Monitoring and Early Warning of Transmission Line External Breakage Based on Satellite-Ground Coordination

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Abstract. This article first proposes a high-precision spatio-temporal registration method between satellite remote sensing images and ground sensors. Then, using satellite remote sensing images, an intelligent identification model for typical external damage hidden dangers of transmission lines based on satellite remote sensing is established to realize intelligent identification of transmission line construction work areas and mining affected areas. Aiming at the results of intelligent identification of construction work areas and mining-affected areas, the proposed YOLOv4-based external damage identification algorithm for transmission lines is used to detect external damage hidden dangers. Through the method in this paper, it is possible to realize a regular general survey of hidden dangers of external damage (construction work area, mining affected area) with full coverage of transmission channels, and carry out targeted 24-hour monitoring on the ground. The test results show that the satellite-ground coordinated transmission line external damage monitoring and early warning in this paper. The method timely and accurately realizes the monitoring and early warning of the external breakage of the transmission line.

1. Introduction

With the continuous increase in the coverage of power grid construction, the total mileage of transmission lines has gradually increased. They have the characteristics of large scale, long distance, and wide distribution. They are usually distributed in remote areas and the operating environment is relatively harsh. Natural disasters such as wildfires and landslides damage the normal operation of overhead transmission lines. At the same time, there are also the dangers of external force damage caused by construction machinery, ultra-high vehicles, and ships, which are random and sporadic [1-3]. At present, relying on drones, online monitoring or line patrol personnel to carry out external damage inspections has problems such as cumbersome flight approval, limited monitoring scope, and serious structural shortage of personnel, which are insufficient to deal with normalized, large-scale external damage early warning, monitoring and rapid Disposal [4-7]. Therefore, studying a transmission line "full coverage, multi-frequency external damage hidden danger survey-drone/online monitoring detailed investigation-personnel verification and rapid disposal" method is an important direction for the construction of smart transmission lines in the future and is of great significance [8-9].

In view of the random distribution and frequent occurrence of external damage of transmission lines, focusing on the current problems of gaps in external damage inspections and delays in post-processing, we developed a satellite remote sensing-based intelligent identification model of typical
external damage hidden dangers of transmission lines and multi-factor coupling of foreign objects in the line. Prediction methods and research on the construction of core data links for external damage hidden dangers in coordination with satellites and grounds, to improve the ability to intelligently prevent external damage of transmission lines, and provide "general survey-detailed investigation-disposal" for the monitoring and early warning of urban transmission and distribution lines with a clear hierarchy and intelligent prevention. Developed a full-coverage external failure monitoring and early warning ground prototype device for the transmission tower Beidou + millimeter wave radar fusion line section, and developed a smart transmission line satellite-to-ground collaborative external failure monitoring and early warning prototype system to provide system support for urban external failure inspections; Realize the prevention of external damage, move the inspection gate forward, avoid problems such as tight and untimely disposal afterwards, and provide an important guarantee for the safe operation of the new power system.

2. High-precision spatio-temporal registration method of satellite remote sensing image and ground sensor

Due to the perspective projection, the tilt of the camera axis, and the attitude of the aircraft in the remote sensing sensor system, as well as the presence of factors such as atmospheric refraction, topographic undulation, earth curvature, and earth rotation outside the system, the imaging of satellite remote sensing images will inevitably appear. Larger geometrical deformation, resulting in image distortion, that is, the geometric figure on the acquired remote sensing image has a certain distortion relative to the actual target shape on the ground, and the actual coordinate value of the ground object is different from the coordinate value of the corresponding pixel point on the image map. The difference in size. The specific performance of this part of the deviation can be seen as effects such as translation, rotation, bending, and zooming. These deviations will affect the imaging effect of remote sensing images to varying degrees, causing the image graphics to be distorted. Therefore, it is usually necessary to perform distortion correction in time before image application to obtain geographic information that is more in line with actual object coordinates. In addition, sensing devices such as satellite remote sensing images, power transmission lines, and fiber gratings have the problem of inconsistencies in the spatial coordinate system. It is also necessary to study the coordinate conversion method to make it under the same coordinate system. This project mainly analyzes and confirms the most reasonable geometric correction method, and selects appropriate geometric correction models and control points for satellite remote sensing images to improve the geometric positioning accuracy of remote sensing images and reduce the repetitive operation of the correction process and the phenomenon of unsatisfactory correction results.

