Research and Design of Hidden Trouble Target Reconfirmation and Repeated Hidden Trouble Target Filtering Technology in Transmission Line Online Monitoring

Yi Yang[1(✉)], Zhengheng Li[1], Nanhao Liu[1], Yu Su[2], Xifeng Yan[1], and Huabo Tao[1]

[1] Zhuhai Sunri Smart Connected Technology Co., Ltd., Zhuhai 519000, China
srzl@cyg.com

[2] Beijing Institute of Technology, Zhuhai, Zhuhai 519000, China

Abstract. Transmission line online monitoring system is an important part of the transmission link of smart grid, and is an important technical means to realize the transmission line state operation, maintenance management, and improve the lean level of production and operation management. This paper introduces a hidden danger target identification and alarm filtering technology based on AI visualization and IOU intersection and comparison algorithm to improve the security and reliability of transmission lines in power system. First through the advanced deep learning target detection model, accurate target identification and classification, and then through the IOU the algorithm calculation continuous time period of the previous target identification box and the current target identification results of the boundary box overlap rate to confirm whether is the same entity, at the same time based on the context storage alarm filtering method, filter out the repeated alarm, reduce the network traffic transmission and server load, and reduce the workload of operational personnel. The experimental results show that the method is effective in enhancing target identification and reducing repeated alarm, and provides an efficient and reliable solution for the transmission line monitoring system.

Keywords: AI visualization · IOU intersection over union algorithm · hidden danger target identification · hidden danger target reconfirmation · repeated hidden danger target filtering

1 Introduction

With the development and expansion of the power system, the demand for the security and reliability of transmission lines is increasing. However, due to the increasing complexity and length of transmission lines, accurately identifying and handling hidden targets has become a challenging task. In order to solve this problem, this paper proposes a hazard target reconfirmation and repeated hazard target filtering technology based on AI visualization and IOU intersection ratio algorithm, aiming to improve the accuracy of target identification and reduce the frequency of repeated alarms. AI visualization

V. C. M. Leung et al. (Eds.): Qshine 2023, LNICST 574, pp. 3–14, 2024.
https://doi.org/10.1007/978-3-031-65123-6_1

technology is a hot research direction in the field of artificial intelligence. Through the combination of image processing, machine learning and computer vision technologies, the automatic analysis and understanding of visual data are realized. In the online monitoring of transmission lines, AI visualization technology can be used to intelligently identify and analyze the image data of transmission lines, so as to further explore the potential hidden danger targets. IOU (Intersection over Union) blending algorithm is one of the commonly used evaluation indicators in computer vision tasks such as target detection and object tracking. It measures the similarity and overlap between two bounding boxes by calculating the ratio between the target bounding box. Based on the characteristics of IOU blending algorithm, improve the accuracy of target identification, reduce the occurrence of error alarm, reduce network traffic, reduce server pressure, and reduce the work burden of operation and maintenance personnel. Through this study, we expect to improve the efficiency and reliability of the on-line monitoring system of transmission lines, and further promote the safe operation and stable development of the power system.

2 Main Research Content

2.1 Hidden Danger Target Identification Method Based on AI Visualization

Target detection algorithms such as Faster R-CNN [1–3], YOLO [4, 5], etc., can realize the automatic detection and boundary box positioning of wire foreign objects, construction instruments, fire smoke and other targets in the transmission line images [1, 6, 7]. Image recognition algorithms such as convolutional neural network (CNN) can identify and classify specific targets. We will make comprehensive use of these technologies to build a hidden dangers target identification system based on AI visualization, so as to realize the accurate identification and monitoring of potential hidden dangers in the online monitoring of transmission lines. First, we constructed a target detection model to identify the wire foreign body, construction equipment, fire smoke and other targets in the transmission line image. Mainly implemented using the YOLOv5 target detection algorithm. Secondly, in order to further improve the accuracy of target recognition, we introduce image recognition technology to classify specific targets [8]. By training the convolutional neural network (CNN) model, the learning and discrimination of detailed features, which is helpful to accurately locate and determine hidden targets. Finally, combined with the results of target detection and image recognition, the intelligent identification and annotation of the hidden dangers in the transmission line image are realized through AI visualization technology. In this way, the operator can quickly and accurately understand, and take the corresponding maintenance and repair measures to ensure the normal operation of the power grid.

