Algorithm Optimization and Verification of Transmission Line Digital Twin and Physical Model

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Abstract: Transmission lines are the lifeline of the power grid. Regular inspection and timely treatment of potential security risks can help to ensure the stable operation of the power network. In order to identify the key components and security risks in transmission lines, this study is based on the actual operation of transmission lines, put forward a target identification algorithm of combining digital twin and physical model, and the current common YOLOX algorithm, Faster-RCNN algorithm comparison analysis, to effectively expand the fusion algorithm feature mapping data, realize the comprehensive integration of spatial information and channel properties and the identification of the target accurately. In view of the research results analysis, through the transmission line digital twin and physical model combining algorithm optimization and validation, the validation index accuracy increased 3.64%, average validation accuracy is as high as 90.71%, identification speed only 10.37 milliseconds, loss value of 0.70711, the transmission line digital twin combined with the physical model algorithm optimization is more practical.

1 INTRODUCTION

Today, energy supply is crucial to the country's economic development and public well-being. China has a vast land area, and the transmission lines undertaking the function of power transmission often need to pass through the mountains and inaccessible areas (Buljak, and Buljak, 2012). The complicated and changeable natural conditions have a great safety impact on the daily operation of the transmission lines and related components and facilities. In the construction process of construction, the power personnel usually carry out scientific and maintenance of the transmission lines based on regular inspection means, and take measures to ensure the safety risks of the transmission lines to ensure the continuity and safety of the power grid operation (Chen, 2015).

Traditional transmission line inspection methods include technical staff holding special instruments along the transmission line, channel field inspection, etc. However, the total mileage of transmission lines in China ranks the first in the world, and the potential damage risk of transmission lines is difficult to predict (Csiszár, 2007). Therefore, this kind of manual inspection mode has problems such as low efficiency, time-consuming and laborious, rising cost and security risks (Ghaedi, and Bardsiri, et al. 2023). With the progress of technology in the field of hardware, unmanned aerial vehicles are gradually used for the regular monitoring of power transmission lines (Li, and Li, 2014). The operator uses advanced equipment such as UAV to visually monitor the key parts of the transmission line and send the obtained model data to the central server (Lin, and Zhang, et al. 2017). Although this method reduces the transmission consumption and potential risks of power resources to a certain extent, it still faces a problem (Trojovska, and Dehghani, et al. 2022).: directly examining a large number of model data will inevitably lead to omissions or errors, and the inspection results will be affected by the personal judgment of the reviewer, so the inspection data will be changed (Vidyasagar, and Vidyasagar, 2020). In view of the problem of low efficiency of transmission line inspection in the power system, many power workers consider the application of digital technology in this field, that is, to use digital equipment or technology to obtain clear image data, and to use specific model processing technology for in-depth analysis (Yang, 2011).

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The diagnostic technology of transmission line component defects adopts typical visual identification technology, The process relies on human intervention, That is, by interpreting the content of the model, People to manually formulate and extract the features (Younes, 2010)., The process is relatively complicated and tedious, And most of the solutions are built for special circumstances, Its lack of elasticity and universality, The challenges mainly include: first, the detection objects of transmission lines have different scale characteristics, Thus a single perspective inspection may lead to the loss of detail features, It will also make the scale difference between the different test objects become more obvious; Second, the variety of detection objects, For example, for the displacement identification of the transmission line flat pressure ring., The difficulty in this type of object identification is the movement of transmission line components, Instead of the device itself, The diversity of its inspection angles increases the difficulty of identification; In addition, multiple test objects may have similar characteristics; Third, the inspection background of the detected objects is very complex, Transmission lines are often laid in mountains, rivers and other areas with complex natural conditions., Related external factors put forward high adaptability and universality requirements for the algorithm model, Such as sunshine, haze, rainstorm and so on. In order to effectively solve the above problems., relevant scholars gradually calculated and put forward the research on the optimization of transmission line algorithm, and adopted the digital twin combination algorithm model as the reference model. This kind of model not only abandons the traditional anchor frame mechanism, but also shows certain advantages in dealing with problems such as target differences. Therefore, the update and iteration of the algorithm combining the transmission line digital twin and the physical model not only maintains the real-time performance of the hidden danger detection, but also surpasses the traditional two-stage detection algorithm in terms of efficiency..

