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Exploration of Visual Inspection and Algorithm Technology for Aerial Transmission Lines

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Abstract: In the era of smart grids, the maintenance and safety inspection of overhead transmission lines increasingly rely on efficient inspection methods. Visual inspection is one of the key links, which combines modern information technology, drones, machine vision, and artificial intelligence (AI) algorithms to improve inspection efficiency and accuracy. Although existing technologies have significantly improved the efficiency and safety of inspections, there are still significant issues in dealing with extreme environments such as storms and high-altitude areas, ensuring stable drone flight, image processing speed, and accuracy. This article believes that continuous technological progress can make visual inspection of transmission lines more intelligent and reliable. Therefore, it intends to conduct an in-depth analysis of the visualization techniques and algorithms for line inspection. This article mainly applies experimental comparison method and analytic hierarchy process to analyze the visual inspection of overhead transmission lines. The experimental results show that the Mask R-CNN (Region-based Convolutional Neural Network) algorithm has the highest accuracy (97.89%) and safety (99.123%) in line recognition.

1. Introduction

The visual inspection of overhead transmission lines is developing towards intelligence and automation. Advanced data analysis and early warning systems have further improved the accuracy and efficiency of inspections, ensuring the safe and stable operation of the power system. State Grid Corporation of China has successfully implemented the first millimeter level high-speed aerial inspection of ultra-high voltage transmission lines using fixed wing drones in Huzhou City, Zhejiang Province, fully safeguarding the stable operation of the energy artery. As a new platform for overhead transmission line inspection, drones are equipped with various types of detection devices on the drone platform, greatly reducing the manpower investment in power line inspection and enabling uninterrupted inspection.

Drones play an important role in the inspection of overhead transmission lines. By carrying sensors such as long-range LiDAR, drones can perform 3D point cloud scanning, form a 3D model of transmission lines, and plan autonomous inspection routes, ultimately achieving autonomous inspection by drones. The patrol robot can crawl along the power transmission line and use the carried detection instruments to conduct close inspections on poles, wires, insulators, line fittings, etc. These methods not only improve inspection efficiency, but also enhance inspection quality. Multiple types of intelligent perception terminals can be equipped with unmanned aerial vehicles, robots, satellite remote sensing and other inspection methods to achieve intelligent diagnosis and dynamic monitoring of line status. The application of augmented reality technology in overhead transmission line inspection is also very extensive. By overlaying virtual images, data, and instructions onto the real world, inspectors can visually see the status of the equipment. The power monitoring system can also achieve functions such as data collection, remote control, event alarm, and data analysis, further improving the operational efficiency of the power system. This comprehensive solution not only improves inspection efficiency, but also assists in the safe, efficient, and green operation of the power grid.

This article first introduces the background of overhead transmission line inspection and analyzes several intelligent methods for inspection. Then, this article reviews the relevant theories of other scholars on visualization technology and transmission lines, and proposes the argument of this article. In the third part, this article constructs a key parameter system for state evaluation, analyzes the basic support technologies for AI image processing, and discusses several object detection algorithms. The fourth part of this article compares the models before and after pruning and deployment, and analyzes the performance of several algorithms. Finally, this article provides a summary.

