Assembling Defect Detection of Atomizer Based on Machine Vision

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***Abstract* - The atomizer is assembled in an automated assembly line, which inevitably creates assembly defects. In this paper, we use machine vision technology to detect assembly defects in atomizer.** **We propose two algorithms: image processing algorithm and deep learning algorithm based on convolutional neural network. For the image processing algorithm, we set the ROI for detection according to the position of different assembly defects, and design the corresponding image processing detection algorithm. For the deep learning algorithm, we adopted the MobileNet model and proposed a new training program to improve the accuracy of the detection. At the end of this paper, we evaluate the performance of the two algorithms, and analyze the advantages and disadvantages of the two algorithms.**

***Index Terms - Atomizer; Assembly defect detection; Machine vision; CNN***

I. Introduction

In industrial automation production, in order to ensure the quality of the product, it is necessary to perform defect detection on the product to eliminate defective products. In practical applications, machine vision is often used for defect detection, which increases the automation of production and reduces labor costs. At present, there are two types of algorithms for machine vision, one is digital image processing algorithm, and the other is deep learning algorithm based on convolutional neural network.

Jiancheng [1] uses the distance measurement method to measure the position of the part to detect whether the syringe is assembled correctly. Jing et al. [2] used the modified Hausdorff distance matching algorithm to detect the position of the part. Ardhy et al. [3] preprocessed the image using an adaptive Gaussian threshold method, and then performed a differential operation on the standard image and the image to be detected to detect whether the PCB board is defective.

In recent years, deep learning technology has made remarkable achievements in the field of image recognition. Image recognition algorithms based on convolutional neural networks have been successfully applied in many fields. In the field of industrial defect detection, some scholars have also begun to use convolutional neural networks for defect detection and classification.

Je-Kang Park et al. designed a simple CNN network structure to detect surface defects of different items. Wu Tong [4] used the X-ray imaging system to collect images of the products and label them, extract the feature of the parts using a convolutional neural network, and then train the deep learning model. Use the model to categorize the internal parts of the assembly to detect missing parts.

The research object of this paper is the atomizer. The assembly process of the atomizer requires several processes. Failure of the gripping of components can result in missing parts. The vibration of the machine, assembly accuracy, etc. may cause the assembly position of the parts to be inaccurate. Combined with the actual situation of production, the assembly defects of the atomizer can be divided into four types: missing workpiece, missing cotton core, missing metal sheet and abnormal wire position. Defect samples are shown in Fig. 1.

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| missing workpiece | missing cotton core |
| missing metal sheet | abnormal wire position |
| normal | |
| Fig. 1. Images of atomizer assembly defects samples | |

At present, there is no research on the detection of atomizer assembly defects. Two algorithms for detecting atomizer assembly defects are proposed in this paper. One is the image processing detection algorithm, and the other is the deep learning detection algorithm based on convolutional neural network.

II. Image Processing Algorithm

*A. Detection Target Location and ROI Setting*

The first step of detection is to locate the target. Since the relative position of the assembly and fixture is known, we can locate the fixture position first, and then set the corresponding ROI according to the position of the defect in the assembly. The specific steps are as follows:

Step-1: Separate the foreground and background. The image has distinct foreground and background, and can be segmented by image binarization to get the fixture and assembly area. Because the background of the image is black, we use fixed threshold binary segmentation. The formula is as follows:

(1)

Step-2: Fixture positioning. Since the wire in the assembly will be outside the scope of the fixture, it needs to be handled. Apply an open operation to the image to eliminate protruding wires. Open operations include corrosion and expansion, which are used to eliminate small objects. After the fixture area is obtained, a contour search is used on the image to obtain the outer rectangular outline of the fixture. The positioning process of the detection target is shown in Fig. 2.

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| original image | binarization |
| open operation | contour |
| Fig. 2. Detection target location | |

Step-3: ROI (region of interest) setting. The corresponding ROI is set according to the occurrence area of various defects. The position of the ROI can be determined based on the relative position of the assembly to the fixture. The ROI settings are shown in Fig. 3.

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| Fig. 3. ROI settings |

*B. Detection of Missing Workpiece*

For the detection of missing workpiece defect, the contour screening method is proposed. Since only the fixture remains after the workpiece is missing, multiple contours appear instead of a full contour when performing a contour search. Filter the small area by setting the contour area threshold for contour filtering. The result of the contour screening is used to judge whether the workpiece is missing. If there is no contour, it can be determined that the workpiece is missing. The contour screening result of the sample with missing workpiece is shown in Fig. 4.