2 DESCRIPTION OF THE RELATED PROBLEMS

2.1 Digital Algorithm of the Transmission Line

In view of the low proportion of power lines in the model, and the targets of different types to be inspected are significantly different in size, so in the algorithm structure of the digital twin combination model, the deep feature integration is carried out by the method of feature map accumulation. Using this kind of hybrid strategy can amplify the data contained in each dimension, and then enrich the details contained in the feature mapping, effectively enhance the description power of the digital twin combined with the model feature mapping, and have a positive effect on the completion of multi-scale target problems, and will not increase the number of features, and effectively reduce the resources required for the model operation. This model subdivides the channel focusing step on the feature diagram of power lines into two single-dimensional feature extraction processes, which helps to accurately determine the target position of power lines in complex scenes and improve the accuracy of target detection. Therefore, the digital algorithm of the transmission line is constructed, as shown in formula (1): $z_c^w(w)$

$$z_c^w(w) = \frac{1}{H}\sum_{0\le j\le H} x_c(j,w) \tag{1}$$

$x_c(j,w)$ In formula (1), H represents the height and represents the output value of the processed c-th channel in the width w direction. According to the above calculation procedure, the feature mapping Z can be obtainedw. Subsequently, the encoded feature map is combined according to the channel dimension, compressed by the convolution kernel of 11, and the activation function is applied to build the feature mapping model f of the middle layer, as shown in formula (2):

$$f = \delta(F(Concat(Z^h, Z^w))) \tag{2}$$

δ In formula _ (2), it represents the nonlinear activation function, F represents the convolution factor, and represents the merging operation of channel splicing. $Concat(Z^h, Z^w)$

2.2 Algorithm Optimization of Transmission Line Digital Twin and Physical Model

$z_c^w(w)$ Based on the above transmission line digital algorithm, the digital twin algorithm is used to reconstruct the decoupled tensor at the channel level and adjust it to the c-dimensional region to form the eigenvector gw. As shown in formula _ _ (3):

$$g^{w} = \sigma(F_{w}(f^{w})) \tag{3}$$

σ In formula _ (3), the Sigmoid activation function represents the convolution process. $F_{w}(f^{w})$ By performing the weighted position multiplication on the input feature graph X, the position data of the feature graph is integrated, and thus an algorithm model combining the digital twin and the physical model of the transmission line is formed, as shown in formula (4): $y_{c}(i,j)$

$$y_{c}(i,j) = x_{c}(i,j) \times g_{c}^{h}(i) \times g_{c}^{w}(j) \tag{4}$$

$x_{c}(i,j)$ $g_{c}^{h}(i)$ $g_{c}^{w}(j)$ $F_{w}(f^{w})$ In formula (4), the total amount of model parameters, the conventional twin feature value and the twin feature value, and the feature map output by the model will be transmitted to the head layer to complete the classification regression task.

2.3 Classification and Treatment of the Loss Value

In the digital twin combination algorithm, in order to distinguish the loss value calculated by the model, when dx increases, that is, the deviation between the prediction box and the actual box is large, so the loss value is calculated from the damage model. $1 - iou^{k}(k = 1,2,3)$ In the face of the situation of large positioning deviation, it gives higher measurement value, which is beneficial to the model to effectively screen the samples with poor accuracy. In view of the above problems, this study based on the digital twin concept, build digital twin combination algorithm of loss function model, designed to improve the prediction accuracy of model prediction, and the detection efficiency of good prediction box further optimization processing, prompting prediction box and the actual marking box, as shown in the formula (5):

$$loss = \begin{cases} 1 - iou^{k}, 0 \le dx \le a \\ -1b(iou), dx \ge a \end{cases} \tag{5}$$

iou In formula (5), it represents the mapping relationship of independent variables in the digital twin combination algorithm, and k represents the loss dimension.

$$\chi_{\mathrm{Re}}^{(3)}(\omega,\omega',\omega) = \frac{e^{4}}{\varepsilon_{0} m^{3}} \sum_{i} \sum_{j>i} \frac{N'_{i\to j}}{\omega_{ij}^{8}} \tag{6}$$

3 EXPERIMENTAL RESULTS AND ANALYSIS

3.1 Analysis of the Test Results

For assessing the accuracy of improved digital twin combination algorithm, this study design group of control experiment, compare the digital twin combined sample differences, based on the traditional physical model characteristic integration, realize the transmission line digital twin and physical model algorithm optimization and validation, and by evaluating the optimal training weights, the specific experimental results as shown in Table 1.

