U.P.B. Sci. Bull., Series D, Vol. 85, Iss. 3, 2023 ISSN 1454-2358

RESEARCH ON MECHANICAL PART DEFECT RECOGNITION METHOD BASED ON MULTI-CLASSIFIER FUSION

Yungao GU[1], Yanjun SHI[2], Tao LI[3]*

The accurate identification of mechanical parts defects is of great significance for improving the machining quality. A method based on machine vision and multi-classifier fusion is proposed for automatic recognition of mechanical parts defects. The improved morphological method of multi-element structure is used for image enhancement to improve the contrast of mechanical parts image. The feature of mechanical part image is obtained by wavelet transform combined with two-dimensional Ostu segmentation as the input of classifier. After image features enter into multiple groups of classifiers, fusion judgment is formed as the final defect recognition result. For 7 kinds of mechanical parts defects, 10 kinds of classifiers are used for defect recognition experiments. The experimental results show that the recognition accuracy of the fusion classifier has been significantly improved, and the XGBT+KNN+RF fusion classifier has the performance of high robustness and high recognition accuracy at the same time. This method is applicable to the quality inspection of mechanical parts.

Keywords: mechanical parts, defect recognition, fusion classifier, machine vision

1. Introduction

The automatic identification of mechanical part defects is of great significance for improving the production and processing efficiency of mechanical industry [1]. In the field of automatic recognition of mechanical parts defects, stroboscopic detection is an early method. Its basic principle is based on the static reflection of human retina to stroboscopic light, which is also similar to the shutter function of camera [2].

After stroboscopic technology, a series of automatic detection technologies developed by various physical methods have emerged, including infrared detection technology, eddy current detection technology and magnetic flux leakage detection technology [3]. Compared with stroboscopic detection, these methods have made great progress and greatly improved the degree of automation. They were once widely used at home and abroad.

Machine vision detection technology is a new kind of detection technology based on the principle of imitating human vision and relying on computer equipment and image processing technology [4]. In terms of concrete

[1] Mechanical and electrical College, Handan University, Handan, 056005, China
[2] Department of Software, Handan University, Handan 056005, China
[3] Department of Software, Handan University, Handan 056005, China
* Corresponding author email: litao9106@126.com

implementation, machine vision also relies on the difference between structured light and natural light. With the help of structured light, such as laser scanning detector, this instrument can obtain better measurement accuracy and sensitivity because of the use of laser beam concentration. But the laser emission device is not only expensive, but also its layout and service life directly determine the effect of machine vision detection. The machine vision detection system based on CCD camera can be used under natural light conditions without additional structural light source, which is its outstanding advantage [5].

The application of machine vision in automatic recognition of mechanical parts defects is essentially a pattern recognition technology. According to various algorithms of machine vision, such as region segmentation, contour extraction, edge detection, the features of mechanical parts and defect parts are obtained, and then compared with the corresponding features of the reference image in the database, so as to determine whether the mechanical parts have defects and what kind of defects [6-8]. It can be seen that the recognition of mechanical parts defects based on machine vision largely depends on the accuracy of machine vision-related feature extraction methods. With the continuous development of this method, the detection method based on single feature exposes the problems of low detection accuracy and low robustness. In this case, the classification method of multi-feature training and learning based on BP neural network is established. With the continuous development of mechanical parts defect classification methods based on machine vision, the means of various classifiers are increasingly rich. Common classifiers include BP (Back Propagation) classifier, LR (Logistic Regression) classifier, DT (Decision Tree) classifier, RF (Random Forest) classifier, SVM (Support Vector Machine) classifier, CNN (Convolutional Neural Networks) classifier, KNN (K-Nearest Neighbors) classifier, etc. [9-14]. Different classifiers show different performance for the machine vision features displayed by different defects.

In this paper, we will build a machine part defect recognition method based on multi-classifier fusion. In this method, multiple classifiers are used at the same time, and the defect features obtained by different machine vision methods will be incorporated into multiple classifiers for fusion judgment of defect types. The method in this paper will show the advantages of accuracy and robustness for the identification of mechanical parts defects.

2. The Proposed Method

2.1 Multi-classifier fusion recognition framework

In order to realize the accurate recognition of the defects of mechanical parts, this paper first adopts the method of machine vision to enhance the image and extract the features, and then transmits the extracted features to multiple classifiers, and fuses the results of the defect recognition obtained by different classifiers to obtain the final defect recognition results.

