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Research on Identification Technology of Aviation Plug Solder Cup

Wei Jiao *, Zhaohua Liu, Zhuangzhuang Zhang

Tianjin University of Technology and Education, Tianjin, China
* Corresponding author: Wei Jiao (Email: 1041188274@qq.com)

ABSTRACT

Aviation plugs are characterized by safety, reliability, waterproof and dustproof which have been widely used in various industries. Aviation plugs are currently mainly welded manually, a method with low welding efficiency and a high error rate. The identification and positioning of the welding cups of aviation plugs is a key point in the automatic technology of welding aviation plugs. This paper proposes a combined algorithm based on YOLOv5 and image processing algorithms to realize the solder cup recognition and localization of aviation plugs. In order to improve the recognition and positioning accuracy of the solder cup of the aviation plug, this paper carries out improvement and optimization on the basis of the original YOLOv5 model: One is to embed the ECA attention mechanism in the network; Second, the Wise-IOU (WIOU) loss function is used to replace the loss function of the original model. Improved YOLOv5 algorithm combined with image processing algorithms. Using algorithms to solder cup images noise reduction, gray scale binarization, Hough transform contour recognition. Finally, the feature extraction match function is used for template matching. This enables the identification and positioning of solder cups for aviation plugs. Experimental validation on a home-made dataset shows that the improved algorithm has improved accuracy in the identification of solder cups for aviation plugs, which meets the needs of aviation plugs for soldering operations.

KEYWORDS

Aviation Plugs; Solder Positioning; YOLOv5; Image Processing Algorithms.

1. INTRODUCTION

Aviation plugs are essential components for connecting electrical circuits. Aviation plugs are generally used with corresponding aviation sockets. When the plug and socket are inserted, they form a full circumference tight connection, which is characterized by reliable connection, low resistance and strong anti-interference ability. And aviation plugs are also characterized by easy maintenance and simplified assembly. The correct selection and use of aviation plugs is an important aspect of ensuring a reliable connection of electrical wiring. Aviation plugs consist of a shell, an insulating layer and a contact body, the end of which is called the contact body solder joint (also known as the solder cup) [1]. Connection of inner core wires in multi-core cables with soldering cups by means of soldering technology, Realize reliable data communication function. Due to the small size and compact structure of the aviation plugs, the solder cups are arranged densely, so in the soldering process, it is easy to appear soldering misalignment, lack of soldering and soldering problems, affecting the normal use of the aviation plugs [2]. As aviation plugs develop in the direction of high-density miniaturization, the number of their solder cups continues to increase, resulting in a further increase in soldering difficulty [3].

With the development of image processing and machine learning technology in recent years, the automatic machine soldering technology of aviation plugs has achieved some success [4-5]. Automatic machine soldering technology offers higher productivity and weld quality. However, automatic machine soldering equipment is expensive and not easy to move. Therefore, automatic machine soldering technology is more suitable for the production of some high-volume, high-precision standard parts. The artificial soldering technology in the portability of the equipment is better, can be on-site to deal with some special soldering requirements or repairs, and in the face of some special circumstances, artificial soldering can be made more reasonable and faster way to deal with. However, manual soldering can result in incomplete soldering, non-correspondence between multi-core cables and welding joints, etc. After completing several soldering tasks, the solders are prone to fatigue and irritability, which leads to further degradation of soldering quality. Therefore, manual soldering is suitable for the production and repair of small quantities and non-standard parts [6-7].

The key to completing the solder is the precise identification and positioning of the solder cups of the aviation plugs [8]. In this paper, based on YOLOv5 and image processing algorithm, a combination of algorithms is proposed to realize the solder cups identification and localization of aviation plugs.

2. IMPROVEMENT OF YOLOV5 AVIATION PLUG RECOGNITION AND LOCALIZATION ALGORITHM

2.1. ECA Attention Mechanism

The ECA (Efficient Channel Attention), as a novel channel attention mechanism, provides the network with more powerful feature representation capabilities by virtue of its efficiency and adaptive properties [9]. In deep convolutional neural networks, the main role of the channel attention mechanism is to enhance the model's attention to important features, thus improving the model's performance on various visual tasks. By introducing channel attention, the model can learn the importance of each channel feature and adjust the output weights of different channels accordingly, making the network pay more attention to the features that are favorable to the current task [10]. The core idea of the ECA module is to capture inter-channel dependencies through one-dimensional convolution. Compared with the traditional attention mechanism, the ECA module avoids the complex process of dimensionality reduction and upgrading, thus realizing the efficient and lightweight characteristics. Specifically, the ECA module first adaptively computes the kernel size of a 1D convolution based on the number of channels k. The kernel size is computed as follows:

$$\mathrm{k} = \left| \frac{\log_2(c)}{\gamma} + \frac{b}{\gamma} \right|_{odd} \tag{1}$$