2. Related Work

The visual inspection of overhead transmission lines is achieved through advanced technological means to achieve comprehensive and real-time monitoring and management of transmission line equipment and environment. Scholars have provided theoretical explanations and in-depth analysis on visualization related technologies. For example, Mansuri L E introduced an AI-based automatic visual inspection system for detecting and evaluating architectural heritage. The system utilizes deep learning (DL) algorithms to analyze images of architectural heritage and identify issues of damage and degradation. It provides an automated tool for protecting and maintaining architectural heritage, reducing reliance on expert manual inspection, but there are adaptability issues for specific types of architectural heritage [1]. In order to improve the efficiency and accuracy of fruit grading and enhance the automation level of agricultural production, Ismail N has developed a real-time visual inspection system that combines computer vision and DL technology to quickly and accurately classify and grade fruits. This method requires a large amount of training data to ensure the accuracy of classification [2]. By introducing a hybrid multi-stage system, Schlosser T explored the role of deep neural network systems in improving automatic visual fault detection in semiconductor manufacturing [3]. Dai J analyzed the research trends of global value chains using bibliometrics and visualization techniques [4]. Cuțitoi A C applied intelligent city analysis, digital twin simulation, and visual modeling techniques, utilizing cognitive data mining algorithms to analyze the pathways of sustainable urban governance networks [5]. Smart city digital twin, 3D modeling and visualization tools, and spatial cognitive algorithms all have an impact on urban construction. Beckett S also discussed their application in AI-based urban design and planning [6]. Ningtyas S visualized the proportion of Indonesian youth and adults with computer information technology skills through data visualization, which is limited by sample selection and survey methods and can be further improved [7]. A R package called ggtranscript is used to visualize and interpret transcript isomers using ggplot2. Gustavsson E K believed that this R package provides a convenient tool for bioinformatics research, helping to understand and analyze transcriptional isomers [8]. Sharma R conducted research using ResearchRabbit and demonstrated how AI tools can assist library users in research discovery and information management [9]. Tian W introduced fluorescence visualization technology to observe the chemical distribution of the air water interface [10]. Some scholars have also studied transmission lines. For example, to understand the impact of inverter base resources on protection systems in modern power systems, Quispe J C reviewed the role of inverter base resources in the challenge of transmission line protection [11]. In the generation of radio frequency pulses in a rotational magnetic nonlinear transmission line with periodic placement of ferrite and permanent magnets, Priputnev P V considered the stability of the material and structure [12]. Mehrjoo Z elaborated on a microwave rotation sensor based on the reflection phase of a lumped resonator at the end of a transmission line [13]. Abed N K proposed a method for detecting faults in power transmission lines based on voltage and current values using the K-nearest neighbor algorithm [14]. Llamo-Laborí H S provided more accurate calculation of corona losses for power system design and operation. They successfully calculated the active conductor corona losses under actual unbalanced transmission line conditions [15]. Ghaddar A used embroidery technology to create a simulated surface plasmon polaron transmission line, which improves wireless signal transmission at microwave frequencies. This study introduces a new type of wearable transmission line design, providing a better data transmission method [16]. Yaseen N K has focused on the protection issues of the power system and proposed a new protection algorithm for renewable energy systems connected to inverters using local information transmission line protection strategies. This can more accurately identify and isolate faults, while considering the impact of distributed energy resources on traditional protection systems [17]. Fayyad A A explored methods based on high-speed decision trees and artificial neural networks for existing transmission line protection technologies. They described a hardware joint simulation method combining high-speed decision trees and artificial neural networks to improve the protection system of transmission lines [18]. To achieve efficient and reliable voltage/power management, Panfilov D I proposed using semiconductor power regulators to balance different modes of three-phase lines in the power system, optimizing the operation of the power system [19]. Claeyssen J R delved into wave propagation in transmission lines and the application of the Heaviside transfer function [20]. Therefore, this article discusses the inspection of overhead transmission lines based on existing technological support.

3. Methods

3.1 Construction of Key Parameter System for State Evaluation of Overhead Transmission Lines

Divide transmission lines into eight types of devices, namely towers, foundations, accessories, conductors, insulators, grounding devices, pipeline environments, and auxiliary devices. Due to the uniqueness of power grids in different regions, some basic parameters have little impact on the evaluation of line status. Therefore, it is necessary to eliminate redundant parameters and simplify the parameter system. This article is based on the records of general, serious, and critical defects of transmission lines in a given regional power grid over the years. The basic parameters are quantified using confidence association rules, and key parameters are obtained through principal component analysis to reduce size. The overall process of constructing the key parameter system for transmission line status assessment is shown in Figure 1:

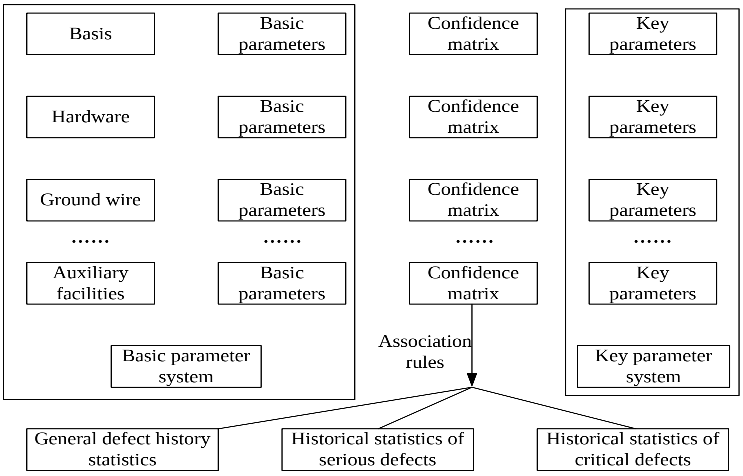

Figure 1: Overall process of constructing the key parameter system for transmission line status evaluation