Among them, the reason for image enhancement is that the contrast of the mechanical part image is generally low and the defect feature is not obvious. Feature extraction provides necessary input for defect classification and recognition of classifier. The fusion of multiple classifiers enhances the accuracy and reliability of mechanical part defect recognition. The overall framework of multi-classifier fusion recognition is shown in Fig. 1.

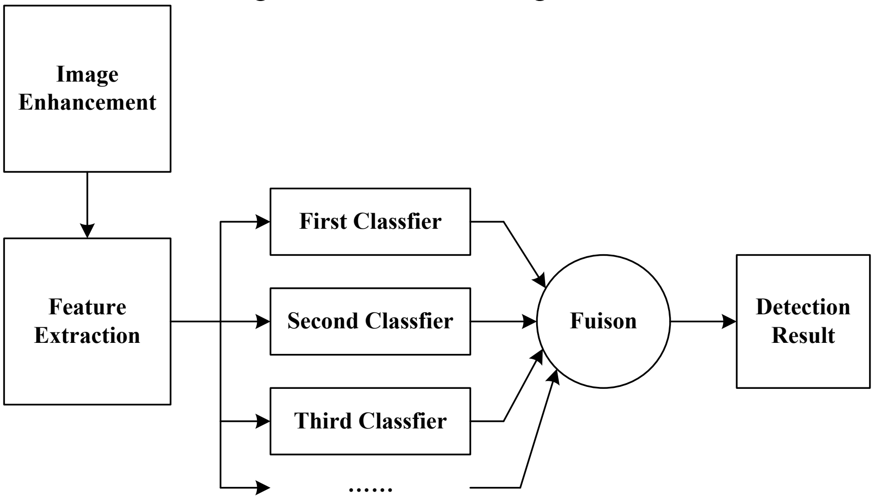


Fig.1 Overall framework of multi-classifier fusion recognition

2.2 Image enhancement of mechanical parts based on morphology

The enhancement method based on morphology is adopted and improved. General morphological segmentation methods use a single structural element. This treatment process is relatively simple, but it is often difficult to meet the requirements of multiple indicators at the same time. For example, when circular structure elements are used, the amount of background removal is large, but some edge details will be eliminated by the morphological processing of circular template; When using linear structure elements, the edge details of the original image can be clearly retained, but the amount of background removal is small.

For this reason, we consider improving the general morphological processing method, and combining a variety of different structural elements to complete morphological processing such as opening and closing operations to achieve more ideal results.

When specific to the binary data of the computer, the template form of the circular structure element and the linear structure element is shown in Fig. 2.

In Figure 2, two structural element templates with the same size of 4*4 are given, one is circular and the other is linear.

0	**1**	**1**	**0**
1	**0**	**0**	**1**
1	**0**	**0**	**1**
0	**1**	**1**	**0**

(a) Circular structural element template

1	**0**	**0**	**0**
0	**1**	**0**	**0**
0	**0**	**1**	**0**
0	**0**	**0**	**1**

(b) Linear structural element template

Fig.2 Templates of different structural elements

When combining these two templates for morphological processing, the specific implementation steps are as follows:

First of all, use the circular structure element to perform open operation on the original image. The circular structure element is represented by S_1, the original image is represented by $f(x)$, and the processing result is represented by A. The processing process is shown in formula (1).

$$A = f(x) \circ S_1 \tag{1}$$

Secondly, the linear structure element is used to perform closed operation on the original image. The linear structure element is represented by $f(x)$, the original image is represented by S_2, and the processing result is represented by B. The processing process is shown in formula (2).

$$B = f(x) \bullet S_2 \tag{2}$$

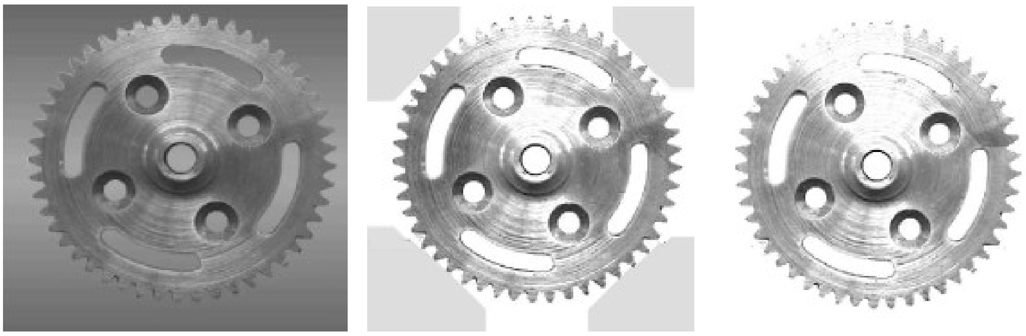
Thirdly, use the original image and the processing results of the previous two steps to make a difference, and the resulting results are represented by A_1 and B_1 respectively, then the processing process is shown in formula (3).

