EnPress Publisher

Robot Electrical Connector Detection Method Based on Yolo

Enguang Liu[1], Guoliang Li[2], Feng Yu[1], Xiaohu Ni[1], Fengming Li[3]

1.Shandong Transportation Institute, Jinan 250102, China
2.Unimation Intelligent Technology Co., Ltd., Jinan 250101, China
3.Shandong Jianzhu University, Jinan 250101, China)

Abstract:In this paper, the YOLOv9 algorithm is used to realize the real-time positioning detection of electrical connectors. Firstly, the camera was used to collect images of the electrical connectors that needed to be detected, and the collected pictures were classified into data sets. Meanwhile, the electrical connectors were classified and labelimg was used to label the category boundary box. Then the labeled data sets were put into the YOLOv9 model for training. According to the trained electrical connector detection model, the detection and identification of electrical connector are realized.

Keywords: Robot; Vision Inspection; Yolo

1. Introduction

The assembly of electric connector is an important part of the manufacturing process of 3C intelligent equipment, and the assembly at this stage is mainly achieved by manual operation and auxiliary special aircraft, and there are problems of low automation, high labor intensity and high labor cost. In recent years, robots have been widely used in the industrial field, which brings opportunities for the development of automation and intelligence in assembly operations. At present, China's smart equipment production capacity, including smart phones, tablets, laptops and desktop computers, all kinds of smart wearable devices manufacturing output has accounted for 70% of the world, at the same time, increasingly improved equipment performance makes the assembly process is gradually becoming more sophisticated and high-speed. However, the assembly space of intelligent equipment assembly is small, the contact is rich, and the relationship is complex, which puts forward higher requirements for the detection and recognition strategy of robots. With the continuous development of visual recognition technology, the detection and assembly method combined with visual recognition has broken through many technical barriers in the field of intelligent assembly.

At present, object detection technology based on deep learning is relatively widely used. Deep learning enables machines to imitate human activities such as thinking and audio-visual, and solve many complex detection and recognition problems. There are many kinds of object detection algorithms based on deep learning [1], which can be divided into two-stage detection algorithm and one-stage detection algorithm. The two-stage detection algorithm includes R-CNN series (such as R-CNN, Fast R-CNN, Faster R-CNN). These algorithms extract candidate regions of fixed size from the image and then classify each candidate region to achieve target detection. However, the one-stage detection algorithm does not need to go through the region proposal stage, and can directly generate the category probability and corresponding position coordinate value of the object. Typical algorithms are YOLO (You Only Look Once) [2] and SSD (Single Shot MultiBox Detector), which have advantages in speed. YOLO algorithm has excellent performance in object detection, especially for small targets and dense targets, its accuracy is higher, multiple targets can be detected at the same time and the detection effect is good, and it is widely used in deep learning-based visual detection.

Kim Sangwon et al. applied the YOLO algorithm to the field of fire detection and proposed a non-domain detection method, which could be applied to fire detection in different scenarios [3]. Shou Li et al. applied YOLO to the detection of automotive wiring harness assembly, enabling flexible and intelligent target detection in automotive assembly [4]. Long Wu et al. proposed a method for detecting targets in hazy weather by using YOLO, which provided important theoretical support for the all-weather application of LiDAR [5]. Shi Weiya et al. applied YOLO to remote sensing small target detection, improving the detection accuracy of small targets in remote sensing [6]. Surjeet Dalal et al applied YOLO to fire detection in smart cities, which significantly improved the accuracy and speed of fire detection [7].Huang Qi [9] from Southwest University of Science and Technology made use of the advantages of YOLO, such as easy training and real-time detection, and improved its accuracy in small target detection through in-depth research and improvement. Wei Ruige [10] from University of Electronic Science and Technology of China proposed a UAV small target detection algorithm with excellent detection accuracy by combining YOLO algorithm and Mask RCNN algorithm.

This topic uses the YOLO target detection algorithm combined with the robot arm to guide the robot arm to accurately and quickly locate and identify various electrical connectors of different specifications through corresponding training, learning and operation, which has important theoretical significance and practical value for improving the level of visual inspection in China's intelligent manufacturing assembly industry.

2. Robot electrical connector positioning and detection process

According to the requirements of the detection task, the detection and positioning process of the robot electrical connector is designed, as shown in Fig 1 .