This formula is used to compute the kernel size k for a one-dimensional convolution, where C is the number of channels of the input feature, and b are hyperparameters. Taking absolute values and rounding down to the nearest odd number is to ensure that the kernel size is odd [11]. After obtaining the kernel size k, the ECA module applies a one-dimensional convolution to the input features to learn the importance of each channel with respect to the others. This process can be represented by the following equation:

$$\mathrm{out} = Conv1D_{\mathrm{k}}(\mathrm{in}) \tag{2}$$

This formula represents the conversion of input feature in to output feature out by a one-dimensional convolutional operation. Conv1Dk denotes a one-dimensional convolutional operation with kernel size k.

The ECA module shows significant advantages in deep convolutional neural networks as an efficient channel attention mechanism [12]. By adaptively computing the kernel size of 1D convolution, the ECA module is able to flexibly capture inter-channel dependencies, thus enhancing the feature representation of the model. Meanwhile, its lightweight and efficient features make the ECA module easy to integrate into various CNN (Convolutional Neural Network) architectures, providing a simple and effective way to enhance network performance.

2.2. WIOU Loss Function

The loss function is a key component in the training process of a target detection model, which determines the direction of model optimization [13]. The WIOU v1 loss function constructs an attention-based bounding box loss. Since it is difficult to avoid the inclusion of low-quality examples in the training data, geometric metrics such as distance and aspect ratio will exacerbate the penalty for low-quality examples, thus degrading the generalization performance of the model. A good loss function should weaken the penalty of geometric metrics when the anchor frame overlaps with the target frame better, without interfering too much with the training, so that the model has better generalization ability [14-15]. On this basis, the distance attention is constructed based on the distance metric, and the WIOU v1 with a two-layer attention mechanism is obtained. The calculation formula is shown below:

$$L_{WIOUv1} = R_{WIOU} L_{IOU} \tag{3}$$

$$R_{WIOU} = \exp\left(\frac{(x - x_{gt})^2 + (y - y_{gt})^2}{(W_g^2 + H_g^2)^*}\right), \quad R_{WIOU} \in [1, e) \tag{4}$$

$$L_{IOU} = 1 - IOU = 1 - \frac{W_i H_i}{S_u}, \quad L_{IOU} \in [0,1] \tag{5}$$

$$IOU = \frac{A \cap B}{A \cup B} \tag{6}$$

$$S_u = wh + w_{gt} h_{gt} - W_i H_i \tag{7}$$

The corresponding parameters in the calculation formula are shown in Fig 1.

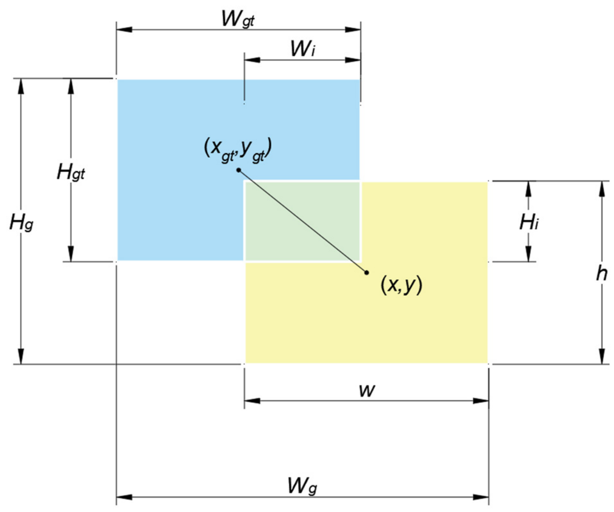

Fig 1. The area of intersection and union of the real box and the prediction box

Note: w, h, (x, y) represent the width and height dimensions and center coordinates of the prediction box, respectively;

W_{gt},H_{gt},(x_{gt},y_{gt}) represent the width and height dimensions and center coordinates of the real box, respectively;

W_i , H_i represent the intersection width and height dimensions, respectively;

W_g, H_g represent the minimum border width and height dimensions respectively.

