Transmission line surface defect detection method based on uav autonomous inspection

Xu Xie
State Grid Chongqing Jiangjin Power Supply Company, Chongqing, 402260, China
*Corresponding author’s e-mail: jjggdyxgs-dkzx@cq.sgcc.com.cn

Abstract. The existing transmission line surface defect detection methods have the problem of incomplete image data set, resulting in a low recognition success rate. A transmission line surface defect detection method based on uav autonomous inspection is designed. The safety of power grid operation is evaluated, the local linearization process is transformed into linear equation expression, the image data set is obtained by uav autonomous inspection, the transmission line state is judged, the corresponding constraint conditions are set, the type of transmission line surface defects are identified, the number of image poles and towers is matched, and the detection mode is optimized by edge detection algorithm. Experimental results: The average recognition success rate of the transmission line surface defect detection method in this paper and the other two detection methods is 59.89%, 51.89% and 52.03%, proving that the transmission line surface defect detection method integrating UAV technology inspection has a wider application space.

1. Introduction
Because the structure of transmission line tower is relatively simple, in the later maintenance process, the requirements of maintenance technology and construction technology are low, so it is widely used in the electric power industry. However, with the increasing demand for electricity, the performance and service life of transmission lines will be improved accordingly. However, when the terrain is complex or the weather is bad, the disadvantages of the manual transmission line defect detection method will be exposed obviously [1-2]. In particular, in some regions with intensive factories, electricity consumption is larger than that of residential users, and there are more transmission lines, causing problems such as safety risks, work efficiency and excessive resource consumption [3]. Unmanned aerial vehicle autonomous inspection is an emerging product proposed with scientific progress, which fully combines unmanned aerial vehicle and detection equipment represented by visible light, replacing the traditional manual inspection method, and no longer requires bulky telescope and infrared imager and other equipment. The working principle of UAV inspection is also very simple. There are two main modes to choose from. The first option is to set flight tasks in the operation terminal of the UAV in advance. The second method is to collect the task information in real time and find the fault point through the image information. In general, uav inspection application in transmission line defect detection has the advantages of flexible operation mode, high work efficiency and low cost. At present, the academic circle has accumulated some research results on the combination of uav autonomous inspection and transmission line surface defects. On the basis of the data intelligent management platform, Li Ning et al. combined with the deep convolutional neural network algorithm to process the relevant video data, obtained the detection results and tested them by labeling the defect locations and classifying them, but ignored the integrity of the image data set in the defect identification process [4]. Li Weisheng et al. used SSD algorithm to expand the data set to improve the generalization ability of network detection, and
calculated the area of the overlapping surface of defect locations to achieve defect target detection, but they did not expand the image data set in detail [5]. Therefore, the related research on the above topic remains to be discussed.

2. Transmission line surface defect detection method based on uav autonomous inspection

2.1. Evaluating the safety of power grid operation

On the whole, the nature of power grid operation is actually a random structure. It is very necessary to detect the surface defects of transmission lines and evaluate the safety of power grid operation. In fact, the safety of power grid operation in a specific region can be reflected by some indicators, including blackout time, blackout probability and blackout loss. In the process of power grid operation, basic data, including transmission line overload, grid abundance and node voltage, are one of the standards to measure the safety of power grid operation [6-7]. In general, the calculation formula of power grid abundance is as follows:

\[ E = \sum_{\alpha \in L} l(\alpha) h(\alpha) \]  

In formula (1), \( \alpha \) represents a certain fault state, \( L \) represents the set of all fault states, \( h \) represents the safety measure coefficient, and \( l \) represents the probability of failure state occurrence. Considering the long-term demand of power grid operation, component capacity and power grid load are usually selected as part of the expected value, which is used as the risk identification of various influencing factors. On this basis, the expression formula of power grid abundance is as follows:

\[ P = \sum_{c \in Q} g_c \]  

In Formula (2), \( g \) represents the probability of occurrence of state \( c \), and \( Q \) represents the set of states in which load warning will occur. Affected by the overload current of power grid lines, there will be a risk represented by the loss of load in some areas with large power demand. According to the numerical change of the variable, the chain reaction caused by the change of the variable is analyzed. The calculation of sensitivity requires local linearization of each transmission line in the power grid, which is transformed into a linear equation, the specific expression formula is as follows:

\[
\begin{align*}
D(\beta, \delta, w) &= 0 \\
R &= A(\beta, \delta, w)
\end{align*}
\]  

