire segment are stored in an individual block, which also keeps its own AI/ML-based programming file to identify/predict the defect. Its programming files are enabled to update the health status after a drone inspection and new data are uploaded to it. Any stake-holding drone can upload its inspection file (photos, videos, infrared camera pictures, ambient sensor data, etc.) to the concerning block. Each line block between tower-to-tower can further consist of sub-blocks to keep an inspection record of the wire segments. With the help of the blocks, wire health status and accordingly wire load decision can be updated.

There are two types of blocks suggested i.e., (1) Tower block (center location of the tower, wire hanging location, number of busy wires hanging locations, keeps reference status, keeps updated status all hanging nodes); (2) Wire block (updated status of all sub-blocks and updated status of wire health and defects along with their location).

6.2 Parallel-plane navigation concept

Towers are a well-established structure (center point, dimensions and wire hanging locations are known), which center point can easily be denoted in GPS form. With reference to the center point, all wire hanging point location is not a big task to figure out. After finding out the GPS location and height of the hanging points, it becomes easy to automate the drone navigation. There is an interesting fact that, due to gravitational force, the conductor (wire) is pulled towards the ground. The wire hanging points at two consecutive towers and the wire itself remains in the same plane. If a UAS can be navigated along the wire and parallel to this plane (making some distance from the wire), then there will only be a task to manage the altitude of the UAS. So, the navigation will be vibration-free, and it is a good approach to automate UAS-based inspections. The utilized CCD camera, Infrared cameras, and ambient sensor can obtain clear data and lead to fault detection accuracy. Challenges associated with vibrations (conductor vibration, quadcopter vibration), navigation control and path planning issues are suggested to cope with a stepwise UAS movement and image acquisition strategy. It will be executed using parallel plan concept. Accurate data acquisition has always been tedious in such live dynamic scenarios.

Stepwise UAS movement and image acquisition strategy is as follows:

- Quadcopter step by step movement will be performed along the transmission line. It will work together with GNSS location, telemetry devices and ultrasonic sensor-based safe distance concept.
- Hovering of the quadcopter in a vertical plane which is parallel to the transmission line vertical plane.

The inspection task can be more effective, accurate and easily manageable by utilizing the parallel plane navigation concept.

Although there are review articles on power line inspection techniques, the vast majority of these works primarily focus on particular transmission components and their associated defects. This review focuses on demonstrating the use of a UAV and DL-based methods for monitoring and inspecting various power transmission line components, such as insulators, conductors, fittings, and spacers.

6.3 Recommendations for further enhancing the use of UAS in power line inspection

Some recommendations have been carefully developed based on the insights and review presented throughout the manuscript. They are designed to serve as actionable guidance for a broad audience, including researchers, practitioners and policymakers involved in the field of power transmission line inspections. The recommendations are as follows:

- Although processing real-time videos and images through deep learning algorithms has been quite useful for instantly recognizing and classifying issues such as vegetation encroachment or structural damage, providing real-time insights to inspection teams. But still, advanced DL approaches (Graph-based Deep Learning, Generative Adversarial Networks (GANs), Deep kernel-based architectures, etc.) can improve defect detection accuracy in many ways.
- With a change of orientation, the same defect looks in a different form, so there is a need for a power line defect image and faulty component image data base. A widely accepted, rich, and comprehensive database of such faulty component images is rarely available.
- By implementing strategies to mitigate electromagnetic field (EMF) interference, such as improved shielding (carbon fibre wrapping around the controller) or intelligent frequency management (installing a real-time kinematics (RTK) system on a drone), power companies can enhance the flying and controlling efficiency of their Unmanned Aerial System in dense EMF regions near live power transmission lines.
- By coordinating multiple drones within a swarm, these Unmanned Aerial Systems can cover extensive areas efficiently, collect real-time data, and identify potential issues with power lines more quickly and accurately.
- By implementing blockchain methodology, power companies can create an unalterable ledger of inspection records, guaranteeing the authenticity of critical maintenance and safety data. This not only enhances data security but also facilitates regulatory compliance and transparency in the maintenance of power infrastructure.