2.1. Spatial coordinate system one and homogenization processing method

The overall research ideas on the spatial coordinate system and spatial homogenization of remote sensing and sensing data related to the transmission corridor are as follows:

① At present, there may be four situations for grid sensors: no positioning timing chip, built-in GPS, GPS+Beidou or Beidou chip. For a traditional sensor without its own chip, its spatial coordinate system is consistent with the coordinate system of the transmission line and substation, which may be the Xi'an 80 coordinate system or the CGCS2000 coordinate system. For the latter two cases, the CGCS 2000 coordinate system used by the Beidou chip is directly used. For the first type of sensor device that only uses GPS chips, the WGS84 coordinate system is used. Therefore, other coordinate systems such as Xi'an 80 coordinate system or WGS84 coordinate system are converted to CGCS2000 coordinate system.

② Convert the GPS reference points and transmission line tower coordinates established by the existing network provinces from the WBS84 coordinate system and the Xi'an 80 coordinate system to the CGCS2000 coordinate system, and combine the 460 transmission towers that have been built to monitor the surface deformation of the Beidou site to construct the CGCS2000 coordinates.
ground control point set under the system is used for the next step of high-resolution satellite remote sensing image coordinate system conversion and high-precision positioning.

3. Based on the ground control point set and other feature points in the above-mentioned CGCS2000 coordinate system, coordinate transformation of sub-meter high-resolution satellite remote sensing images. For the satellite remote sensing images that will be programmed in the future, the CGCS2000 coordinate system is defined directly in the geometric correction process to avoid the secondary conversion of the coordinate system. For the existing historical archived satellite remote sensing images, if the coordinate system is not CGS2000, a seven-parameter model (Bulff-Walsa model) is used for coordinate system conversion. By choosing more than 3 points with the same name as evenly as possible, the coefficients of the seven-parameter model are calculated by the least square method, and then based on the calculated coefficients, the coordinate system conversion of the satellite remote sensing image is completed by the seven-parameter model.

4. In the process of coordinate conversion using the seven-parameter model, due to the large single file of satellite remote sensing images and the continuous observation of time series (such as meteorological satellites), this project optimizes the homogenization processing (resampling) method and studies a fast based The multi-weight flux conservation resampling algorithm of the polygon cutting algorithm resamples the image data, and compares and analyzes the algorithm and three commonly used resampling algorithms (nearest neighbor interpolation, bilinear interpolation, cubic convolution interpolation) Performance in terms of information fidelity and processing speed.

5. Combined with the research content of topic 1 (1), through the high-resolution satellite remote sensing image coordinate system conversion and the high-precision registration between the multi-scale and multi-temporal satellite remote sensing image, the multi-scale and multi-temporal satellite remote sensing image Coordinate system one is CGS2000.

Through the above steps, complete the remote sensing and sensing data spatial coordinate system (CGS2000 coordinate system) related to the transmission corridor.

2.2. Unified time coordinate system
The overall research ideas on the time coordinate system and time homogenization of the remote sensing and sensor data related to the transmission corridor are as follows:

For the time coordinate system, the current satellite remote sensing image uses Universal Time Coordinated (UTC), which is accurate to the second. All kinds of sensors in the power grid only use GPS chips, and GPS time (GPST) is used. If GPS + Beidou dual-mode or Beidou independent timing is used, Beidou time (BDT) is used. Both GPST and BDT are International Atomic Time, with accuracy exceeding microseconds, and there is a slight difference between them.

This project uses UTC or Beijing time as the unified time coordinate system. Combine the GPS and Beidou timing time with the leap second correction value and the number of jump seconds, and convert it into UTC, which is consistent with the time coordinate system used in satellite remote sensing images. In order to facilitate the practical application of various services of the domestic power grid, the time difference brought by the Beijing Eastern eighth District time zone can be added to the UTC time, and the satellite remote sensing and various sensor time can be uniformly converted into Beijing time, that is, Beijing time can be simply converted to UTC+8 hours.

3. Intelligent identification model for typical hidden dangers of transmission lines based on satellite remote sensing
According to the 9 major environmental inspection objects specified in the Overhead Transmission Line Operating Regulations", using the Caffe deep learning framework, and referring to the network structure characteristics of the AlexNet convolution model, a design with 3 convolutional layers and 2 full Connecting the layer and a SoftMax layer of the transmission line satellite remote sensing patrol convolutional neural network (Power Transmission Corridor convolutional neural network, PTCnet).
Figure 1 The structure diagram of the transmission line inspection convolutional neural network model (PTCnet)