In formula (3), \( D \) represents the power grid operation state variable, \( R \) represents the power grid operation control variable, \( \beta \) represents the independent parameter in the linear equation, \( \delta \) represents the branch admittance matrix parameter in the power grid, and \( w \) represents the reactive power of the balance node. When the load is adjusted in the power grid, the variation of load points should be regarded as the sum of the power of all branches in order to meet the active power balance condition of the power grid operation. In order to improve the efficiency of power grid safety assessment, if the power grid can operate normally under multiple serious fault conditions, the emergency ranking can be carried out according to the fault degree and risk coefficient of components. Based on the above description, complete the steps to evaluate the power grid operation security.

2.2. Uav autonomous inspection to obtain image data set

In the method of transmission line surface defect detection, it is necessary to combine the autonomous inspection technology of UAV to obtain image data set. Uav inspection technology is the integration of communication technology, electronic technology and aviation technology [8-10]. The image acquisition function requires that the UAV is equipped with a camera or camera with good performance to take inspection photos. With images and video taken by drones, the state of the transmission lines can be basically determined. Uav inspection terminal mainly consists of aircraft, ground station and communication link, as shown in Figure 1:
According to Figure 1, the core device of uav inspection terminal is the master chip and various sensors to realize the smooth execution of instructions and tasks. In the uav inspection process, scientific and reasonable inspection route should be formulated, and the inspection task should be discretized on the basis of ensuring the continuity of flight path and space. The principle of route planning for uav inspection is to include as many target points as possible on the way according to the preset departure place and inspection destination. Then the expression formula of the total range constraint condition of uav cruising path is:

$$G = \sum_{n=1}^{m} e_n$$  \hspace{1cm} (4)

In Formula (4), $m$ represents the maximum step size, $n$ represents the minimum step size, and $e$ represents the step size node. When there are problems such as broken insulators and self-explosion or tower fittings falling off on the line, uav inspection technology can detect abnormal hot spots, identify the line and wire clip and other devices, and quickly judge the starting heat source and the cause of heating. The main objects of uav inspection include the transmission line surface, the corridor where the transmission line is located and the use state of tower parts. Especially when the range of transmission lines is larger and the distance is longer, the endurance of uav is also higher. Based on this, the steps of obtaining image data set are completed.

2.3. Identifying transmission line surface defect types

Transmission lines are often surrounded by dense forests, so there are often nests built on them. Once birds move along power lines, their food or feces can be a source of pollution that affects the insulation strength of the insulators, potentially causing a regional power grid failure. And affected by the outdoor natural weather, the nest is often blown down by the wind, so the transmission line around the tower will be a great probability of tripping phenomenon. When the aluminum wire on the surface of the output wire is scattered, the diameter of the wire becomes larger, which will directly lead to the change of the surface slope. According to the operation principle of convolutional neural network, the expression formula of output image size can be obtained:

$$H = \frac{(\phi - 1)}{K}$$  \hspace{1cm} (5)

In Formula (5), $\phi$ represents the bias parameter, and $K$ represents the number of output channels. The more common manifestation of wire strand breaking defect is that there are several burrs of different lengths on the surface of wire, or the morphological characteristics of multi-strand wire change from neat direction to scattered split. These two features appear on the image as wire widths that are even
several times larger than the normal width. In the surface lines of transmission wires, they are wrapped in a fixed order, and the traverse direction Angle is also an important basis for judgment. Meanwhile, glass insulators are also an important part of transmission lines. Insulators are mainly responsible for blocking live wires to form grounding circuits and supporting wires. They are the comprehensive embodiment of both electrical and mechanical properties. Considering the exposure intensity, shooting Angle and image background environment, the coverage of inspection samples is expanded. Based on this, the steps to identify the types of transmission line surface defects are completed.