2.3. Dataset Creation and Environment Setup

In this paper, three representative aviation plugs are selected as research objects. The selected models are GX20-12P, Y2M-32TK, and Y2M-37TK. As shown in Fig. 2.

Fig 2. Aviation plugs (models GX20-12P, Y2M-32TK, Y2M-37TK, respectively)

Shooting at different angles, different brightness, and different aviation plugs, and introducing certain objects of interference to increase the complexity of the data set, thus improving the robustness of the system. The image acquisition is shown in Fig. 3.

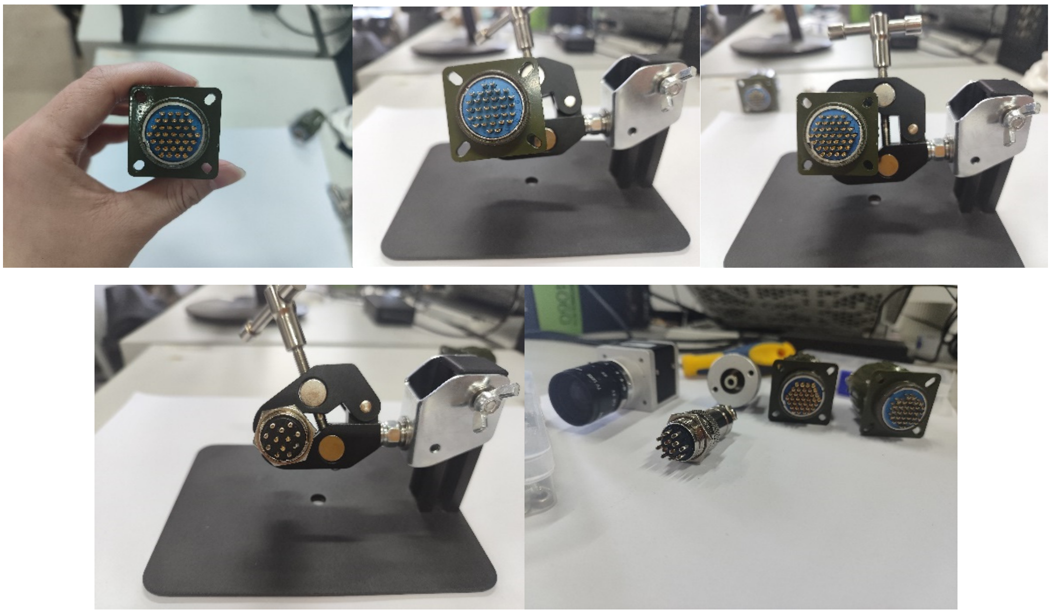

Fig 3. Images about different shooting angles

The number of samples collected only by photographing is insufficient, so data enhancement is needed to increase the number of samples. Data enhancement is performed on the dataset by randomly changing the exposure and saturation of the image, rotating, translating transformation of the image. The dataset is randomly disrupted and randomly assigned to create training set, validation set and test set as per 8:1:1.

The hardware platform for this experiment utilized a 12th Gen Intel(R) Core(TM) i5-12490F processor with a memory size of 32GB, a graphics processor of NVIDIA GeForce RTX 4060, a graphics card with a memory size of 8GB, and a system with a 64-bit operating system of Windows 10 version. Pytorch1.8.1 deep learning environment was configured using Anaconda software. In addition, PyCharm 2023.3.4 was used as the development tool and the programming language Python version 3.8.13.

3. SOLDER CUPS LOCALIZATION ALGORITHM BASED ON IMAGE PROCESSING ALGORITHM

Using image processing algorithms, the aviation plugs solder cups image gray scale binarization processing, noise reduction, Hough transform contour recognition, and finally using feature extraction match function to go to the template matching, so as to achieve the recognition and positioning of the aviation plugs solder cup.

Color images can be converted to grayscale images by system function algorithm, maximum value method, mean value method or weighting method. The mean value method is to sum the pixel values of the three RGB channels at each position by traversal and then replace the pixel value at that position, the maximum value method is to select the maximum pixel value of the three channels by traversal instead of the pixel at the original position, and the weighting method is to weight the three pixels by using the weights.