7 Conclusions and remarks

In this paper, a comprehensive review of UAS for power transmission line inspection with a focus on existing automated visual inspection systems is presented. Many advanced techniques and platforms have been developed so far, each of them has its own merits and flaws. Therefore, a detailed literature survey about these techniques, platforms and sensors has been reviewed in this manuscript to enhance advanced research work on power lines. Firstly, different modes of power transmission line inspection are presented with their approaches to detect defects. Then image acquisition with fault identification and diagnosis are analyzed from the aspects of different image features such as image color, shape, texture and deep features. Next, a survey on fault diagnosis of power line components is presented including tower corrosion, surface fault of insulator, broken strand of conductor, vegetation encroachment and missing pin of fitting etc. The necessary information required for inspection of power transmission lines includes different issues/planning, i.e., mapping, navigation, pole detection, collision avoidance and fault detection of components are discussed/illustrated with the basic facts. Further a solution to power line inspection and data analysis system which is mainly dependent on deep learning and blockchain technology is discussed tackling the challenges. This system consists of data preprocessing, an illustration of our pipeline model, fault detection method, data management and automating an effective inspection. Finally, we have discussed the challenges and limitations of this domain and suggested research directions in terms of quality and quantity of datasets, endurance of flight, embedded application, and detection of small objects and evaluation of baseline. UAS and AI is still an emerging and promising area in overhead power transmission line inspection.

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Declarations

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References

1. Bjarnadottir, S., Li, Y., Stewart, M.G.: Risk-based economic assessment of mitigation strategies for power distribution poles subjected to hurricanes. Struct. Infrastruct. Eng. **10**(6), 740–752 (2014)
2. França, G.B., de Oliveira, A.N., Paiva, C.M., de Faria Peres, L., da Silva, M.B., de Oliveira, L.M.T.: A fire-risk-breakdown system for electrical power lines in the North of Brazil. J. Appl. Meteorol. Climatol. **53**(4), 813–823 (2014)
3. Silberberg, P., Leishman, R.C.: Aircraft Inspection by Multirotor UAV Using Coverage Path Planning. In 2021 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 575–581, Athens, Greece (2021). https://doi.org/10.1109/ICUAS51884.2021.9476718
4. Broska, L.H., Poganietz, W.R., Vögele, S.: Extreme events defined—a conceptual discussion applying a complex systems approach. Futures **115**, 102490 (2020)
5. Siddiqui, Z.A., Park, U.: A drone based transmission line components inspection system with deep learning technique. Energies **13**(13), 3348 (2020)
6. LaCommare, K.H., Eto, J.H., Dunn, L.N., Sohn, M.D.: Improving the estimated cost of sustained power interruptions to electricity customers. Energy **153**, 1038–1047 (2018)
7. Castillo, A.: Risk analysis and management in power outage and restoration: A literature survey. Electric Power Systems Research **107**, 9–15 (2014)
8. Matikainen, L., Lehtomäki, M., Ahokas, E., Hyyppä, J., Karjalainen, M., Jaakkola, A., Heinonen, T.: Remote sensing methods for power line corridor surveys. ISPRS J. Photogramm. Remote. Sens. **119**, 10–31 (2016)
9. Katrasnik, J., Pernus, F., Likar, B.: A survey of mobile robots for distribution power line inspection. IEEE Trans. Power Delivery **25**(1), 485–493 (2009)
10. Billinton, R., Singh, G.D.: Reliability assessment of transmission and distribution systems considering repair in adverse weather conditions. In: IEEE CCECE2002. Canadian Conference on Electrical and Computer Engineering. Conference Proceedings (Cat. No.02CH37373), vol. 1, pp. 88-93. Winnipeg, MB, Canada (2002). https://doi.org/10.1109/CCECE.2002.1015180
11. Dobson, I., Carreras, B.A., Lynch, V.E., Newman, D.E.: An initial model fo complex dynamics in electric power system blackouts. In: Proceedings of the 34th Annual Hawaii International Conference on System Sciences, pp. 710–718. Maui, HI, USA (2001). https://doi.org/10.1109/HICSS.2001.926274
12. Carreras, B.A., Lynch, V.E., Sachtjen, M.L., Dobson, I., Newman, D.E.: Modeling blackout dynamics in power transmission networks with simple structure. In: Proceedings of the 34th Annual Hawaii International Conference on System Sciences, pp. 719–727. Maui, HI, USA (2001). https://doi.org/10.1109/HICSS.2001.926275
13. Samotyj, M.: The Cost of power disturbance to industrial and digital economy companies. Consortium for electrical infrastructure to support a digital society, an initiative by EPRI and the Electrical Innovation Institute (2001). https://books.google.co.in/books?id=YiIXHAAACAAJ
14. Matikainen, L., Lehtomäki, M., Ahokas, E., Hyyppä, J., Karjalainen, M., Jaakkola, A., ... Heinonen, T.: Remote sensing methods for power line corridor surveys. ISPRS Journal of Photogrammetry and Remote sensing, 119, 10–31 (2016) https://doi.org/10.1016/j.isprsjprs.2016.04.011
15. Song, Q., Zeng, Y., Xu, J., Jin, S.: A survey of prototype and experiment for UAV communications. Sci. China Inf. Sci. **64**, 140301 (2021). https://doi.org/10.1007/s11432-020-3030-2

