Research on surface micro-defect detection method for metal parts based on YOLOv5

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ABSTRACT

To improve the accuracy of identifying non-conforming parts and improve production efficiency, this paper proposes an intelligent identification method for micro defects in metal parts based on the YOLOv5 algorithm. This method first preprocesses the collected images and then extracts part features by enhancing fixed features, extracting image defect feature points, and training the YOLO network. Then, based on the YOLOv5 algorithm, an intelligent recognition model is established to achieve intelligent recognition of micro defects in parts. The experimental results show that the detection accuracy of this method is higher than 93.9%, with an average detection time of 2.57ms, which is better than the comparison method and has an ideal detection effect.

Keywords: Image processing, YOLO, micro defect detection

1. INTRODUCTION

In the industrial domain, the occurrence of safety accidents is largely attributed to the missed and misjudged inspection of mechanical parts[1]. As an indispensable part of industrial production, metal mechanical parts can directly affect the overall performance and subsequent sales of the parts due to their surface micro-defects, which can even lead to accidents in machinery when severe[2]. Currently, in various defect detection methods for metal parts, there is still a lack of effective detection methods specifically targeting hole-type parts[3]. Due to uneven illumination inside the holes of such parts, with shadows occupying the majority of the area, manual inspection methods often suffer from blind spots and are time-consuming. Moreover, subjective judgments may lead to cases of false positives and false negatives, resulting in an overall decrease in part acceptance rate[4].

Intelligent recognition of parts has gained significant attention from scholars in recent years, leading to the emergence of various defect recognition methods[5-7]. For instance, Dai proposes a defect detection algorithm for metal material workpiece surfaces based on an improved Region Convolutional Neural Network (RCNN). To prevent certain classification data shortages during model training and to avoid overfitting issues resulting from a small dataset during system testing, data augmentation is applied to the original images. The algorithm incorporates a multi-stage Region of Interest (ROI) pooling layer design to eliminate system bias caused by ROI pooling rounding, achieving efficient and accurate detection of surface defects on parts[8]. Similarly, Zhan proposed a part surface micro-defect detection method based on image processing. By employing denoising and defect extraction techniques on internal surface images of the parts, intelligent recognition of surface defects was achieved[9]. While both of these methods can accomplish intelligent recognition of mechanical parts, there is still room for improvement in terms of accuracy and efficiency. Against this backdrop, this paper presents an intelligent recognition method for micro-defects in mechanical parts based on the YOLOv5 algorithm.

2. SURFACE MICRO-DEFECT DETECTION DATA PREPROCESSING

2.1 Image data acquisition of mechanical parts

Due to the fact that micro defects that are difficult to detect are generally the inner walls of cavity structures, the data acquisition equipment for this study is a rotatable area array CCD camera, which combines rotary motion and linear feed motion to capture the complete surface image of the parts multiple times for stitching. After collecting basic images under stable lighting, image preprocessing such as wavelet transform is performed. The specific process is as follows:

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(1) A starting point is found at the center axis position of the part, followed by a linear feed motion on the part to travel a certain distance, and then a rotational motion is performed on the part to obtain an image of one revolution.

(2) Continue repeating step (1) until the internal surface image of the entire part is captured.

(3) Wavelet decomposition is performed on the noisy image to obtain approximation and detail coefficients at multiple scales.

(4) The coefficients are modified based on the chosen thresholding method. Soft thresholding sets coefficients below a threshold to zero, preserving only significant features, while hard thresholding zeros out coefficients below a threshold.

(5) The denoised image is reconstructed from the modified coefficients, including the original approximation coefficients and the modified detail coefficients.

(6) By scaling the image grayscale, the scale transformation of mechanical component images is effectively completed.

2.2 Defect feature extraction

In an image, the edge can be regarded as any property of a pixel, and the edge features of the defect image can be obtained by using algorithms to calculate the features in the neighborhood where the pixel is located. The edge is a vector value with two characteristics: amplitude and direction. The amplitude represents the overall gradient amplitude of the defect image, and the direction represents the direction perpendicular to the gradient direction of the image, which is the direction where the grayscale value is maximally extended. The grayscale value changes with the edge of the image. When the grayscale value is parallel to the edge, the change is relatively gentle, while when the two are perpendicular, the grayscale value will undergo drastic changes.

There are many edge detection algorithms extended through the above methods. After a comprehensive comparison, this article chooses the Canny edge detection operator to extract defect edges. The Canny operator not only has good noise resistance for images containing noise[10] but also accurately detects true edge points with minimal error points.

2.3 Yolov5 model training

Based on the Canny edge extraction results, Typical micro defect categories are manually annotated. And the YOLOv5 model is trained using the prepared dataset. Hyperparameters, learning rates, etc., are adjusted to optimize model performance during the training process.