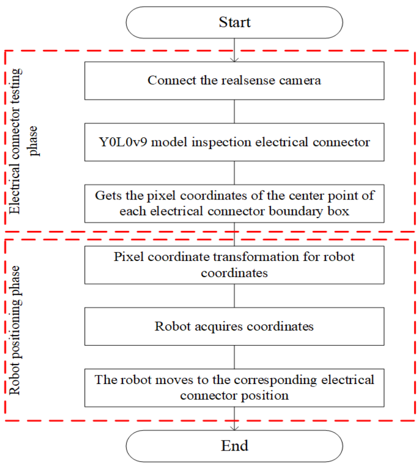

Fig.1 Flow chart of robot electrical connector detection and positioning

The positioning strategy of electrical connector based on visual recognition proposed in this paper mainly includes two processes: the detection stage of electrical connector and the positioning stage of robot. YOLOv9 is used to detect the category and position of electrical connector, pass the coordinates to the robot arm, and guide it to the correct position. The specific steps are as follows:

Step 1: Start the YOLOv9 detection environment and UR5e robotic arm, connect the realsense camera, and prepare a complete experiment environment;

Step 2: Use the detection model trained in Chapter 3 to conduct classification detection of electrical connectors, and preliminarily obtain pixel coordinates of each electrical connector boundary box;

Step 3: The pixel coordinates are converted to the robot arm coordinates through the transformation matrix calculated by nine-point calibration;

Step 4: The UR5e robot arm is controlled remotely through TCP/IP protocol to obtain the corresponding electrical connector coordinates in turn;

Step 5: The UR5e robot arm moves to the upper part of each electrical connector detection space according to the obtained electrical connector coordinates to complete the electrical connector detection and positioning.

3. YOLO target detection principle and structure composition

The core idea of YOLO principle is relatively straightforward. As shown in Figure 3.1, if it is necessary to predict which objects are contained in the image, the input image is first evenly divided into S×S squares, each of which is responsible for predicting the object category, and each grid generates two anchor boxes with height and width (h1,w1), (h2,w2), respectively, according to the empirical value. The matching degree between the predicted anchor frame and the real value is compared and judged, that is, the Intersection over Union (IoU) is calculated, and the offset X, Y, H, W of the anchor frame and their confidence are calculated at the same time. The anchor frame with low confidence is filtered and the anchor frame with the confidence is kept, and the accurate detection effect is finally presented.

The components of YOLO include: network architecture, basic network, feature extraction layer, mesh partitioning, boundary box prediction, non-maximum suppression, loss function, etc. Programmable Gradient Information (PGI) [10] is a kind of programmable gradient information to deal with the loss of original information in the process of deep network learning. In the process of model training and learning, after layer learning, feature extraction and spatial transformation, when the front propagates to a certain layer, the corresponding loss needs to be calculated, and the gradient information needs to be updated through backpropagation to ensure the effect of model training. However, the farther the layer is from the loss, the worse the update effect will be obtained.

As shown in Figure 2, (a) is the most original training structure of YOLO. When undergoing training and learning, loss calculation and updating gradient information, the update effect will be weakened during the propagation and updating process. In order to ensure the loss and updating effect, an auxiliary branch is introduced on the basis of the original structure, as shown in Figure (d), an additional branch (gray) is introduced into the original input data. At the same time, the branch is directly connected to the output layer (white) to improve the effect of updating gradient information with computational loss, and make up for the information lost in the shallow layer due to continuous feature extraction during the training process. It is worth noting that the branch introduced to improve the compensation effect of lost information only exists in the training and learning process, and does not exist in the actual test and application environment. With this method, YOLOv9's target detection performance on the MS COCO dataset greatly outperforms existing real-time target detectors in all aspects.