It can be seen from Figure 1 that the AlexNet model has 5 convolutional layers and 2 fully connected layers. The standard input image size of the AlexNet model is 227 pixels $\times$ 227 pixels. The AlexNet model reduces the image size from 227 pixels $\times$ 227 pixels to 13 pixels $\times$ 13 by passing the input image through the convolution pooling operation of the first and second convolutional layers. Pixel size, the third and fourth convolutional layers mainly do convolution operations and increase the number of feature layers, and after the fifth convolutional layer pooling operation, the image size is reduced to 6 pixels $\times$ 6 pixels. And finally sent to 2 fully connected layers and a SoftMax layer for classification. Compared with the 1000 classification tasks of the ILSVRC large-scale image library, the transmission line inspection application has the characteristics of fewer satellite remote sensing image samples and fewer classification categories, and the transmission line inspection training samples are usually collected with sample points as the center. The neighborhood participates in model training, and the neighborhood size is much smaller than the model input of 227 $\times$ 227. In solving the problem of transmission line inspections (essentially the pixel-level land cover classification of remote sensing images), AlexNet and others have problems such as the sample form does not match the network input and output requirements. The model input design is too small to build a network structure with a certain depth. The sample size the information of the sample point in the center that has been flooded by the conference has been selected. For this reason, this research combines the characteristics of the scale of the patrol object of the transmission line and the characteristics of the AlexNet model to design a convolutional neural network model PTCNet with 3 convolutional layers, 2 fully connected layers and a SoftMax layer. PTCNet effectively alleviates the contradiction between too small training sample size and too large model design input size. The input size of the PTCNet model is 27 $\times$ 27. After the first layer of convolutional pooling operation, the image size is reduced to 13 $\times$ 13. The second layer does convolution and feature layer extraction, and passes through the third layer of convolution pool. The transformation operation obtains an image with a size of 6 pixels $\times$ 6 pixels, and finally sends 2 fully connected layers and a SoftMax layer for classification. The specific model structure is shown in Figure 4-10. When training the model, we need to sample data of different sizes to a standard size (27 $\times$ 27) as the standard input of the model. The sampling method uses the nearest neighbor sampling method to maintain the spectral information of the remote sensing image as much as possible. The model classification stage collects a certain size of neighborhood information for each pixel of the data to be classified and performs the same upsampling operation as the training sample as the input of the trained model to determine the attribution category of each pixel. The design of the model PTCNet and the model of this research Training is done on the Caffe deep learning framework.

4. YOLOv4-based method for identifying hidden danger targets from ground sensors on transmission lines

YOLOv4 preprocesses the input sample set of hidden danger target pictures: including uniform adjustment of the resolution size, color adjustment, flipping, and rotation of the sample pictures to reduce the influence of the sample background on target recognition. Then the YOLOv4 algorithm is used to model Training.
The flow chart of the detection of hidden danger targets outside the transmission line based on YOLOv4 is shown in Figure 2. It includes three stages: preprocessing the image sample set, model training, and testing of the target image to be detected.

![Flow chart of detection of hidden danger targets outside transmission lines](image)

The detection steps are as follows:

1. Preprocessing the sample set
   1) Collect a sample set of pictures of hidden dangers outside the transmission line, uniformly number the names of the picture samples, and then uniformly adjust the picture resolution to 608×608;
   2) Use the method of sample enhancement to adjust the color, flip, and rotate the sample image;
   3) Use the labeling tool to label the target category and border of the sample set;
   4) Organize sample sets and annotation files according to the format of the VOC2007 data set, and generate training sample sets and test sample sets.

2. Model training
   1) According to the sample set data of this project, modify the learning rate, batch number and other related parameters in the configuration file;
   2) Use the CSPDarknet53 network to extract the characteristics of the hidden danger target of the input prototype picture;
   3) Use the Neck module to fuse the feature vectors at high and low levels to generate 3 feature maps of different sizes for multi-scale prediction of the target;
   4) Substitute the prediction result and the actual target border and category in the annotation file into the loss function calculation formula to obtain the loss value;
   5) Use the neural network back propagation method to automatically adjust the network structure parameters, repeat steps 2)-4), until the model meets the accuracy requirements or the number of training times, the model file is generated.

3. Model test
   1) Enter the test sample set of hidden danger pictures;
   2) Use the network forward propagation to get the frame and category of the target;
   3) Calculate the IOU coincidence degree according to the target predicted frame and actual frame;
4) Obtain the confidence level according to the IOU value and category probability obtained in step 3);
5) Set the IOU threshold to filter to the prediction box with the smaller IOU value, and use the maximum suppression algorithm for the remaining prediction boxes to obtain the final prediction result.