2.4. Edge detection algorithm optimizes detection mode
It is a key step to detect the surface defects of transmission lines to obtain insulator contour information. Image edge detection is adopted to extract image edge. In order to meet the requirements of real-time detection, the corresponding single-stage detector is used to directly extract the boundary frames of transmission lines from the images collected by UAV after partially reducing the accuracy requirements, so as to improve the detection speed. Under the condition of known infrared image pixels, the nonlinear distortion of uav cruise equipped camera lens is obtained, which is expressed by Taylor series associated with the distance of light center. The expression formula is as follows:

$$
\begin{cases}
  i = i_i \left(1 + \frac{1}{\eta}\right) \\
  j = j_i \left(1 - \frac{1}{\eta}\right) \\
  f = i_i^2 + j_i^2
\end{cases}
$$

In Formula (6), $i_i$ represents pillow distortion amplitude, $j_i$ represents barrel distortion amplitude, and $\eta$ represents radial distortion coefficient. According to the specific detection task, all information passing on the line is summarized, and the periodic update period is set according to the detection task. In the actual operation process, in order to avoid electromagnetic interference, a certain safe distance should be kept between uav and live wire. Due to the fixed size of the pall image of most UAVs, it is difficult to locate the key areas of transmission lines. Based on this, the steps of optimizing the detection mode are completed.

3. Experimental test

3.1. Experimental preparation
In order to verify the effectiveness of the transmission line surface defect detection method presented in this paper, experimental tests are carried out. In order to meet the requirements of parallel computing tasks in experimental tests, GPU cluster is selected as the processing platform. In view of VC++ application development mainly has WIN API and MF ‘c two modes, the programming language is C++ and Python. The experiment uses the positioning effect of the single-stage detector and selects virtualStick as the control mode terminal. And during the experiment, the change process of the horizontal direction was observed first. At the same time, the observation amount required by the experiment is set as the distance between the UAV and the transmission line to be detected. And set the state variable as the speed in the horizontal direction of UAV inspection. The initial state of the experiment is that the distance between uav and the transmission line to be detected is 20m, and the initial speed is 0.8m/s. In addition, the experiment process is set as the shortest distance between the route inspected by UAV and the position of the transmission line, and the UAV hovers over when it flies 15m away from the transmission line. The time sequence interval is set to 0.3s, and the feedback cycle of image information is 0.1s. In the above experimental environment, experimental tests are carried out and experimental results are obtained.
3.2. Experimental result

The transmission line surface defect detection method based on deep learning and the transmission line surface defect detection method based on FPGA are selected for experimental comparison with the transmission line surface defect detection method in this paper. Under the conditions of different detection distances, the recognition success rate of the three detection methods was tested. The higher the value, the better the performance of the method. The experimental results are shown in Table 1-3:

| Table 1 Recognition success rate at detection distance of 500m (%) |
|---------------------------------------------------------------|
| Number of experiments | Transmission line surface defect detection method based on deep learning | Transmission line surface defect detection method based on FPGA | The transmission line surface defect detection method in this paper |
|----------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| 1                    | 78.56                                           | 73.56                                           | 79.84                                           |
| 2                    | 76.34                                           | 72.89                                           | 81.22                                           |
| 3                    | 77.66                                           | 74.61                                           | 80.69                                           |
| 4                    | 75.39                                           | 73.06                                           | 81.35                                           |
| 5                    | 74.28                                           | 74.15                                           | 82.05                                           |
| 6                    | 76.58                                           | 76.28                                           | 83.16                                           |
| 7                    | 76.39                                           | 77.14                                           | 82.56                                           |
| 8                    | 73.65                                           | 78.09                                           | 83.79                                           |
| 9                    | 72.51                                           | 75.61                                           | 82.46                                           |
| 10                   | 74.09                                           | 74.22                                           | 83.11                                           |

| Table 2 Recognition success rate at detection distance of 1000m (%) |
|---------------------------------------------------------------|
| Number of experiments | Transmission line surface defect detection method based on deep learning | Transmission line surface defect detection method based on FPGA | The transmission line surface defect detection method in this paper |
|----------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| 1                    | 56.47                                           | 56.11                                           | 61.23                                           |
| 2                    | 51.20                                           | 52.08                                           | 63.48                                           |
| 3                    | 53.69                                           | 53.46                                           | 62.54                                           |
| 4                    | 52.47                                           | 54.17                                           | 64.16                                           |
| 5                    | 53.66                                           | 53.02                                           | 63.28                                           |
| 6                    | 58.16                                           | 54.15                                           | 65.97                                           |
| 7                    | 52.33                                           | 53.77                                           | 66.18                                           |
| 8                    | 51.27                                           | 52.04                                           | 65.28                                           |
| 9                    | 54.29                                           | 52.19                                           | 64.39                                           |
| 10                   | 55.10                                           | 51.27                                           | 63.88                                           |