2.2 Hidden Danger Target Revalidation Method Based on IOU Algorithm

In this study, IOU was used to achieve revalidation and repeated filtering of hidden danger targets [9, 10]. The IOU intersection and ratio algorithm confirms the accuracy of the same entity by calculating the overlap rate between the bounding box of the previous object identification result and the current object identification result in a continuous time period, so as to improve the accuracy of the target identification. This revalidation process can greatly reduce the occurrence of misidentification, ensuring that only real hidden danger targets can trigger alarms, and improving the reliability and accuracy of the system. When a hidden danger target is identified, we will use the IOU intersection ratio algorithm to determine the degree of overlap between the target and the previously confirmed hidden danger target. An IOU value is obtained by calculating the ratio of the intersection region to the union region occupied by the bounding boxes of the two targets. The application formula of the IOU blending algorithm in the hidden danger target reidentification method is as follows:

$$IOU = \frac{S_a \cap S_b}{S_a \cup S_b} \tag{1}$$

The pixel location information of the image of the same hidden danger type target, contains two diagonal vertex coordinates $\mathrm{Aa}_{(x1,y1)}$, $\mathrm{Ba}_{(x2,y2)}$; the pixel location information of the image of the same hidden danger type target, contains two diagonal vertex coordinates $\mathrm{Ab}_{(x3,y3)}$, $\mathrm{Bb}_{(x4,y4)}$; $\mathrm{S_a}$ is a rectangle of hidden danger target a; $\mathrm{S_b}$ is a rectangle of hidden danger target b; $S_a \cap S_b$ it is the intersection of rectangle Sa and rectangular $\mathrm{S_b}$. The calculation formula is as follows:

$$\Delta \mathrm{x1} = \max(\mathrm{x1}, \mathrm{x3}) \tag{2}$$

$$\Delta \mathrm{y1} = \max(\mathrm{y1}, \mathrm{y3}) \tag{3}$$

$$\Delta \mathrm{x2} = \min(\mathrm{x2},\ \mathrm{x4}) \tag{4}$$

$$\Delta \mathrm{y2} = \min(\mathrm{y2},\ \mathrm{y4r}) \tag{5}$$

$$S_a \cap S_b = (\Delta \mathrm{x2} - \Delta \mathrm{x1}) * (\Delta \mathrm{y2} - \Delta \mathrm{y1}) \tag{6}$$

If $\Delta \mathrm{x1} > \ = \Delta \mathrm{x2}$ or $\Delta \mathrm{y1} > \ = \Delta \mathrm{y2}$, $S_a \cap S_b$ the value is 0 and the IOU value is 0; $S_a \cup S_b$ is the union of rectangular S_a and rectangular S_b, the calculation formula is as follows:

$$\mathrm{Sa} = \ (\mathrm{x2} - \mathrm{x1}) * (\mathrm{y2} - \mathrm{y1}) \tag{7}$$

$$\mathrm{Sb} = \ (\mathrm{x4} - \mathrm{x3}) * (\mathrm{y4} - \mathrm{y3}) \tag{8}$$

$$S_a \cup S_b = \mathrm{Sa} + \mathrm{Sb} - \ (S_a \cap S_b) \tag{9}$$

We will set a reasonable IOU threshold. If the IOU value exceeds the set threshold, the two targets are considered to be the same entity, that is, the hidden danger target has been confirmed before. To improve the accuracy and robustness of target tracking, this method also considers the continuity of targets in time. We control the continuous recognition requirements of targets by setting two hyperparameters: the continuous recognition time of AI image is N, and the continuous loss time of hidden danger targets is V. In the continuous AI image recognition time N, if the same target object is less than V in the continuous recognition time range, we will determine the target object as an effective hidden danger target, output the related information, and send the alarm information. If the continuous recognition loss time reaches or exceeds V, the target object is considered a false positive and needs to be discarded. The setting of N and V can be adjusted according to the actual requirements to accommodate the target recognition and monitoring tasks in different scenarios. Shown in Fig. 1.