5. Experimental analysis

5.1. The results of the inspection of the hidden dangers of the transmission line satellite remote sensing external damage
Obtain satellite remote sensing image data in May 2021, inspect the surrounding environmental features (hidden hazards) of a total of 41 base poles and towers in the designated section of the Niugong Line, and obtain floating objects around the designated section of the Niugong Line transmission channel in May 2021 (Mulch, plastic greenhouse, tarpaulin, etc.), buildings (violating construction and color steel plate construction), forests (arbors), construction work areas, water bodies, under-line piles, bridges and crossings (lines and lines, lines and highways, etc.) Lines and railways) and other objects of the inspection results.

![Figure 3 Examples of plastic greenhouses and construction work areas near the designated section of Beijing Tongzhou Niugong Line](image)

5.2. Recognition results of hidden danger targets from ground sensors on transmission lines
This article uses Ubuntu 18.04 operating system, GPU hardware selection NVIDIA GTX 1080Ti, software CUDA9.0, CUDNN7.0. Build a model training and test environment based on the Keras framework, and use YOLOV4 algorithm model to identify hidden danger targets outside transmission lines. Output categories and borders of hidden danger targets in and outside the detected pictures.

5.2.1. Data set production
According to the actual on-site monitoring video and image information of the transmission line, a data set for model training and recognition was produced, including construction machinery, cranes, and tower cranes 3 types of external damage hidden danger targets, a total of 3825 pieces. Among them, 1362 are construction machinery and 1,184 are cranes. Zhang, 1279 for tower cranes. This data set covers target image samples under different background content, light intensity, and weather conditions, which can reduce the impact of image background on target recognition and improve model accuracy. The data set is based on a 7:3 ratio Divided into training set and test set.

5.2.2. Model training and testing
First, modify the relevant parameters of the configuration file of the pre-training model to suit the characteristics of this project. In addition, replace the 9 anchor boxes of this project with the anchor
boxes in the corresponding positions in the configuration file. Then, Load the pre-trained model under the Keras framework, and enter the image sample set for model training.

Save the model file generated after training, and combine the test sample set obtained during the data set production to test the performance of the model. Select the test samples of the target image characteristics of different projects to detect the model in complex backgrounds, different poses, different lighting, and different Performance under weather and multiple targets. Figure 4 shows the recognition results of similar targets in different background content. The experimental results show that the model can recognize targets in different backgrounds and reduce the need for image background. Content dependence. Figure 5 shows the recognition results of the same target in different poses. Experimental results show that the model can recognize targets in different poses and enhance the recognition of target poses.

![Figure 4 Target recognition under different background content](image1)

![Figure 5 Target recognition in different poses](image2)

The algorithm in this paper is compared with commonly used image recognition algorithms, and the comparison results are shown in Table 1. From Table 1, it can be seen that compared with the commonly used Faster RCNN and SSD algorithms, the AP and mAP values of each category of the algorithm in this paper are higher than Other algorithms, the average single image recognition speed is faster, indicating the superiority of the algorithm in this paper.

| Different Algorithms | AP(%) | mAP(%) | Recognition Speed |
|---------------------|-------|--------|-------------------|
|                     | construction machinery | crane | Tower crane |       |
| Faster RCNN         | 92.02% | 89.72% | 90.43% | 90.39% | 0.19 |
| SSD                 | 89.92% | 87.03% | 88.45% | 88.46% | 0.08 |
| Ours                | 92.61% | 91.53% | 92.18% | 92.11% | 0.07 |
6. Conclusions and prospects
In view of the random distribution and frequent occurrence of transmission lines, this paper proposes a satellite-to-ground coordinated transmission line monitoring and early warning method, focusing on the current gaps in the inspection of the external damage and the delay in post-processing. First, a high-precision spatio-temporal registration method between satellite remote sensing images and ground sensors is proposed. Then, using satellite remote sensing images, an intelligent identification model based on satellite remote sensing for typical external damage hazards of transmission lines is established to realize intelligent identification of transmission line construction work areas and mining affected areas. Aiming at the results of intelligent identification of construction work areas and mining-affected areas, the proposed YOLOv4-based external damage identification algorithm for transmission lines is used to detect external damage hidden dangers. The algorithm in this paper and two other commonly used image recognition algorithms are used to test the actual transmission line field picture sample set. The experimental results show that the algorithm in this paper has higher recognition accuracy, and the average single picture recognition speed is faster, which meets the front end of the model. The deployment requirements verify the superiority of the algorithm.

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