Table 1: Results of the ablation experiments

Algorithm	Test And Verify /%	Time Consuming /Ms
Digital Twinning Combination Algorithm	90.71	10.37
Faster-Rcnn	87.07	12.23
Yolov5	76.27	13.42
Yolov4	70.60	16.06
Yolov3	61.68	25.15
Physics Model Algorithm	66.34	66.81

After the optimization of the digital twin combination algorithm, its performance is effectively improved. The improved digital twinning binding algorithm A has increased the verification results from 87.07% to 89% compared to the physical algorithm model. However, the digital twin combination algorithm B integrates the CA module based on the characteristics of the algorithm A, which improves the verification results to 89.99%. The digital twin combination algorithm C even integrates the above three technologies, and the final verification result reached 90.71%. The iterative upgrade of the digital twin combination algorithm A to the algorithm C gradually realizes the increasing function of the algorithm model, which proves the effectiveness of the transmission line digital twin combination algorithm proposed in this paper.

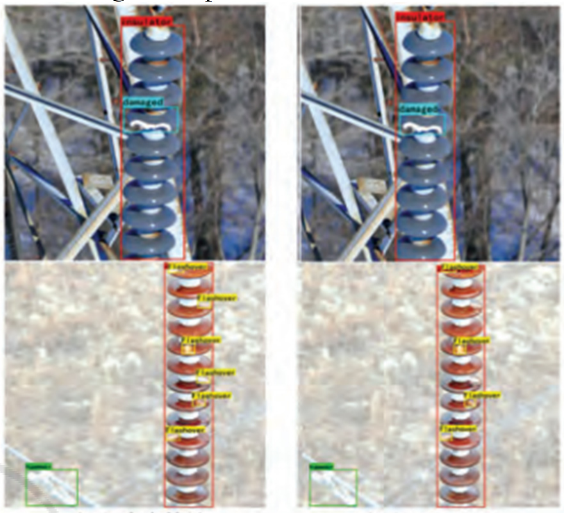
In this paper, the current target detection technology in the field of digital twin combination evaluates the safety of transmission lines in the form of verification score. In view of the detection of transmission line components and their defects, the accuracy and timeliness are clearly required, this research compares different algorithm models in terms of processing time, and the specific test results are shown in Table 2.

Table 2: Detection results of the different algorithms

Research Topic:	Research Methods:	Progress (%)
Digital construction	Mathematical simulations, electrical experiments	60
Operational prediction	Power deep learning, data analysis	80
Transmission line twin digital loss calculations	Power modeling, numerical analysis	40
Twin maintenance optimization	Operations Research and Decision Tree Analysis for Transportation	30

Among the identification targets of the above algorithm, different algorithm models show different levels in terms of accuracy, among which the average verification accuracy of the digital twin combination algorithm is as high as 90.71%; in the calculation of the model recognition speed, the most prominent performance is the digital twin combination algorithm, and the recognition speed is only 10.37 ms. In this paper, the digital twin combination algorithm model has made special adjustments to the transmission line architecture to make the algorithm model more streamlined and accurate.

In order to comprehensively check the identification efficiency of various algorithm models, the detection results are displayed graphically, as shown in Figure 1. After observing the graphical data, it can be seen that the digital twin combination algorithm developed in this study has better identification ability for closely distributed transmission line targets compared with the traditional physical algorithm model. Although Faster-RCNN, as a two-step recognition algorithm, performs well in missing targets, it brings the problem of false identification, that is, the same target is repeatedly identified many times under the same environment. According to comprehensive analysis, the digital twin combination algorithm of transmission line has higher verification accuracy, faster recognition speed and lower error value.



1Figure 1: Visual results of the different algorithms

3.2 Verification of Generalization Capability

In the detection of transmission lines, it may encounter interference from various external conditions, such as unclear images, exposure problems caused by overbright light, etc. In view of this, this study takes the above external factors into consideration, and the disturbed algorithm model is analyzed and realizes visual processing, so as to test the applicability and generalization ability of the proposed algorithm. As shown in Figure 2.

2 Figure 2: Detection results in the model-based fuzzy state

As shown in Figure 2, it is clearly observed that the digital twin combination algorithm proposed in this study presents robust recognition performance despite objective disturbances such as overexposure and picture blur. In addition, other algorithms show a certain degree of detection bias, such as the Faster-RCNN algorithm misidentifies the balance ring as the balance ring itself; in the fuzzy model scenario, the insulator damage is not effectively detected, but the digital twin combination algorithm accurately identifies, so it has high identification accuracy.