The captured aviation plugs images were grayed out using three methods and the results are shown in Fig. 4.

(a) Original image

(b) Gray scale image after system function operation

(c) Gray scale image after transformation by mean value method

(d) Gray scale image after transformation by the maximum value method

(e) Gray scale image after weighting method transformation

Fig 4. Image of gray scale processing results

By comparing the original image and the three gray scaling methods effect images, so this paper uses the weighted average method to achieve image gray scale processing.

Aviation plugs image filtering method, the common methods are mean filtering method, median filtering method, gaussian filtering method and bilateral filtering method.

By comparing the results of various types of filtering methods for aviation plugs image processing and denoising, it is found that the mean value and gaussian filtering roughened the image, and the median filtering needs to spend a lot of time, which affects the efficiency of the recognition and detection of aviation plugs. Bilateral filtering method not only removes the noise of the aviation plugs image, but also does not appear blurring phenomenon, which meets the requirements of the aviation plugs image on the image filtering, therefore image denoising process is carried out using bilateral filtering method.

The acquired aviation plugs image contains not only solder cups that need to be processed, but also interfering information such as square shells and golden circles, so it is necessary to perform a background removal operation on the aviation plugs image to exclude the interference of information other than the solder cups on the recognition.

The ROI region can be obtained using Hough transform contour recognition. The results are shown in Fig.5.

(a)Edge detection (b) Silhouette recognition

Fig 5. Image of Hough transform contour recognition

Separate the ROI region as a matching template. Matching is carried out by means of feature point matching, and the feature extraction match function is used to go for template matching so as to realize the solder cups localization. The matching result is shown in Fig.6.

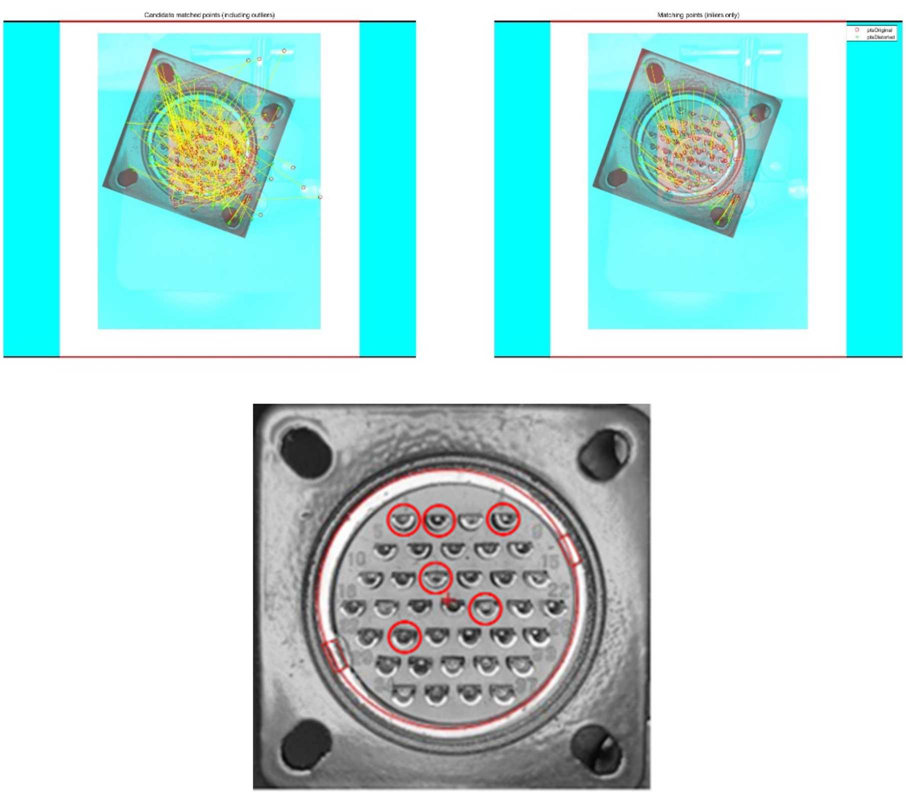

Fig 6. Image of solder cups matching results

4. EXPERIMENTAL VERIFICATION

4.1. Verification of Recognition Accuracy

According to the requirements of the actual detection environment in this paper, the accuracy (P), recall (R), mean average precision (mAP) and detection frame rate (FPS) are used as the evaluation indexes.