$$\begin{aligned} A_1 &= f(x) \Theta A \\ B_1 &= f(x) \Theta B \end{aligned} \tag{3}$$

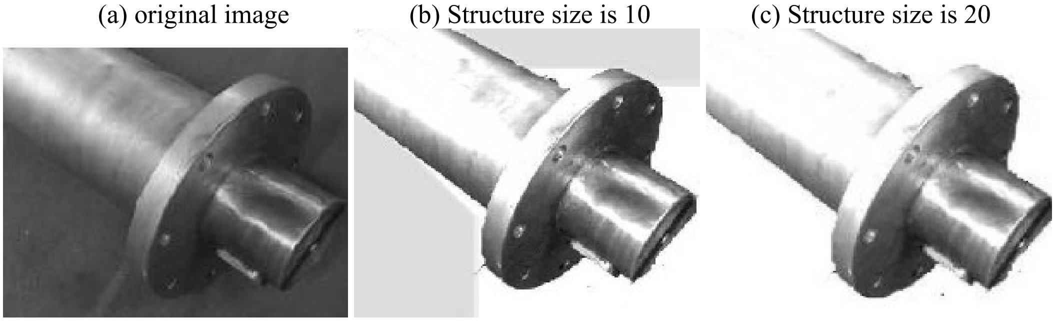
Finally, the two processing results obtained in the previous step can be subtracted to obtain the final segmentation result without background, as shown in formula (4).

$$C = A_1 \Theta B_1 \tag{4}$$

In order to verify the effectiveness of the improved morphological segmentation method, we selected the part images of gears and shafts to carry out the experiments respectively. At the same time, we used linear structural elements and circular structural elements to carry out the segmentation processing according to the steps of the improved method, and the results are shown in Fig. 3.



(a) original image (b) Structure size is 10 (c) Structure size is 20



(a) original image (b) Structure size is 10 (c) Structure size is 20

Fig.3 Enhancement results of improved morphology

Fig. 3 shows the improved morphological processing results of this paper, using linear structure elements and circular structure elements at the same time. It can be seen from the processing results that when the size of the structural element is 10, the background is obviously cut off. When the size of the structural element is 20, the background element is basically completely cut and the target area is clearly displayed. This fully shows the effectiveness of the improvement measures in this paper. The size of structural element is 20, which is also a parameter used in subsequent processing.

2.3 Feature extraction of mechanical part image

According to the principle and characteristics of mechanical part image, this paper combines wavelet transform and Ostu domain value segmentation to construct a new image feature extraction method. High frequency information and low frequency information can be obtained from the images of all levels of resolution of wavelet transform. Among them, high-frequency information is rich in image details and noise, while low-frequency information is rich in image contour. Traditional Ostu segmentation is based on the original image. If this process is carried out on the low-frequency components of wavelet transform, the impact of noise and other interfering details can be avoided.

If $x(t)$ represents integrable function, then the continuous wavelet related to its Fourier transform $\phi(w)$ can be defined in the form of formula (5).

$$WT_x(a,b) = \frac{1}{\sqrt{a}} \int x(t)\phi^*\left(\frac{t-b}{a}\right)dt = \langle x(t), \phi_{ab}(t) \rangle \tag{5}$$

Based on this, the inverse wavelet transform is shown in formula (6).

$$x(t) = \frac{1}{C_\phi} \int_0^\infty \frac{da}{a^2} \int_{-\infty}^{+\infty} WT_x(a,b) \frac{1}{\sqrt{a}} \phi\left(\frac{t-b}{a}\right) db \tag{6}$$

Here, a and b represents the scale of wavelet transform and the displacement of wavelet transform. Here, $\phi_{ab}(t)$ can be expressed as follows.

$$\phi_{ab}(t) = \frac{1}{\sqrt{a}} \phi\left(\frac{t-b}{a}\right) \tag{7}$$

The scale a of wavelet transform is used for scaling $\phi(x)$. The larger the scale, the wider $\phi(\frac{t}{a})$ it will be. The samller the scale, the narrower $\phi(\frac{t}{a})$ it will be. In other words, the size of a can represent the range of wavelet analysis. When wavelet transform is used in time domain analysis, a changes to represent the analysis range of time domain, that is, a represents the resolution of time domain, and this is an inverse relationship.