The support level $S(X \Rightarrow Y)$ is expressed as:

$$S(X \Rightarrow Y) = \frac{\partial(X \cup Y)}{M} \tag{1}$$

M is the total number of things, and the confidence level $C(X \Rightarrow Y)$ is expressed as:

$$C(X \Rightarrow Y) = \frac{\partial(X \cup Y)}{\partial(X)} \tag{2}$$

This article presents the calculation results of the confidence level of the association rules for general defects, major defects, and critical defects based on the basic parameters of the hardware unit, as shown in Table 1.

Table 1: Confidence of Basic Parameters of Hardware Units

	Critical defect	Serious defect	Common defect
Heat generation of tension clamp drainage plate	0.168	0.163	0.519
Defect of connecting hardware opening pins	0.002	0.014	0.621
Heating situation of the connecting tube	0.223	0.171	0.568
Corrosion and wear of fittings	0	0.002	0.243
Defects in the split pin of the suspension clamp bolt	0.001	0.006	0.792
Loosening and detachment of tension clamp bolts	0.248	0	0.499
Suspension line clamp bolt missing nut situation	0	0.086	0.666
Defect situation of anti-vibration hammer	0.001	0	0.838
Missing or damaged spacer	0	0	0.350
Damage of heavy hammer leads to wind deflection of wires	0.500	0	0.500

A more practical and targeted differential evaluation model for transmission line status has been developed using the hierarchical analysis method, fuzzy comprehensive evaluation method, and the corresponding key parameter weight differential fitting method. The evaluation of this transmission line was based on the differential condition evaluation model and the evaluation model that did not consider adjusting the weight of different operating interval parameters. The evaluation results were compared with those of national and southern transmission lines, as shown in Table 2:

Table 2: Comparison of Evaluation System Results

Unit	Weight	Differentiation state value in this article	State grid	China Southern Power Grid
Ground wire	0.22	99.34	99.56	99.41
Basis	0.08	100	100	100
Insulator	0.16	96.85	96.63	98.11
Tower	0.09	99.81	98.12	98.12
Grounding device	0.09	100	100	100
Hardware	0.16	90.51	90.63	91.98
Auxiliary facilities	0.09	98.76	99	99
Channel environment	0.11	100	100	100

The evaluation results of the overall status of the transmission line using this method, as well as the evaluation guidelines of State Grid Corporation of China and Southern Power Grid Corporation, are both normal, indicating that this method can objectively and accurately evaluate the status of overhead transmission lines.

3.2 Basic Support Technologies for AI Image Processing

Heterogeneous computing platforms have become the dominant computing mode in DL, allowing for high computing throughput in highly parallel computing and heterogeneous multi-core computing. They are suitable for computationally intensive and highly parallel applications, especially for applications such as graphics and matrix computing. DL mainly includes two stages: development and deployment, including three main stages: sample processing, model formation, and inference detection. In practical applications, different networks have been developed based on different training frameworks. At present, the main DL training frameworks include Caffe, TensorFlow, Torch, etc. Special data format interfaces and model definition methods are commonly used to achieve end-to-end training. This article is based on a universal DL framework for integration and optimization, aiming to achieve unified integration of data processing and models. The core technology roadmap is to develop integrated solutions based on DL frameworks, integrating examples, models, and resources through interfaces with data processing systems and DL systems, and supplementing the end-to-end training ecosystem. A DL system consists of sample management, model optimization, and resource allocation, which can achieve functions such as sample function analysis, image preprocessing, sample classification statistics, model formation monitoring, and resource utilization monitoring. The main interface can define custom training settings, allowing users to autonomously adjust settings, customize model structure, optimize resource configuration, and other functions. Sample image processing technology creates data models through data iteration, and the key is to conduct large-scale training.

In order to achieve a proportional driving mode and achieve more effective driving efficiency, affine transformations are performed on the image, such as rotation and displacement. Common methods such as image mirroring can also be used to increase training modes. Meanwhile, this article uses image deletion methods to improve image quality:

$$I(\mathrm{a}) = K(a)s(a) + X(1 - s(a)) \tag{3}$$

The central idea of super-resolution restoration technology is to estimate the high-frequency components of signals that exceed the cutoff frequency of the imaging system, in order to improve image resolution. In the initial stage of this technology, only a single image is processed, and this method has inherent limitations in image restoration because the information available for a single image is limited.