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| Fig. 4. a sample with missing workpiece |

*C. Detection of Missing Cotton Core*

For the detection of missing cotton core defect, a pixel statistical method is proposed. The cotton core is bright white when imaged, and the cotton core is judged to be missing by counting the proportion of white pixels in the ROI. If the ratio is less than the set threshold, it is determined that the cotton core is missing, and vice versa. The steps for white pixel statistics are as follows:

Step 1: Determine whether the pixel is a white pixel. The binarization method is used. The gray value of more than 250 is white pixel. The specific steps are as follows:

(2)

Step 2: Count the number of pixels in the ROI area and the number of white pixels in the ROI area. Calculate the proportion of white pixels.

*D. Detection of Missing Metal Sheet*

For the detection of missing metal sheet defect, the template matching method is used. The metal claw is a mark of whether or not the metal piece is stored, so that the detection of the metal piece can be converted into the detection of the metal claw. In order to eliminate the interference of some unrelated regions, we do not directly perform template matching on the original image, but performs template matching on the preprocessed image. Preprocessing operations include closed operations and binarization. The closed operation eliminates black holes, and the binarization operation splits the bright white area, that is, the detected target. Then use template matching for detection. The template matching uses the normalized squared difference method, and the formula is as follows:

(3)

The detection process of the sample with the metal piece is shown in Fig. 5.

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| original image | close operation |
| binarization | template matching |
| Fig. 5. metal sheet missing detection | |

*E. Detection of Abnormal Wire Position*

For the detection of abnormal wire position defect, a measurement distance method based on pixel statistics is proposed. According to the distance between the wire and the vertical side of the metal claw, we can judge whether the position of the wire is abnormal.

Similarly, we preprocessed the image, including closing and binarization, to get the target of the detection. Then, the distance between the wire and the metal claw is measured. If the distance is not within the normal range, it is determined that the wire position is abnormal, and vice versa.

The specific steps of the measurement distance method based on pixel statistics are as follows:

Step-1: Calculate the number of white pixels in each column of the ROI, using the pixel statistics method proposed above.

Step-2: Numerical filtering. Set a threshold to filter values ​​less than this threshold in order to eliminate non-detected areas.

Step-3: Numerical smoothing. Smoothing the sequence of values makes it easier to get to the maximum.

Step-4: Calculate the distance. A large number of white pixels appear at the wire and metal jaws, which are two maxima in the numerical sequence. The distance between these two extremes is the distance between the wire and the metal claw.

The process of measuring the distance is shown in Fig. 6.

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| (a) original image |
| Pixel number  Column coordinates  (b) projection curve |
| Pixel number  Column coordinates  (c) numerical smoothing |
| Fig. 6. Distance measurement |

II. Deep Learning Algorithm

*A. Data Enhancement*

Since we don't have enough pictures, and the deep learning algorithms require a lot of pictures for training, it is necessary to carry out appropriate data enhancement to increase the diversity and quantity of samples, and thus improve the robustness of the algorithm. According to the characteristics of the detection environment, the following two data enhancement methods are used:

(1) Position offset. The relative position of the fixture and camera can be slightly offset due to mounting accuracy. Randomly shifting the image slightly to improve the adaptability of the algorithm to the installation location.

(2) Brightness and contrast conversion. Different production environments, light sources, and machine vibrations can cause changes in the brightness and contrast of an image. Appropriate brightness and contrast transform enhancements to the image allow the algorithm to adapt to changes in brightness and contrast.

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| low brightness | high brightness |
| Fig. 5. contrast transformation | |

*B. Model Selection*

We make a preliminary selection of the model. We selected several commonly used convolutional neural network for experiments, including Alex, VGG and MobileNet. We used these networks to build three deep learning models. Then, these models were trained and evaluated. The detection accuracy of each model and the detection time of a single picture are shown as TABLE I.

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| TABLE I  Accuracy and detection time of each model | | |
| Model | Accuracy | Detection time |
| Alex | 92.61% | 24.78ms |
| VGG | 63.04% | 105.30ms |
| MobileNet | 97.83% | 5.31ms |

From the table, it can be found that the MobileNet network has the highest accuracy and the shortest detection time. Therefore, this paper chooses MobileNet for deep learning algorithm design.

MobileNet is a network based on deep separable convolution. The diagram of depth separable convolution is shown in Fig. 7. Depthwise separable convolution consist of two layers: depthwise convolution and pointwise convolution. Depthwise convolution apply k×k×1 filter to per each input channel individually. Pointwise convolution apply 1×1×N convolution to create a linear combination of the output of the depthwise layer. MobileNet use both batchnorm and ReLU nonlinearities for both layers.

input

k×k×1 filter

1×1×N filter

output

depthwise

convolution

pointwise

convolution

Fig. 7. depthwise separable convolution

Compared with ordinary convolution, the parameter quantity and calculation amount of the depth separable convolution are greatly reduced, which reduces the complexity of the model and improves the detection speed. Therefore, it is more suitable for real-time industrial testing. The overall structure of MobileNet is shown in Fig. 8.