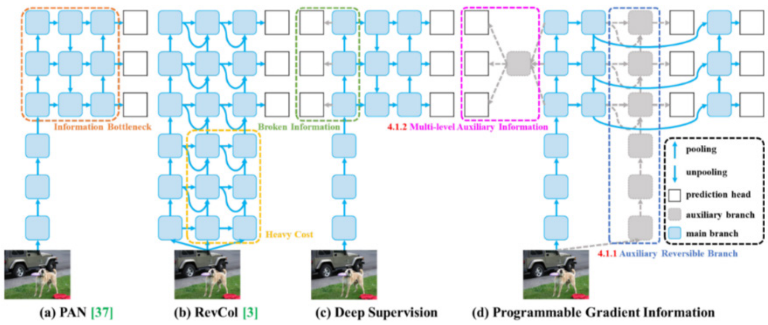

Fig.2 YOLOv9 Improvement Scheme

4. Electrical connector data set construction

The construction of the data set first requires image acquisition and labeling of the detected objects. The Realsense camera is used for image acquisition of the electrical connector panel of the detection, and no less than 100 images are collected, and the influence information such as lighting and Angle is comprehensively considered. The collected images are processed in different degrees to obtain better training results. Then, the captured images were annotated. First, the labeling annotation software was installed by running the pip install labeling command in the built python virtual environment, and the annotated format was changed to YOLO. Then the electrical connectors were classified into five categories. They are Type-C, Micro USB, Type-A, Type-B and RJ-45 respectively, and each image is labeled with category labels. After the annotation is completed, the corresponding annotated image file and text file will be generated, and the image file corresponds to the text file one by one.

The number of datasets is divided according to the size of the dataset and the number of available samples, and the randomness of the data should be ensured to avoid problems such as skewed duplication of the data. In general, the training set accounts for 60% to 80% of the total data, which is used for model training and parameter tuning. The validation set accounted for 10%-20% of the total data, which was used for hyperparameter adjustment and model selection. The test set, which accounts for 10% to 20% of the total population, is used for the performance evaluation of the final model.

According to the above data set division method, 104 electrical connector panels to be detected are collected in this paper. The training set contains 86 images, and the validation set and the test set use 18 images together.

5. Detection model training and detection localization results

The model algorithm is verified on the robot electrical connector detection and positioning platform based on YOLOv9 and UR5e industrial manipulator.

5.1 Model training

After setting up YOLOv5 and YOLOv9 environments and processing the data set appropriately, the data set can be used for model training. First, replace the train, val, and test paths in the COCO.yaml file with the corresponding dataset paths, where train is the training set, val is the validation set, and test is the test set. And change the data in names to the split label category in the same order as when the label was made. The parameters are selected as shown in Table 1.

Table 1 Parameter selection

Parameter Name	Parameter Meaning	Parameter selection
weights	Model weights file	yolov9-c-converted.pt
cfg	Model configuration file	yolov9-c.yaml
hyp	Hyperparameter file press	hyp.scratch-high.yaml
epochs	Total number of training rounds	100
batch-size	Batch size	2
img-size	Input image resolution size	640
rect	Whether to use rectangle training	False
resum	Continue training from the break-point	
nosave	Not saving the model	False
notest	No test	False
noautoanchor	No automatic anchor adjustment	False
evolve	Whether to perform hyperparameter evolution	False
cache-images	Whether to cache images in memory ahead of time	False
name	Dataset Name	
device	Training equipment	0
multi-scale	Whether to perform multi-scale training	False
single-cls	Whether the dataset has only one class	False

The corresponding evaluation index data of each interface detection model are shown in Table 2:

Table 2 Model evaluation indicators

Interface category	Precision	Recall	Accuracy	F1
Type-C	0.57	0.89	0.86	0.69
Micro-USB	0.93	1	0.98	0.96
Type-B	1	1	1	1
Type-A	0.66	0.86	0.89	0.75
RJ-45	1	1	1	1

5.2 Testing result

The trained model can accurately detect each electrical connector and indicate the center point coordinates of the bounding box. The red bounding box indicates that the electrical connector is identified as the Type-C interface, the confidence levels are 0.88 and 0.75, respectively, and the center point coordinates are (819.5, 2145.0) and (1192.5, 2148.0), respectively. The pink bounding box indicates that the electrical connector is recognized as a Micro-USB interface, the confidence values are 0.48 and 0.78, respectively, and the center point coordinates are (1758.0, 2172.0) and (2142.5, 2169.5), respectively. The orange bounding box indicates that the electrical connector is recognized as a Type-A interface with confidence values of 0.51 and 0.57, respectively, and the center point coordinates are (2810.0, 2180.5) and (3250.0, 2188.0), respectively. The yellow bounding box indicates that the electrical connector is recognized as Type-B interface, the confidence degrees are 0.87 and 0.85, respectively, and the center point coordinates are (3835.0, 2228.0) and (4278.0, 2233.0), respectively. The green bounding box indicates that the electrical connector is identified as the RJ-45 interface with the confidence of 0.91 and 0.88, respectively, and the center point coordinates are (4784.5, 2287.0) and (5232.5, 2301.0), respectively. According to the actual detection results, the model can be applied to the subsequent actual detection links.