3.3 Object Detection Algorithm

The purpose of object recognition is to find specific categories and positions of visual objects based on the provided digital images. Firstly, a certain number of candidate boxes can be generated by dragging the window across the entire image. Then, the attributes of the candidate boxes can be extracted, classified using classification methods such as decision trees and AdaBoost, and compared with manually extracted features to determine whether the target in the candidate box is the desired target. Confidence is not calculated through maximum suppression. There are basically two DL-based object recognition algorithms: R-CNN's two-step object recognition algorithm and Yolo's one-step object recognition method.

The advantage of YOLO is its fast speed, which enables end-to-end training and detection, but it is not accurate enough for detecting small objects. Faster R-CNN is an improvement on R-CNN. Faster R-CNN introduces region generation networks that share weights with convolutional neural networks, and these regions are fed into classification and regression branches for further processing. Mask R-CNN is an extension of Faster R-CNN, which increases the ability to segment target instances. It adds parallel branches to generate pixel level masks for each target, while performing object detection and instance segmentation, providing accurate contour information for each detected object.

4. Results and Discussion

4.1 Technical Support

Drone inspections provide fast and comprehensive coverage from different perspectives, reducing personnel costs and worker risks. It is equipped with high-definition or infrared cameras, which can take detailed photos of the circuit. Foldable neural networks are widely used for detecting image objects and can identify problems such as damage, corrosion, and looseness of circuit components in complex environments. Yolo, Faster R-CNN, masked R-CNN, and other algorithmic models are used to locate and classify transmission towers, lines, and anomalies. By annotating and training the image data collected using DL models, the model gradually learns to identify potential risks. The drone is equipped with an infrared thermal camera that can detect any thermal abnormalities, such as overheating, overload, or other issues. These images are further processed with algorithms, such as using heat maps (thermal gradients) to analyze hotspots and provide early warning.

4.2 Model Pruning and Hardware Deployment

Model pruning techniques include removing redundant and unnecessary parameters from the model to obtain a network with essentially unchanged performance, but this significantly reduces model parameters and computational complexity, allowing for higher detection speeds in embedded devices. The weight pruning process mainly involves assigning some weight parameters in the weight matrix, reducing computational costs. The goal of channel pruning is:

$$J = \sum \mathrm{j}(g(a,w),b) + \alpha \sum h(\mu) \tag{4}$$

W is a trainable weight, and $\sum h(\mu)$ is a sparse induced penalty for the scaling factor.

In addition, this article utilizes an embedded AI computing platform to deploy on visualization tools. The Ubuntu 16.14 system can be installed on the virtual machine to install the Jetson TX3. The trained. pt model can be converted into a weight model in. wts format.

4.3 Results and Analysis

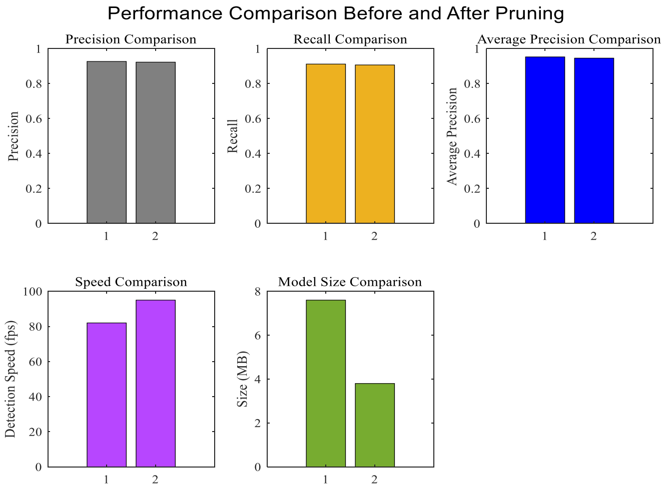

Figure 2: Comparison of model performance before and after pruning

As shown in Figure 2, in the accuracy comparison, the accuracy of the original model is 0.927, and the accuracy after pruning is 0.923. In the comparison of recall rates, the recall rate of the original model was 0.912, and the recall rate of the pruned model was 0.907. In the comparison of average accuracy, the original model has an average accuracy of 0.953, and the pruned model has an average accuracy of 0.946. In the speed comparison, the original model has a detection speed of 82, and the pruned model has a detection speed of 95. In the comparison of model sizes, the original model size was 7.6MB, and the pruned model size was 3.8MB. After retraining and fine-tuning, the accuracy and recall of the pruned model decreased by only a few thousandths, but the performance in model size and detection speed was significantly improved.