16. Lan, M., Zhang, Y., Zhang, L., Du, B.: Defect detection from UAV images based on region-based CNNs. In 2018 IEEE International Conference on Data Mining Workshops (ICDMW) (pp. 385–390). IEEE. (2018)
17. Jalil, B., Leone, G.R., Martinelli, M., Moroni, D., Pascali, M.A., Berton, A.: Fault detection in power equipment via an unmanned aerial system using multi modal data. Sensors (Basel, Switzerland). **19** (2019)
18. Zhang, L., Yan, L., Meng, L., Li, X., Huang, S.: The application study of helicopter airborne photoelectric stabilized pod in the high voltage power line inspection. In: 2012 International Conference on Optoelectronics and Microelectronics, pp. 232–235. Changchun, China (2012). https://doi.org/10.1109/ICoOM.2012.6316261
19. Ahmed, M.F., Mohanta, J.C., Zafar, M.N.: Development of smart quadcopter for autonomous overhead power transmission line inspections. Mater. Today: Proc. **51**, 261–268 (2022). https://doi.org/10.1016/j.matpr.2021.05.271
20. Mao, T., Ren, L., Yuan, F., Li, C., Zhang, L., Zhang, M., Chen, Y.: Defect recognition method based on HOG and SVM for drone inspection images of power transmission line. In 2019 International Conference on High Performance Big Data and Intelligent Systems (HPBD&IS) (pp. 254–257). IEEE. (2019)
21. Nawaz, H., Ali, H.M., Laghari, A.A.: UAV communication networks issues: a review. Arch. Comput. Meth. Eng. **28**(3), 1349–1369 (2021)
22. Zhai, Y., Cheng, H., Chen, R., Yang, Q., Li, X.: Multi-saliency aggregation-based approach for insulator flashover fault detection using aerial images. Energies **11**(2), 340 (2018)
23. Qayyum, A., Saad, N.M., Kamel, N., Malik, A.S.: Deep convolutional neural network processing of aerial stereo imagery to monitor vulnerable zones near power lines. J. Appl. Remote Sens. **12**(1), 014001 (2018)
24. Liu, C., Wu, Y., Liu, J., Sun, Z., Xu, H.: Insulator faults detection in aerial images from high-voltage transmission lines based on deep learning model. Appl. Sci. **11**(10), 4647 (2021). https://doi.org/10.3390/app11104647
25. Wilken, N.J., Gouws, R.: Development of a quadcopter for power line inspection. (2014). https://www.semanticscholar.org/paper/Development-of-a-quadcopter-for-power-line-Wilken-Gouws/16660b3b259c5070230f553c518a6032bd5a7b04
26. Shukla, S.K., Koley, E. Ghosh, S.: Detection and classification of open conductor faults in six-phase transmission line using wavelet transform and naive bayes classifier. In: 2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), pp. 1–6. Coimbatore, India (2017). https://doi.org/10.1109/ICCIC.2017.8524343
27. Haibin, W., Yanping, X., Weimin, F., Xiaoming, S., Li, J.: Damper detection in helicopter inspection of power transmission line. In: 2014 Fourth International Conference on Instrumentation and Measurement, Computer, Communication and Control, pp. 628–632. Harbin, China (2014). https://doi.org/10.1109/IMCCC.2014.134
28. Song, Y., Wang, L., Jiang, Y., Wang, H., Jiang, W., Wang, C., ... Han, D.: A vision-based method for the broken spacer detection. In 2015 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER) (pp. 715–719). IEEE. (2015)
29. Vinyals, O., Blundell, C., Lillicrap, T., Wierstra, D.: Matching networks for one shot learning. Adv. Neural. Inf. Process. Syst. **29**, 3630–3638 (2016)
30. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y.: Generative adversarial networks. Communications of the ACM. **63**(11), 139–144 (2020)
31. Yang, T. W., Yin, H., Ruan, Q. Q., Da Han, J., Qi, J. T., Yong, Q., ... Sun, Z. Q.: Overhead power line detection from UAV video images. In 2012 19th International Conference on Mechatronics and Machine Vision in Practice (M2VIP) (pp. 74–79). IEEE. (2012)