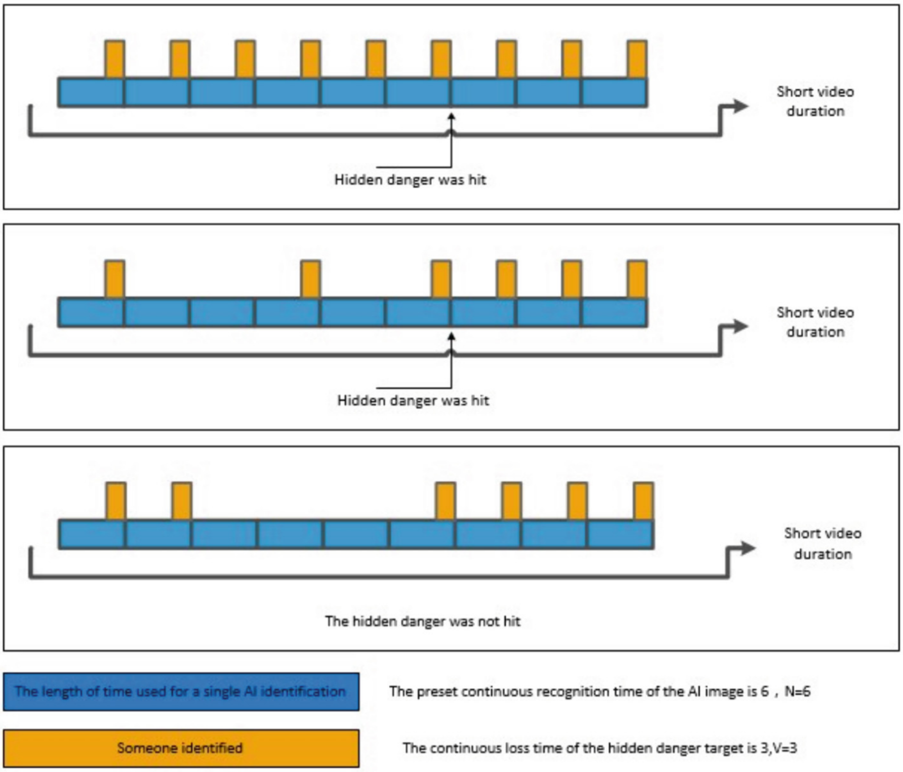

Fig. 1. Schematic diagram of the hidden danger target revalidation method based on the IOU intersection and ratio algorithm

2.3 Repeat the Hidden Danger Target Filtering Method

After successfully confirmed as the same entity and issued an alarm, the system in the subsequent target identification process we can effectively filter out the repeated alarm of the same entity, by using the context storage to record its ID has alarm information, the system can confirm whether repeated alarm, avoid repeated report the same target alarm, thus reduce unnecessary traffic transmission, reduce the server pressure, and reduce the workload of operational personnel repeated alarm filtering, improve the efficiency and accuracy of alarm processing. In the identification process, with the continuous increase of new image data, we need to maintain a target file database to store the confirmed hidden danger target information, including its location, type, expiration time (frame serial number), etc. Each time a new target is identified, the IOU is calculated with the target in the file database, and the repeat target is determined by comparing with the threshold and expiration time (frame number). When two targets are judged to be the same entity, the subsequent processing will automatically ignore the repeated alarm for that target, reducing manual intervention and redundant work.

The overall algorithm flow chart is shown in Fig. 2.