| Table 3 Recognition success rate at detection distance of 2000m (%) |
|---------------------------------------------------------------|
| Number of experiments | Transmission line surface defect detection method based on deep learning | Transmission line surface defect detection method based on FPGA | The transmission line surface defect detection method in this paper |
|----------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| 1                    | 29.48                                           | 26.33                                           | 33.14                                           |
| 2                    | 28.45                                           | 35.14                                           | 32.05                                           |
| 3                    | 29.16                                           | 34.97                                           | 33.71                                           |
| 4                    | 25.33                                           | 23.66                                           | 34.56                                           |
| 5                    | 24.99                                           | 24.88                                           | 33.19                                           |
| 6                    | 23.60                                           | 29.30                                           | 32.61                                           |
| 7                    | 25.47                                           | 26.18                                           | 33.09                                           |
| 8                    | 24.11                                           | 27.10                                           | 32.45                                           |
| 9                    | 26.92                                           | 26.03                                           | 35.06                                           |
| 10                   | 25.11                                           | 25.47                                           | 36.19                                           |
As can be seen from Table 1, the average recognition success rate of the transmission line surface defect detection method in this paper and the other two detection methods is 82.02%, 75.55% and 74.96%. As can be seen from Table 2, the average recognition success rate of the transmission line surface defect detection method in the paper and the other two detection methods is 64.04%, 53.86%, 53.23%; As can be seen from Table 3, the average recognition success rate of the proposed transmission line surface defect detection method and the other two detection methods is 33.61%, 26.26% and 27.91%, proving that the proposed transmission line surface defect detection method has better performance.

4. Conclusion
The method of transmission line surface defect detection designed in this paper can meet the demand of actual operation. By describing defect types and characteristics in detail, uav inspection technology is used to solve the problem of incomplete image data set, which enriches the number of relevant image samples and improves the recognition success rate of detection method to a certain extent. Due to the limited research conditions, the research on intelligent applications such as uav reshooting is not comprehensive enough, and relevant deficiencies will be constantly improved in the future.

References
[1] X Wang, Yan Z, Zeng Y, et al. (2021) Research on correlation factor analysis and prediction method of overhead transmission line defect state based on association rule mining and RBF-SVM[J]. Energy Reports, 7:359-368.
[2] Han J, Yang Z, Zhang Q, et al. (2019) A method of insulator faults detection in aerial images for high-voltage transmission lines inspection[J]. Applied Sciences, 9(10): 2009.
[3] Liang H., Zuo C, Wei W. (2020) Detection and Evaluation Method of Transmission Line Defects Based on Deep Learning[J]. IEEE Access, 8:38448-38458.
[4] LI Ning, ZHENG Qian, XIE Gui-wen, et al. (2019) Detection of defects in transmission line based on the unmanned aerial vehicle image recognition technology [J]. Electronic Design Engineering, 27(10): 102-106, 112.
[5] Li Weixing, Zheng Wulue, Wang Ning. (2019) Research on Detection Method of Insulator Defects on Transmission Lines Based on SSD Algorithm[J]. Instrumentation Customer, 26(8): 1-4.
[6] Aghanoori N, Masoum M, Abu-Siada A, et al. (2020) Enhancement of microgrid operation by considering the cascaded impact of communication delay on system stability and power management[J]. International Journal of Electrical Power & Energy Systems, 120(12):105964.
[7] Bankovi B, Filipovi F, Mitrovi N, et al. (2020) A Building Block Method for Modeling and Small-Signal Stability Analysis of the Autonomous Microgrid Operation[J]. Energies, 13.
[8] Zhou Y, Rui T, Li Y, et al. (2019) A UAV patrol system using panoramic stitching and object detection[J]. Computers & Electrical Engineering, 80(4):106473.
[9] Santos N P, Lobo V, Bernardino A. (2020) Two: tage 3D model–based UAV pose estimation: A comparison of methods for optimization[J]. Journal of Field Robotics, 2020(1).
[10] Keller J. (2019) Industry to develop magnetic anomaly detector (MAD)-equipped UAV for anti-submarine warfare (ASW)[J]. Military & Aerospace Electronics, 30(8):30-30.