32. Li, Q., Ren, S.: A real-time visual inspection system for discrete surface defects of rail heads. IEEE Trans. Instrum. Meas. **61**(8), 2189–2199 (2012)
33. Munawar, H.S.: Image and video processing for defect detection in key infrastructure. Mach. Vis. Inspect. Syst. Image Process. Concepts, Methodol. Appl. **1**, 159–177 (2020)
34. Li, X., Li, Z., Wang, H., Li, W.: Unmanned Aerial Vehicle for Transmission Line Inspection: Status, Standardization, and Perspectives. Front. Energ. Res. **9**, 336 (2021)
35. Zhang, Y., Huang, X., Jia, J., Liu, X.: A recognition technology of transmission lines conductor break and surface damage based on aerial image. IEEE Access **7**, 59022–59036 (2019)
36. Nguyen V.N., Jenssen, R., Roverso, D.: Automatic autonomous vision-based power line inspection: A review of current status and the potential role of deep learning. Int. J. Electr. Power Energy Syst. **99**, 107-120 (2018). https://doi.org/10.1016/j.ijepes.2017.12.016
37. Liu, X., Miao, X., Jiang, H., Chen, J.: Data analysis in visual power line inspection: An in-depth review of deep learning for component detection and fault diagnosis. Annual Reviews in Control. (2020)
38. Xaircraft. https://xaircraft.squarespace.com/aircraft/ [accessed November 9, 2019]
39. Chen, Q., Li, Y., Yang, G., Jin, T., Zhang, Z., Zhang, S.: Detection and analysis of ultraviolet corona discharge for earth switch grading ring. In: 2019 IEEE International Conference on Computational Electromagnetics (ICCEM), pp. 1–3. Shanghai, China (2019). https://doi.org/10.1109/COMPEM.2019.8779093
40. Tang, X., Zhang, Y. B.: Application of ultraviolet imaging technology to the discharge of high-voltage corona. J. North China Inst. Water Conserv. Hydroelectric Power, 5. (2011)
41. Ha, H., Han, S., Lee, J.: Fault detection on transmission lines using a microphone array and an infrared thermal imaging camera. IEEE Trans. Instrum. Meas. **61**(1), 267–275 (2011)
42. Reddy, M.J.B., Mohanta, D.K.: Condition monitoring of 11 kV distribution system insulators incorporating complex imagery using combined DOST-SVM approach. IEEE Trans. Dielectr. Electr. Insul. **20**(2), 664–674 (2013)
43. Arastounia, M., Lichti, D.D.: Automatic object extraction from electrical substation point clouds. Remote Sens. **7**(11), 15605–15629 (2015). https://doi.org/10.3390/rs71115605
44. Munawar, H. S., Maqsood, A. (2017). Isotropic surround suppression based linear target detection using hough transform. Int. J. Adv. Appl. Sci.
45. Lu, M., Bagheri, M., James, A.P., Phung, T.: Wireless charging techniques for UAVs: A review, reconceptualization, and extension. In: IEEE Access. **6**, 29865–29884 (2018). https://doi.org/10.1109/ACCESS.2018.2841376
46. Liu, Y., Mejias, L.: Real-time power line extraction from unmanned aerial system video images. In 2012 2nd International Conference on Applied Robotics for the Power Industry (CARPI) (pp. 52–57). IEEE. (2012)
47. Tavakoli, M., Nafar, M.: Human reliability analysis in maintenance team of power transmission system protection. Protect. Control Modern Power Syst. **5**(1), 1–13 (2020)
48. Song, B., Li, X.: Power line detection from optical images. Neurocomputing **129**, 350–361 (2014). https://doi.org/10.1016/j.neucom.2013.09.023
49. Li, Z., Liu, Y., Hayward, R., Zhang, J., Cai, J.: Knowledge-based power line detection for UAV surveillance and inspection systems. In: 2008 23rd International Conference Image and Vision