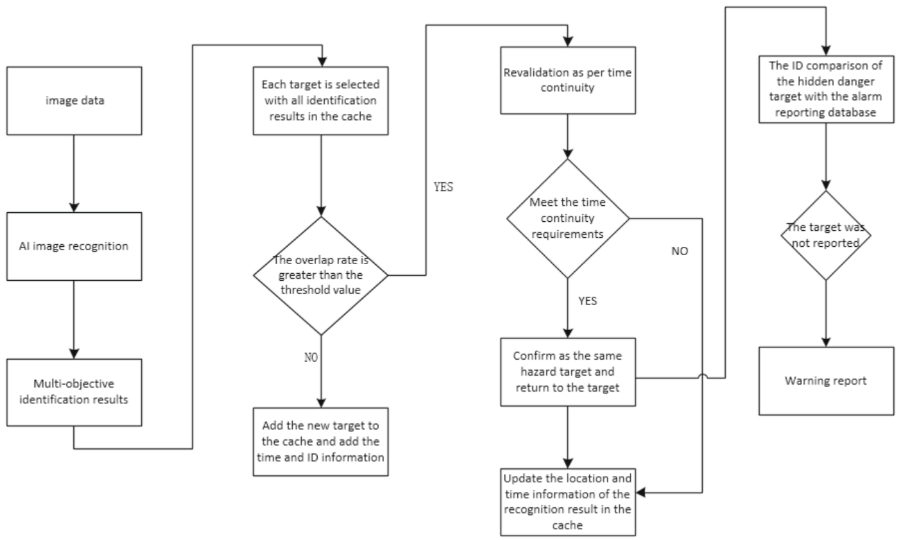

Fig. 2. Flow chart of the overall algorithm

3 Experimental Test and Result Analysis

3.1 Experimental Design

In this experiment, we used the experiment of target detection based on the core RK1126 embedded platform. The platform uses the Linux operating system with a kernel version of 4.19.11, with a built-in 2.0TopsNPU neural network coprocessor and supporting YOLOv5 target detector capability. The software package of this platform comes with the image processing function library, which facilitates us to preprocess the images. In addition, as an embedded platform, this platform has been widely used in transmission line online detection projects. As a test target platform, it can test the effect of this method in practical application. The platform is configured with 2G memory and Based on the yolov5s_relu_rv1109_rv1126_out_opt.rknn pre-training model provided by Rockchip Microelectronics Co, Conduct the testing and validation. The experimental design steps are performed as follows:

(1) Data preparation: select the image sequence related to people in the VOT2018 data set as the test data set to facilitate the identification of the pre-training model;
(2) Preprocessing: For the input image, the image processing API provided by RK1126SDK is used to conduct the necessary preprocessing, including image scaling, normalization and other operations, to meet the input requirements of the target detection model;
(3) Target detection: Target detection was performed using the yolov5s_relu_rv1109_rv1126_out_opt.rknn pre-trained model provided by Ruixin Microelectronics. The model has been adapted on the RK1126 platform of Rocchip, by calling the example code, can directly achieve the target detection function;
(4) Target identification and revalidation: After the completion of the target detection, the detected target is identified and reconfirmed by adding the hidden danger target revalidation algorithm to the sample code. Since the pre-training model has already included the human target detection type, we can use the output results of the model for target identification, and reconfirm the results, to ensure that the detection results are accurate and effective;
(5) Repeat target filtering: In order to filter out the repeat target, the target is processed based on the position, type, expiration time (frame serial number) and other information of the detected target. Repeated targets can be judged by recording the confirmed target information and comparing it with the subsequently detected target information.

3.2 Experimental Results

The publicly available YOLOv5 pre-training model and the public image sequence dataset were used for test validation. From the test results, using the public YOLOv5 pre-training model can not well identify a certain type of target objects, such as "handbag", "baseball_glove", "car", "trunk", you can see the following misidentification examples (see Fig. 3 and Fig. 4):

In this experiment, the continuous recognition time of the AI image is 7, the continuous loss time of the hidden danger target is 3, and the IOU threshold is greater than 35. The following experimental results are obtained according to the above conditions (see Fig. 5):

The above images are the continuous image sequence, the cyan box is the AI image recognition result, and the pink purple box is the final result after the target reconfirmation. It can be seen from the above image sequence that even if the target object can not be correctly identified in the second frame, the final result can still be correctly output in the seventh frame, meeting the design requirements. After the image sequence recognition results again, the misidentification was found in the AI image recognition results. However, after combining the hidden target reidentification method based on the IOU intersection and comparison algorithm, the misidentification results were filtered out. The experimental results are shown in Fig. 6:

Fig. 3. "handbag" was correctly identified with the YOLOv OLOv5 pre-trained model