3×3 Depthwise Conv

BN

ReLU

1×1 Conv

BN

ReLU

Input

Conv

Depthwise Separable Conv × 13

Avg Pool

FC

Softmax

Output

Fig. 8. Structure of MobileNet

*C. Training Program Improvement*

Model training requires continuous traversal of samples. Each sample is a single image. For defect detection tasks, we believe that this training program is not the best. Usually, whether a product is defective or not is based on the difference between it and the normal product. That is, a normal picture is required for defect detection. Based on this idea, this paper proposes a new training program. Each sample used in model training consists of two pictures, one is a standard normal picture and the other is any picture in the training set. The diagram of training program is shown in Fig. 9.

normal

image

image dataset

one sample

Model

Fig. 9. training method

IV. Experiment

*A. Detection Using Image Processing Algorithm*

We use image processing algorithms for defect detection. Since the detection results of the image processing algorithm largely depend on the setting of the parameters. The principle of setting the parameters of this paper is to make the error rate smaller when the defect detection rate is increased as much as possible. After constant adjustment of parameters, the optimal detection result of the algorithm is shown in TABLE II. The detection rate refers to the proportion of samples in this category that are correctly detected. The error rate refers to the proportion of samples that are not in this category detected as this category.

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| TABLE II  Dtection Result Of Image Processing Algorithm | | |
|  | detection rate | error rate |
| missing workpiece | 100% | 0% |
| missing cotton core | 100% | 0% |
| missing metal sheet | 100% | 0.43% |
| abnormal wire position | 100% | 0.85% |
| normal | 98.72% | 0% |

From the table, we can see that the algorithm can detect defects 100%.This is because the parameters we set are more stringent. The rate of false positives is not very high and can meet the requirements of testing.

*B. Detection Using Deep Learning Algorithm*

Our model is designed based on the MobileNet network. We used the original training program and the improved training program proposed in this paper to carry out model training and respectively perform defect detection. The test results of the original training program are shown in TABLE III. The test results of the improved training program are shown in TABLE IV.

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| TABLE III  Dtection Result Of Original Deep Learning Algorithm | | |
|  | missing detection rate | false detection  rate |
| workpiece missing | 100% | 0% |
| cotton core missing | 100% | 0% |
| metal sheet missing | 100% | 1.41% |
| abnormal wire position | 83.33% | 0% |
| normal | 97.93% | 2.35% |

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| TABLE IV  Dtection Result Of Proposed Deep Learning Algorithm | | |
|  | missing detection rate | false detection  rate |
| workpiece missing | 100% | 0% |
| cotton core missing | 100% | 0% |
| metal sheet missing | 100% | 0% |
| abnormal wire position | 83.33% | 0% |
| normal | 100% | 2.35% |

From these two tables, we can see that the detection accuracy of proposed training program is improved compared to the original training program, but the accuracy of the abnormal wire defect has not been improved. The reason is that the difference between the sample with abnormal wire position and the normal sample is small. This also shows that the convolutional neural network is not sensitive to small changes in the image.

*C. Comparison*

We compare the performance of the two algorithms by the above experiment. We get the following conclusions. The defect detection rate of the image processing detection algorithm is relatively high, and small defects can be accurately detected. However, it is cumbersome to design different algorithms for each defect. The deep learning algorithm based on convolutional neural network has higher overall accuracy, but the detection accuracy of small defects is relatively low. The versatility of deep learning algorithms is better than image processing algorithms. Both algorithms have their own advantages and disadvantages, so when selecting an algorithm, it should be matched according to the actual requirements of task and the advantages and disadvantages of the algorithm.

V. Conclusion

This paper proposes two algorithms to detect the assembly defects of the atomizer. We designed corresponding image processing detection algorithm for different assembly defects, which can detect defects by 100%. We also proposed a deep learning detection algorithm based on convolutional neural network. It is based on the MobileNet network and the proposed training scheme, which improve the accuracy of detection. Both algorithms have their own advantages and disadvantages. For industrial detection, it is usually required that the defect can be detected 100%. So, the image processing algorithm is more suitable for our task.

In future research, we will try to combine the advantages of the two algorithms to design a new algorithm. Improve algorithm versatility while ensuring that defects are correctly detected.

Acknowledgment

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