Computing New Zealand, pp. 1–6. Christchurch, New Zealand (2008). https://doi.org/10.1109/IVCNZ.2008.4762118
50. Zhu, L., Cao, W., Han, J., Du, Y.: A double-side filter based power line recognition method for UAV vision system. In: 2013 IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 2655–2660. Shenzhen, China (2013). https://doi.org/10.1109/ROBIO.2013.6739874
51. Castellucci, P.B., Lucca, L.C., SantAnna, M., Traballe, G., Mustacio, V.H., da Silva, J.F.R., Vallin, S.: Pole and crossarm identification in distribution power line images. In: 2013 Latin American Robotics Symposium and Competition, pp. 2-7. Arequipa, Peru (2013). https://doi.org/10.1109/LARS.2013.48
52. Sampedro, C., Martinez, C., Chauhan, A., Campoy, P.: A supervised approach to electric tower detection and classification for power line inspection. In 2014 International Joint Conference on Neural Networks (IJCNN) (pp. 1970–1977). IEEE. (2014)
53. Jabid, T., Ahsan, T.: Insulator Detection and Defect Classification using Rotation Invariant Local Directional Pattern. Int. J. Adv. Comput. Sci. Appl. **9**(2), 265–272 (2018). https://doi.org/10.14569/IJACSA.2018.090237
54. Tragulnuch, P., Chanvimaluang, T., Kasetkasem, T., Ingprasert, S., Isshiki, T.: High voltage transmission tower detection and tracking in aerial video sequence using object-based image classification. In 2018 International Conference on Embedded Systems and Intelligent Technology & International Conference on Information and Communication Technology for Embedded Systems (ICESIT-ICICTES) (pp. 1–4). IEEE. (2018)
55. Chen, B., Miao, X.: Distribution line pole detection and counting based on YOLO using UAV inspection line video. J. Electric. Eng. Technol. **15**(1), 441–448 (2020)
56. Kim, J., Nguyen, A.-D., Lee, S.: Deep cnn-based blind image quality predictor. IEEE Trans. Neural Netw. Learn. Syst. **30**(1), 11–24 (2018). https://doi.org/10.1109/TNNLS.2018.2829819
57. Cerón, A., Mondragón, I., Prieto, F.: Real-time transmission tower detection from video based on a feature descriptor. IET Comput. Vision **11**(1), 33–42 (2017)
58. Bian, J., Hui, X., Zhao, X., Tan, M.: A monocular vision–based perception approach for unmanned aerial vehicle close proximity transmission tower inspection. Int. J. Adv. Rob. Syst. **16**(1), 1729881418820227 (2019)
59. Maeda, K., Takahashi, S., Ogawa, T., Haseyama, M.: Estimation of deterioration levels of transmission towers via deep learning maximizing canonical correlation between heterogeneous features. IEEE J. Select. Top. Signal Process. **12**(4), 633–644 (2018)
60. Bian, J., Hui, X., Yu, Y., Zhao, X., Tan, M.: A robust vanishing point detection method for UAV autonomous power line inspection. In 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO) (pp. 646–651). IEEE. (2017)
61. Wang, D., Li, W., Liu, X., Li, N., Zhang, C.: UAV environmental perception and autonomous obstacle avoidance: A deep learning and depth camera combined solution. Comput. Electron. Agric. **175**, 105523 (2020). https://doi.org/10.1016/j.compag.2020.105523
62. Ahmad, J., Malik, A.S., Abdullah, M.F., Kamel, N., Xia, L.: A novel method for vegetation encroachment monitoring of transmission lines using a single 2D camera. Pattern Anal. Appl. **18**(2), 419–440 (2015)
63. Wang, Z.: Applied research on deep learning defect detection of key components on transmission towers. Civil Aviation University of China, Tianjin, China (2018)
64. Jifeng, D., Yi, L., Kaiming, H., Jian, S. R. F. C. N.: Object Detection via Region-Based Fully Convolutional Networks. People's Posts Telecommun. Press. (2016)
65. Demiane, F., Sharafeddine, S., Farhat, O.: An optimized UAV trajectory planning for localization in disaster scenarios. Comput. Netw. **179**, 107378 (2020)