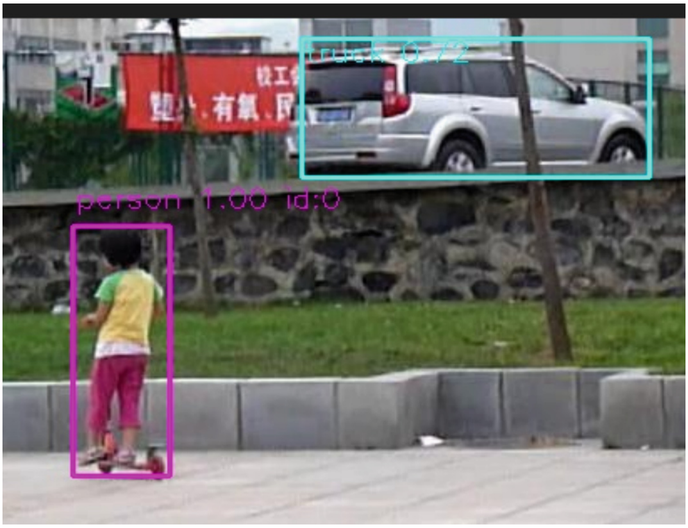

Fig. 4. "Track" was misidentified with the YOLOv OLOv5 pre-train model

Figure 6 is a thumbnail of the recognition operation from frames 21 to 36. It can be seen from the frame 21 image that "car" is likely to be misidentified as "trunk" and appears in frames 21, 24, 25 and 29. Since this experiment set the condition of V = 3 for the continuous loss of the hidden danger target, and the AI image recognition was not misidentified again in the three frames 26, 27 and 28, so even if the misidentified target appeared again in frame 29, it was not output to the final result. This result meets the design requirements.

Fig. 5. Reconfirmation effect of the hidden danger target

Fig. 6. Hidden danger target to the misidentification filtering situation

When adding the hidden danger target reconfirmation method based on IOU delivery and comparison algorithm for this experiment, we add ID number, expiration time (frame serial number) and other information to each confirmed hidden danger target, and add it to the file database for preservation, so that it can be used again during restart and reduce the duplication of hidden danger reporting. With the help of the ID number and the ID number, we can easily confirm whether we need to alarm according to the ID number (see Fig. 7).

When analyzing the change of ID number in the whole image sequence, it is found that the overlap of the confirmed hidden target will cause errors. On the one hand, the AI image recognition loses the target when the hidden target overlaps, and the target overlap changes to reduce the IOU intersection ratio and form the new target; the ID changes over the set value V when the target appears again. The specific experimental results are shown in Fig. 8:

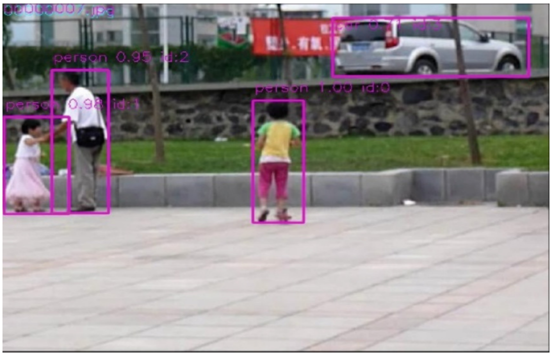

Fig. 7. Hidden danger target with an ID number

Fig. 8. When the hidden danger target identification is lost and the IOU threshold decreases

As can be seen from the above image sequence recognition results (see Fig. 9 and Fig. 10), when the hidden targets overlap, it will lead to the loss of AI image recognition, and the new recognition target frame is different in size from the original, resulting in the IOU overlap rate is lower than the threshold and form a new object. A newly formed recognition target box also appeared in the following images, resulting in the final output of a confirmed hidden target with a new ID 10, and the target object with ID 0 was replaced to another overlapping object. ID number displacement occurs when the hidden dangers of the same type overlap. This problem will not occur if the hidden dangers of the same type do not overlap. In addition, considering the practical application scenarios, this problem will only cause one repeated alarm.