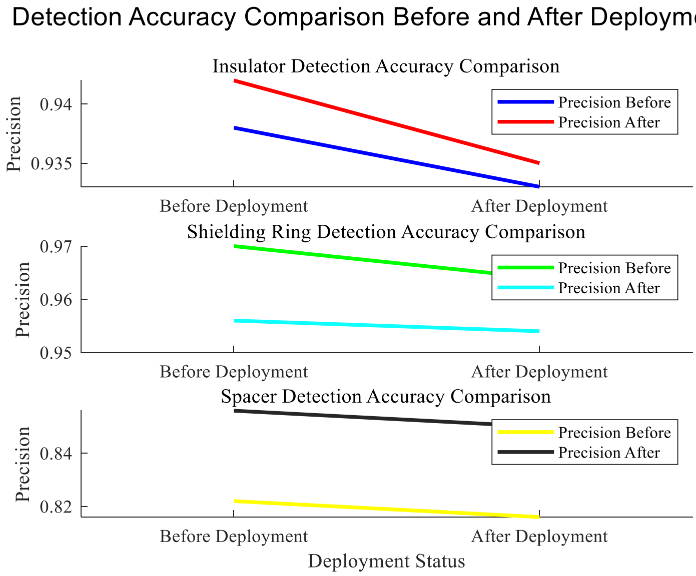

Figure 3: Comparison of detection accuracy before and after deployment

As shown in Figure 3, in insulator detection, the accuracy of the original model is 0.938 and the recall rate is 0.942. The deployed accuracy is 0.933 and the recall rate is 0.935. In the pressure equalization ring detection, the accuracy of the original model is 0.970 and the recall rate is 0.956. The deployed accuracy is 0.964 and the recall rate is 0.954. In the detection of spacer bars, the accuracy of the original model is 0.822 and the recall rate is 0.856. The deployed accuracy is 0.816 and the recall rate is 0.850. The detection effect of the deployed model remains basically unchanged and can meet the requirements of practical implementation.

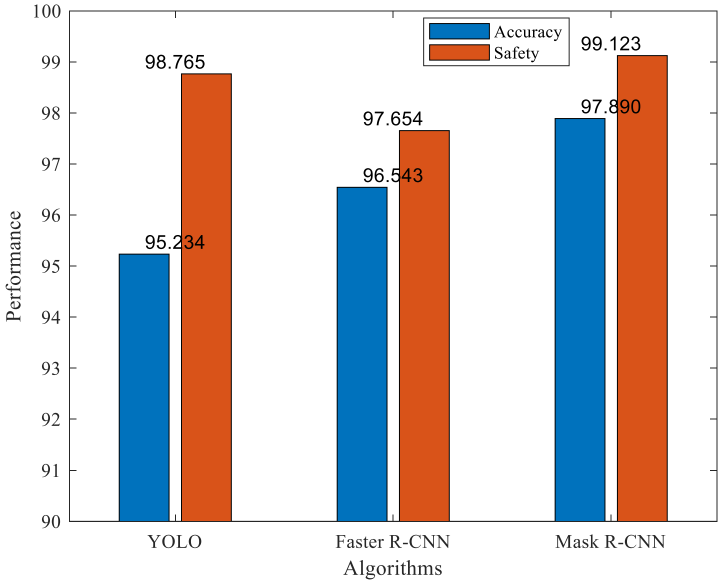

Figure 4: Performance comparison of different algorithms in transmission line inspection

As shown in Figure 4, this article can observe that the YOLO algorithm has a recognition accuracy of 95.234% (the lowest) and a security level of 98.765%. The recognition accuracy and security results of the Faster R-CNN algorithm have the smallest difference, with an accuracy of 96.543% and a security of 97.654% (the smallest).

5. Conclusions

Cable transmission lines are mainly laid underground or underwater using cables. This type of line is more complex during construction and maintenance, and has poor adaptability to the environment. On overhead transmission lines, patrol drones can effectively detect and identify various obstacles, and plan obstacle crossing behaviors. The visual inspection of overhead transmission lines achieves comprehensive and real-time monitoring and management of transmission lines through various advanced technologies such as drones, robots, and intelligent monitoring systems. This article conducted experimental tests on the accuracy and recall of models before and after deployment and pruning. This article suggests that further exploration can be conducted on the applications of augmented reality, intelligent robots, and other technologies in the inspection process.

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