After enhancing the fixed features of mechanical parts, the width and depth feature points of mechanical part defects are extracted based on the detected results. The intersection point of the skeleton and curve of the mechanical part is set as the feature point of the metal surface defect width, and the position is represented in the form of (x_i, y_i). The position-fitting line distance is calculated using the distance search algorithm. The key characteristic parameters expression is as follows:

$$\begin{cases} d_{Li} = |\alpha_L x_i + \beta_L y_i + \gamma_L| p(m,n) \\ d_{Ri} = |\alpha_R x_j + \beta_L y_i + \gamma_R| p(m,n) \end{cases} \tag{1}$$

where d_{Li} and d_{Ri} both represent the obtained image line fitting distance; α, ω, ρ are parameters. Based on the calculation results, the line fitting distance values are arranged in descending order, with the maximum fitting distance value being marked. Following this sorting, the image defect distance threshold is searched for according to the algorithm, enabling the extraction of mechanical part structure width feature points for training in YOLOv5.

3. MICRO-DEFECT DETECTION METHOD BASED ON YOLOv5

Based on the extracted part image feature point results, an intelligent part recognition model is constructed using the YOLOv5 algorithm. Since the input of the YOLOv5 algorithm should be an image, it is necessary to first convert the extracted feature points into a form suitable for the model input, that is, map the position information of the feature points to the corresponding image. Subsequently, a YOLOv5 intelligent part recognition model is constructed, utilizing the aforementioned input.. The model loss function consists of coordinate error, confidence error, and classification error. Coordinate error is mainly composed of center coordinate error and width height coordinate error, expressed as:

$$\text{obj}_{\text{loss}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} [(x_i - \widehat{x_i})^2 + (y_i - \widehat{y_i})^2 + \left(\sqrt{w_i} - \sqrt{\widehat{w_i}}\right)^2 + \left(\sqrt{h_i} - \sqrt{\widehat{h_i}}\right)^2] \tag{2}$$

where S^2 represents the grid size; B represents the number of prior boxes in each grid; I_{ij}^{obj} represents the presence of an object in the *j*th BBox of grid *i*; x_i, y_i, w_i, and h_i respectively represent the horizontal and vertical coordinates, height, and width of the image center point; $\widehat{x_i}$,$\widehat{y_i}$, $\widehat{w_i}$ and $\widehat{h_i}$ represent the true values of x_i, y_i, w_i, and h_i, respectively. The confidence error of BBox containing the target can be expressed as:

$$\text{b}_{\text{loss}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} \left(C_i - \widehat{C_i}\right)^2 \tag{3}$$

where C_i represents the target confidence of the image center point; $\widehat{C_i}$ represents the true value of C_i. The classification error can be expressed as:

$$\text{c}_{\text{loss}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} (p_i(c) - \widehat{p_i}(c))^2 \tag{4}$$

where $p_i(c)$ respectively represents the predicted values of the category to which the image center point belongs; $\widehat{p_i}(c)$ respectively represent the true values of $p_i(c)$.

4. EXPERIMENT AND DISCUSSION

To verify the effectiveness of the proposed method, it will be tested. Randomly we select 400 images of mechanical parts, and use the methods proposed in this paper and References[8,9] to identify mechanical part images. The test results are shown in Figure 1.

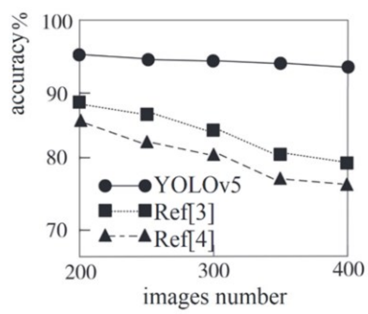

Figure 1. Detection accuracy of different methods.

As shown in Figure 1, as the number of images increases, the detection accuracy of different methods gradually decreases. However, compared with the other two methods, the detection accuracy of our method always remains above 93.9%, and the trend of change is relatively stable, resulting in better application effects.

To further validate the effectiveness of the method proposed in this paper, the average time required for detecting defect images using three methods was tested. The experimental results are shown in Table 1.

Table 1. Comparison of time consumption of different algorithms.

Methods	**Average time/ms**
YOLOv5	2.57
Reference[3]	5.63
Reference[4]	6.12

According to Table 1, the average time used for the method in this article is 2.57ms, which is significantly better than the control group, indicating that the application of this method can improve the automatic recognition efficiency of micro defects in metal parts.

5. CONCLUSION

The article proposes an intelligent recognition method for mechanical parts based on the YOLOv5 algorithm and compares it with other methods. This method has high detection accuracy and low detection time, which is superior to the comparison method and has a certain application value.

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