66. Chen, J., Xu, X., Dang, H.: Fault detection of insulators using second-order fully convolutional network model. Math. Problems Eng., 2019. (2019) https://doi.org/10.1155/2019/6397905
67. Wang, X., Deng, Y., Duan, H.: Edge-based target detection for unmanned aerial vehicles using competitive Bird Swarm Algorithm. Aerosp. Sci. Technol. **78**, 708–720 (2018). https://doi.org/10.1016/j.ast.2018.04.047
68. Cheng, W., Song, Z.: Power pole detection based on graph cut. In 2008 Congress on Image and Signal Processing (Vol. 3, pp. 720–724). IEEE. (2008)
69. Mirallès, F., Pouliot, N., Montambault, S.: State-of-the-art review of computer vision for the management of power transmission lines. In Proceedings of the 2014 3rd International Conference on Applied Robotics for the Power Industry (pp. 1–6). IEEE. (2014)
70. Ullah, Z., Al-Turjman, F., Mostarda, L., Gagliardi, R.: Applications of artificial intelligence and machine learning in smart cities. Comput. Commun. **154**, 313–323 (2020)
71. Sun, C., Jones, R., Talbot, H., Wu, X., Cheong, K., Beare, R., Berman, M.: Measuring the distance of vegetation from powerlines using stereo vision. ISPRS J. Photogramm. Remote. Sens. **60**(4), 269–283 (2006)
72. Luque-Vega, L. F., Castillo-Toledo, B., Loukianov, A.,Gonzalez-Jimenez, L. E.: Power line inspection via an unmanned aerial system based on the quadrotor helicopter. In MELECON 2014–2014 17th IEEE Mediterranean electrotechnical conference (pp. 393–397). IEEE. (2014)
73. Zormpas, A., Moirogiorgou, K., Kalaitzakis, K., Plokamakis, G. A., Partsinevelos, P., Giakos, G., Zervakis, M.: Power transmission lines inspection using properly equipped unmanned aerial vehicle (UAV). In 2018 IEEE International Conference on Imaging Systems and Techniques (IST) (pp. 1–5). IEEE. (2018)
74. Menéndez, O., Pérez, M., Auat Cheein, F.: Visual-based positioning of aerial maintenance platforms on overhead transmission lines. Appl. Sci. **9**(1), 165 (2019)
75. Wang, Q., Jin, T., Mohamed, M.A.: An innovative minimum hitting set algorithm for model-based fault diagnosis in power distribution network. IEEE Access **7**, 30683–30692 (2019)
76. Chen, L., Lin, L., Tian, M., Bian, X., Wang, L., Guan, Z.: The ultraviolet detection of corona discharge in power transmission lines. Energy Power Eng. **5**(04), 1298 (2013)
77. Shea, J.J.: Corona performance of high-voltage transmission lines. In: IEEE Electr. Insul. Mag. **20**(2), 54–54 (2004). https://doi.org/10.1109/MEI.2004.1283282
78. Hu, W.T., Wang, S.H.: Brief discussion on influence factors in detecting corona discharge by UV detector. North China Electric Power **1**, 6–9 (2009)
79. Zakeri, H., Nejad, F.M., Fahimifar, A.: Rahbin: A quadcopter unmanned aerial vehicle based on a systematic image processing approach toward an automated asphalt pavement inspection. Autom. Constr. **72**, 211–235 (2016)
80. Yokoyama, N., Ochi, Y.: Path planning algorithms for skid-to-turn unmanned aerial vehicles. J. Guid. Control. Dyn. **32**(5), 1531–1543 (2009)
81. Bretas, A.S., Phadke, A.G.: Artificial neural networks in power system restoration. IEEE Trans. Power Delivery **18**(4), 1181–1186 (2003)
82. Tattaris, M., Reynolds, M.P., Chapman, S.C.: A direct comparison of remote sensing approaches for high-throughput phenotyping in plant breeding. Front. Plant Sci. **7**, 1131 (2016)
83. Liu, Y., Dai, H.N., Wang, H., Imran, M., Wang, X., Shoaib, M.: UAV-enabled data acquisition scheme with directional wireless energy transfer for Internet of Things. Comput. Commun. **155**, 184–196 (2020)
84. Zhang, Z., Wu, J., Dai, J., He, C.: A novel real-time penetration path planning algorithm for stealth UAV in 3D complex dynamic environment. IEEE Access **8**, 122757–122771 (2020)