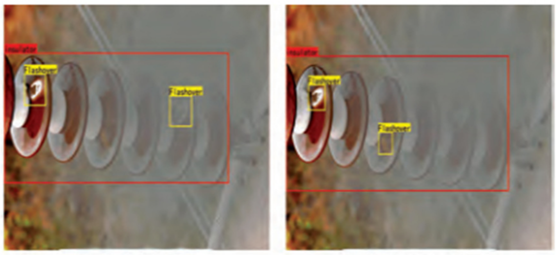


Figure 3: Detection results under haze interference state

Under the same conditions, for the identification targets of different algorithms, the excellent detection results shown by the digital twin combination algorithm also reflect the powerful performance of the model. As shown in Figure 3, the identification ability of different algorithms has obvious differences in the environment of poor light or haze interference environment. In contrast, YOLOv5 and Faster-RCNN algorithms have a certain degree of misdetection, while the digital twin combination algorithm shows a relatively excellent detection efficiency in the identification performance. As shown in the Figure 4.

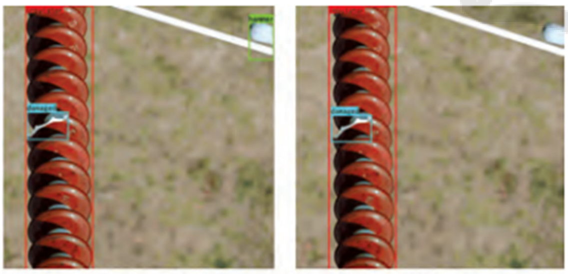


Figure 4: Detection results of different defects in the same environment

In order to further verify the applicability and generalization ability of different algorithms in the data set, a new region was selected for comparative analysis, and applied to the identification target of transmission lines collected from other regions. The final measurement results are basically the same, as shown in Figure 5.

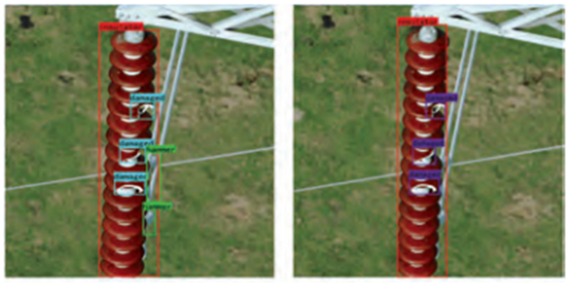


Figure 5: Identification of the targets in another region

As shown in the figure, the digital twin combination algorithm proposed in this paper is excellent, and no omission or misdetection has been found. Based on the above analysis, for the comparative analysis of different algorithms, the detection effect of YOLOv4 is relatively poor, failed to identify any detection target, other algorithms failed to identify the shock hammer target, only the digital twin combination algorithm detected the shock hammer target. In addition, Faster-RCNN algorithm does not perform well in detecting intensive targets, and the problem that the same target is frequently identified multiple times is more serious, but the digital twin combination algorithm can accurately detect, so it is further proved that the digital twin combination algorithm has strong applicability and generalization ability.

3.3 Calculation and Analysis of the Loss Value

In the above digital twin combination algorithm, the k value is set as 2 according to experience, and the b value is calculated through the digital twin combination algorithm, and moderate approximate calculation is implemented. Finally, the loss value of the digital twin combination algorithm is 0.70711. The specific calculation results are shown in Figure 6.

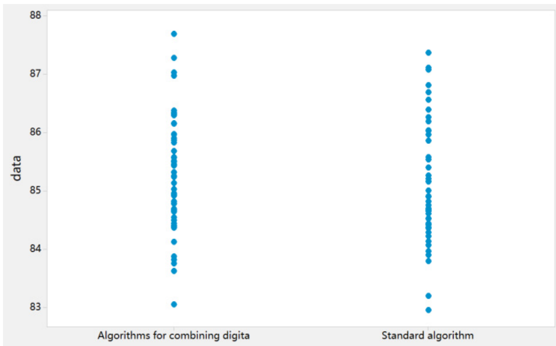


Figure 6: Loss values of the digital twin-binding algorithm

4 CONCLUSIONS

To sum up, this study for the core components of transmission lines and safety hidden trouble accurate detection, based on the actual operation situation, put forward a transmission line digital twin combined with physical model of target identification algorithm, and with the current commonly used YOLOX algorithm, Faster-RCNN algorithm comparative analysis, through the integration of local characteristic analysis, accurate comparison of different algorithms and generalization ability, loss value. By classification management and index comparison, through the transmission line digital twin and physical model algorithm optimization and validation, the accuracy increased by 3.64%, average validation accuracy of 90.71%, identification speed only 10.37 milliseconds, loss value of 0.70711, in different algorithms of various index in the highest, the transmission line digital twin and physical model algorithm combined positive influence on transmission line detection.

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Research and demonstration of full lifecycle digital application of power grid engineering based on GIM+GIS+IoT data fusion

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