Fig. 9. The ID number displacement phenomenon occurs when the hidden dangers of the same type overlap with each other (Frame 54 comes with a normal ID number)

Fig. 10. The ID number displacement phenomenon occurs when the hidden dangers of the same type overlap with each other (Frame 68 forms a new ID number)

3.3 Results Analysis

In the experiment, we paid special attention to the effect of hidden danger target revalidation and repeated target filtering, and the results of these two aspects were analyzed as follows:

(1) Reconfirmation effect: through the reconfirmation of the detected target, the authenticity of the hidden danger target can be verified. The experimental results show that the proposed reconfirmation method can effectively filter out some false positive results and reduce the false positive rate. This means that our revalidation method can improve the accuracy of hidden danger target identification and effectively reduce the false alarms.
(2) Repeat target filtering effect: the repeated target filtering algorithm based on IOU is used to filter out the repeated targets. The experimental results show that the algorithm can effectively identify and filter out repeated targets, reducing the number of repeated alarms. In the case of no filtering, an alarm will be reported every time a hidden danger is identified. Even if the same hidden danger is still or moving on the screen, an alarm will be reported. If a monitoring shot is conducted in 30 min, that is, there will be 48 repeated alarms a day. After adding this algorithm, the number of repeated alarms per day is 0 when no new hidden danger is confirmed. Compared with the previous problems of repeated hidden dangers, this algorithm has greatly reduced the workload of screening repeated alarm places, and improved the efficiency of the overall target detection system.

4 Conclusion

Through the experiment of hidden danger target reconfirmation and repeated target filtering, our target detection system shows obvious advantages in these two aspects. The reconfirmation method can improve the accuracy of hidden danger target identification, reduce the false alarm rate, and improve the reliability of the overall monitoring system. The repetitive target filtering algorithm effectively identifies and eliminates the repeated target, reduces the redundant alarm and processing work, and improves the working efficiency of the system. These results further demonstrate the feasibility and effectiveness of our target detection system and provide strong support for practical applications. Using this method combined with AI visualization technology can improve the accuracy and efficiency of hidden danger target identification, provide a reliable solution for the online monitoring of transmission lines, and lay a foundation for the future construction and development of smart grid in the future. In addition, we also note that the proposed method may have some limitations in some specific scenarios, such as when the target disappears for a long time, when the targets overlap with each other or move quickly. These are the directions of our further improvement in the future, and also deserve more further research and exploration.

Fund Project. 2022 Zhuhai Industry-University-Research Cooperation Project: Development and application of transmission line online monitoring and intelligent inspection system based on AI visualization and multi-sensor fusion, Project number: 2220004002695.

References

1. Liu, C., Ying, J., Yang, H., et al.: Flying object recognition algorithm based on region CNN. Transducer Microsyst. Technol. **40**(1), 110–113, 117 (2021)
2. Ren, S.Q., He, K.M., Girshick, R., et al.: Faster R-CNN: towards real-time object detection with region proposal networks. IEEE Trans. Pattern Anal. Mach. Intell. **39**(6), 1137–1149 (2017)
3. He, K.M., Gkioxari, G., Dollár, P., et al.: Mask R-CNN. In: Proceedings of 2017 IEEE International Conference on Computer Vision, Venice, Italy, pp. 2980–2988. IEEE (2017)
4. Redmon, J., Farhadi, A.: YOLO9000: better, faster, stronger. In: Proceedings of 2017 IEEE Conference on Computer Vision and Pattern Recognition. Honolulu, USA, pp. 6517–6525. IEEE (2017)
5. Wu, H.B., Wei, X.Y., Liu, M.H., et al.: Improved YOLOv4 for dangerous goods detection in X-ray inspection combined with atrous convolution and transfer learning. Chin. Opt. **14**(6), 1417–1425 (2021)
6. Redmon, J., Divvala, S., Girshick, R., et al.: You only look once: unified, real-time object detection. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, pp. 779–788. IEEE (2016)
7. Zhou, B., Li, J.F.: Human action recognition combined with object detection. Acta Automatica Sinica **46**(9), 1961–1970 (2020)
8. He, Y.T., Che, J., Wu, J.M.: Pedestrian multi-target tracking method based on YOLOv5 and person re-identification. Chin. J. Liquid Cryst. Displays **37**(7), 880–890 (2022)
9. Cheng, M., He, F., Yang, H., Gong, X., Gao, W.: An intelligent monitoring method and system for transmission lines. Shandong Province: CN 113989663 A (2022)
10. Du, Q., Zhang, N., House, T.L.: A method for high voltage transmission line based on target tracking algorithm. Guangdong Province: CN113076899B (2023)