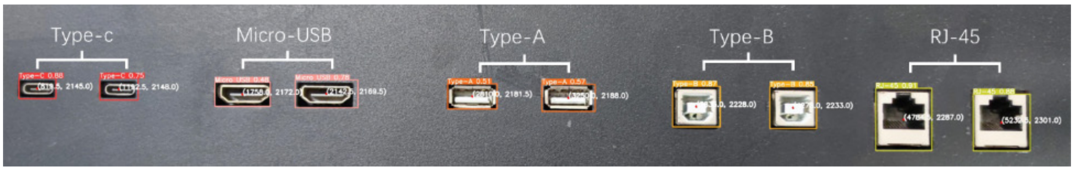

Fig. 3 Test results of electrical connector detection effect

The model detection weights trained in the YOLOv9 target detection algorithm are used to detect the electrical connector detection panel. At the same time, the pixel coordinates of the detection bounding box center point of each electrical connector in the obtained detection results are output as a text file, and the coordinates are converted in the remote communication control program of the manipulator, and the final manipulator coordinates are passed into the UR5e manipulator. Through experiments, the sum of the detection accuracy data of various categories of electrical connectors is divided by the number of electrical connector categories, and the detection success rate of the detection model reaches 88.32%. At the same time, the model can accurately input the coordinates and guide the robot to move above the corresponding electrical connector, indicating that the electrical connector positioning strategy based on visual recognition proposed in this paper can realize the corresponding detection task. It verifies that the method has high feasibility.

6. Conclusions

Aiming at the recognition task of electrical connectors for robots in the process of intelligent equipment assembly, this paper proposes a detection and positioning strategy of electrical connectors based on visual recognition, so that robots can accurately identify different types of electrical connectors and accurately move to the corresponding positions. The electrical connector recognition model based on YOLOv9 is studied to improve the accuracy of electrical connector detection. A detection and recognition experiment is designed on the UR5e robot platform to verify the feasibility of the strategy, which provides theoretical basis and corresponding technical support for the application of robots in detection and recognition tasks in the assembly process of intelligent equipment.

References

[1]Lu Yuchao. Research on Object detection Algorithm Based on deep learning [D]. Jiangsu: Jiangnan University, 2023.

[2]Xu Yanwei, Li Jun, Dong Yuanfang, Zhang Xiaoli. A Survey of YOLO Series Object Detection Algorithms [J]. Computer Science and Exploration, 2024.

[3]Kim Sangwon;Jang In su;Ko Byoung Chul.Domain-free fire detection using the spatial–temporal attention transform of the YOLO backbone[J].Springer Nature.

[4]Shuo Li;Mingzhe Yuan;Wenhong Wang;Feidao Cao;Hongyan Shi;Yuhang Zhang;Xiangpu Meng.Enhanced YOLO- and Wearable-Based Inspection System for Automotive Wire Harness Assembly[J].MDPI.

[5]Long Wu;Fuxiang Gong;Xu Yang;Lu Xu;Shuyu Chen;Yong Zhang;Jianlong Zhang;Chenghua Yang;Wei Zhang.The YOLO-based Multi-Pulse Lidar (YMPL) for target detection in hazy weather[J]. Elsevier.

[6]Shi Weiya;Zhang Shaowen;Zhang Shiqiang.CAW-YOLO: Cross-Layer Fusion and Weighted Receptive Field-Based YOLO for Small Object Detection in Remote Sensing[J]. Tech Science Press.

[7]Surjeet Dalal;Umesh Kumar Lilhore;Magdalena Radulescu;Sarita Simaiya;Vivek Jaglan;Ashish Sharma. A hybrid LBP-CNN with YOLO-v5-based fire and smoke detection model in various environmental conditions for environmental sustainability in smart city[J].Pu-

bMed.

[8]ZHANG Qi. Research on small object detection Algorithm Based on YOLO Network [D]. Sichuan: Southwest University of Science and Technology, 2023.

[9]Wei Ruige. Research on UAV Small Target Detection Algorithm Based on Deep Learning [D].Sichuan: University of Electronic Science and Technology of China, 2022

[10]Chien-Yao Wang,I-Hau Yeh.YOLOv9:Learning What You Want to Learn Using Programmable Gradient Information[J].Institute of Information Science,Academia,Sinica,Taiwan,National Taipei University of Technology,Taiwan,Department of Information and Computer Engineering, Chung Yuan Christian University, Taiwan.

About the author:

Enguang Liu (1983.12), male, Han, Shandong Zibo, Junior Engineer, Degree, Shandong Transportation Institute, Research on Vision Inspection Technology and Robotics