Precision is for the prediction results and indicates how many of the samples that were predicted as positive were actually positive. Recall is for the original sample and indicates how many of the positive cases in the sample were predicted correctly. Mean Average Precision, under different confidence thresholds, the model predicts multiple sets of P and R for a given category, and the average precision (AP) is the area enclosed by the P-R curve, while mAP is the mean of the APs for all categories [16].

$$P = \frac{TP}{TP + FP} \tag{8}$$

$$R = \frac{TP}{TP + FN} \tag{9}$$

$$\mathrm{m}AP = \frac{1}{classes} \sum_{i=1}^{classes} \int_0^1 PRdR \tag{10}$$

Where TP stands for positive samples predicted as positive cases, FP stands for negative samples predicted as positive cases, and FN predicts positive samples predicted as negative cases.

The optimized YOLO algorithm in this paper is tested against several other algorithms. The results are shown in Table 1.

Table 1. Chart of Comparison results

arithmetic	P(%)	R(%)	mAP@0.5(%)	mAP@0.5-0.95(%)	FPS
Faster R-CNN	86.8	77.1	80.3	40.2	10
YOLOv5s	87.3	78.7	82.4	41.1	109
YOLOv5n	89.3	78.8	82.1	40.1	77
YOLOv8	89.1	79.3	83.5	41.7	99
YOLOv5+GIOU Loss	80.7	74.5	75.9	37.3	109
YOLOv5+WIOU Loss	89.1	79.3	83.5	41.7	112
YOLOv5+ECA	86.8	77.1	80.3	40.2	112
Improved YOLOv5s	91.3	90.6	95.7	45.6	133

In order to visualize the accuracy and robustness of the improved algorithm, the detection effects in the same test set are compared and analyzed. The comparison chart is shown in Fig. 7.

The comparison reveals that YOLOv5 has mis-tests and omissions. The optimized model reduces the generation of these cases and improves the corresponding detection accuracy.

4.2. Solder Cup Positioning Verification

In the dataset, 500 images of aviation plugs were randomly selected as experimental samples, and solder cups No. 1, 2, 4, 12, 20, and 24 were used as locating solder cups. Experimental verification of the positioning accuracy of the solder cup is carried out. The experimental results are shown in the Table 2:

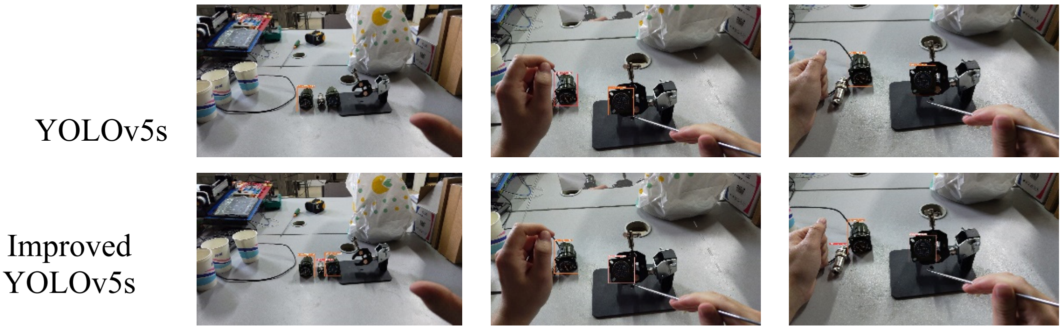

Fig 7. Image of test results comparison

Table 2. Chart of positioning by different numbers

Solder Cup Code	1	2	4	12	20	24
Number of positioning successes	500	500	500	499	500	499
Number of positioning failures	0	0	0	1	0	1

From the above table, it can be seen that the optimized algorithm in this paper can reach 99% accuracy in aviation plugs solder cups positioning. Meet the solder cup localization work requirements.

5. CONCLUSION

Aviation plugs are the basic components of electrical connectors and have been widely used in various fields. With the development of aviation plugs in the direction of high-density miniaturization, the number of solder cups is also increasing, resulting in a further increase in the difficulty of solder. The improved algorithm proposed in this paper in the aviation plugs solder cups identification, accuracy has been improved to meet the needs of aviation plugs solder operations. The research of aviation plugs solder technology is of great significance.

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