85. Sun, J., Tang, J., Lao, S.: Collision avoidance for cooperative UAVs with optimized artificial potential field algorithm. IEEE Access **5**, 18382–18390 (2017)
86. Huang, S., Teo, R.S.H., Tan, K.K.: Collision avoidance of multi unmanned aerial vehicles: A review. Annu. Rev. Control. **48**, 147–164 (2019)
87. Basso, M., de Freitas, E.P.: A UAV Guidance System Using Crop Row Detection and Line Follower Algorithms J. . Intell. Robotic Syst. **97**(3), 605–621 (2020)
88. González-Sieira, A., Cores, D., Mucientes, M., Bugarín, A.: Autonomous navigation for UAVs managing motion and sensing uncertainty. Robot. Auton. Syst. **126**, 103455 (2020)
89. Park, J., Cho, N.: Collision avoidance of hexacopter UAV based on LiDAR data in dynamic environment. Remote Sensing **12**(6), 975 (2020)
90. Minaeian, S., Liu, J., Son, Y. -J.: Effective and efficient detection of moving targets from a UAV's camera. In: IEEE Trans. Intell. Transp. Syst. 19(2), 497–506 (2018). https://doi.org/10.1109/TITS.2017.2782790
91. Amarat, S. B., Zong, P.: 3D path planning, routing algorithms and routing protocols for unmanned air vehicles: a review. Aircraft Engin. Aerospace Technol. (2019)
92. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S. and Dean, J.: A guide to deep learning in healthcare. Nature medicine **25**(1), 24–29 (2019). https://doi.org/10.1038/s41591-018-0316-z
93. Redmon, J., Farhadi, A.: Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767 (2018)
94. Zia, S., Yuksel, B., Yuret, D., Yemez, Y.: RGB-D object recognition using deep convolutional neural networks. In Proceedings of the IEEE International Conference on Computer Vision Workshops (pp. 896–903). (2017)
95. Loghmani, M.R., Planamente, M., Caputo, B., Vincze, M.: Recurrent convolutional fusion for RGB-D object recognition. In: IEEE Robot. Autom. Lett. **4**(3), 2878–2885 (2019). https://doi.org/10.1109/LRA.2019.2921506
96. Zhang, X., Ma, J., Huang, S., Cheng, Z., Lee, T. H.: Integrated planning and control for collision-free trajectory generation in 3D environment with obstacles. In 2019 19th International Conference on Control, Automation and Systems (ICCAS) (pp. 974–979). IEEE. (2019)
97. Hamid, U.Z.A., Saito, Y., Zamzuri, H., Rahman, M.A.A., Raksincharoensak, P.: A review on threat assessment, path planning and path tracking strategies for collision avoidance systems of autonomous vehicles. Int. J. Veh. Auton. Syst. **14**(2), 134–169 (2018)
98. Aggarwal, S., Kumar, N.: Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges. Comput. Commun. **149**, 270–299 (2020)
99. Hadiwardoyo, S.A., Calafate, C.T., Cano, J.C., Krinkin, K., Klionskiy, D., Hernández-Orallo, E., Manzoni, P.: Three dimensional uav positioning for dynamic uav-to-car communications. Sensors **20**(2), 356 (2020)
100. Mohanta, J.C., Keshari, A.: A knowledge based fuzzy-probabilistic roadmap method for mobile robot navigation. Appl. Soft Comput. **79**, 391–409 (2019)
101. Dai, X., Mao, Y., Huang, T., Qin, N., Huang, D., Li, Y.: Automatic obstacle avoidance of quadrotor UAV via CNN-based learning. Neurocomputing **402**, 346–358 (2020). https://doi.org/10.1016/j.neucom.2020.04.020
102. Padhy, R. P., Ahmad, S., Verma, S., Bakshi, S., Sa, P. K.: Localization of unmanned aerial vehicles in corridor environments using deep learning. In 2020 25th International Conference on Pattern Recognition (ICPR) (pp. 9423–9428). IEEE. (2021)
103. Microdrones. https://www.microdrones.com/en/integrated-systems/mdmapper/ mdmapper1000plus/ [accessed November 9, 2019]
104. AeryonSkyranger R60. https://www.flir.com/products/skyranger-r60 [accessed October 29, 2019]
105. Mohanta, J.C., Parhi, D.R., Mohanty, S.R., Keshari, A.: A control scheme for navigation and obstacle avoidance of autonomous flying agent. Arab. J. Sci. Eng. **43**(3), 1395–1407 (2018). https://doi.org/10.1007/s13369-017-2899-y
106. Ahmed, M. F., Narayan, Y. S.: Fabrication and Testing Of Quadcopter Prototype for Surveillance
107. SZ DJI Technology Co. Ltd. https://www.dji.com/mavic-2/infospecs [accessed November 8, 2019]
108. Yang, Y., Wang, L., Wang, Y., Mei, X.: Insulator self-shattering detection: a deep convolutional neural network approach. Multimed. Tools Appl. **78**(8), 10097–10112 (2019)
109. Lu, Y., Huang, X., Dai, Y., Maharjan, S., Zhang, Y.: Blockchain and federated learning for privacy-preserved data sharing in industrial IoT. IEEE Trans. Industr. Inf. **16**(6), 4177–4186 (2019)
110. Sun, J., Yao, X., Wang, S., Wu, Y.: Blockchain-based secure storage and access scheme for electronic medical records in IPFS. IEEE Access **8**, 59389–59401 (2020)
111. Alvares, P., Silva, L., Magaia, N.: Blockchain-Based Solutions for UAV-Assisted Connected Vehicle Networks in Smart Cities: A Review, Open Issues, and Future Perspectives. Telecom **2**(1), 108–140 (2021). https://doi.org/10.3390/telecom2010008
112. Parimal Mehta, Rajesh Gupta, Sudeep Tanwar: Blockchain envisioned UAV networks: Challenges, solutions, and comparisons, Computer Communications, Volume 151, Pages 518–538, ISSN 0140–3664 (2020) https://doi.org/10.1016/j.comcom.2020.01.023
113. Mistry, I., Tanwar, S., Tyagi, S., Kumar, N.: Blockchain for 5G-enabled IoT for industrial automation: A systematic review, solutions, and challenges. Mech. Syst. Signal Process. **135**, 106382 (2020)
114. Alsamhi, S.H., Ma, O., Ansari, M.S.: Convergence of Machine Learning and Robotics Communication in Collaborative Assembly: Mobility, Connectivity and Future Perspectives. J. Intell. Robot. Syst. **98**, 541–566 (2020). https://doi.org/10.1007/s10846-019-01079-x
115. Grando, R.B., de Jesus, J., Kich, V.A., et al.: Double Critic Deep Reinforcement Learning for Mapless 3D Navigation of Unmanned Aerial Vehicles. J. Intell. Robot. Syst. **104**, 29 (2022). https://doi.org/10.1007/s10846-021-01568-y
116. Sanchez-Lopez, J.L., Molina, M., Bavle, H., et al.: A Multi-Layered Component-Based Approach for the Development of Aerial Robotic Systems: The Aerostack Framework. J. Intell. Robot. Syst. **88**, 683–709 (2017). https://doi.org/10.1007/s10846-017-0551-4
117. Scanavino, M., Avi, A., Vilardi, A., et al.: Unmanned Aircraft Systems Performance in a Climate-Controlled Laboratory. J. Intell. Robot. Syst. **102**, 24 (2021). https://doi.org/10.1007/s10846-021-01392-4

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