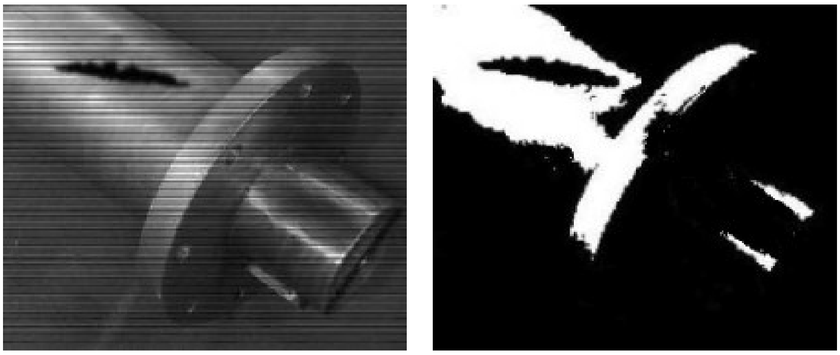
Compared with the one-dimensional Ostu method, the two-dimensional Ostu method adds the neighborhood average gray level, thus extending the one-dimensional gray level histogram to the two-dimensional gray level histogram, that is, the probability of the normal image gray level and the neighborhood average gray level occurring simultaneously. Its basic operation process is as follows:

If the original image is represented by f, its gray level is assumed to be $L(0,1,\cdots,L-1)$, the total number of pixels of the whole image is N, and the average gray level of the neighborhood is L.

Further, if i is used to represent the gray level of a pixel, and j is used to represent the domain average gray level corresponding to the pixel, then its joint probability density can be calculated, as shown below:

$$\begin{gathered} P_{i,j} = \frac{f_{i,j}}{N}, \quad i,j = 0,1,2,\cdots,L-1 \\ \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P_{i,j} = 1 \end{gathered} \tag{8}$$

The processing accuracy of two-dimensional Ostu method is higher than that of one-dimensional Ostu method. Therefore, this paper selects wavelet transform combined with two-dimensional Ostu method to achieve feature extraction of mechanical parts. The extraction effect is shown in Figure 4.



(a) original image (b) Wavelet+2D Ostu segmentation result
Fig.4 Feature extraction effect of mechanical part image

It can be seen from Figure 4 that there are banded defects on the mechanical parts in the original image, which are effectively extracted through wavelet and two-dimensional Ostu segmentation.

3. Experimental results and analysis

Different defects detected by different classifiers can lead to scattered detection results. In practice, multiple defects often coexist. So, the purpose of this study is to find a combination of classifiers with universal classification ability for common types, which is also the significance of the experimental research process.

According to the multi-classifier fusion method of mechanical part defect recognition proposed in this paper, the experimental research is carried out next. According to the common classification algorithms of defect recognition, this paper selects KNN classifier, DT classifier, SVM classifier, NB classifier, BP classifier, LR classifier, Adaboost classifier, RF classifier, GBDT classifier, XGBT classifier as candidate classifiers. The defect categories of mechanical parts involved in the classification include seven categories: point defect, multi-point defect, hole defect, porous defect, linear defect, multiline defect and ribbon defect. These seven types of defects are included in each classifier for defect recognition and classification after enhancement processing and feature extraction according to the method of machine vision. The classification accuracy of 10 classifiers for 7 types of defects is shown in Table 1.

Table 1

Recognition accuracy of each classifier for different defects

	defect 1	defect 2	defect 3	defect 4	defect 5	defect 6	defect 7	average
KNN	54.21	90.18	80.36	75.59	49.64	66.98	82.18	73.35
DT	18.93	64.16	72.50	77.30	4.41	28.17	67.53	51.01
SVM	0.00	0.65	7.77	96.18	8.58	55.47	51.60	26.45

NB	0.21	1.53	20.45	30.75	1.14	0.07	51.65	22.32
BP	23.79	77.84	71.64	62.89	20.95	65.32	75.14	59.40
LR	0.08	49.30	20.46	77.25	0.00	33.08	52.21	36.11
Adaboost	39.33	61.22	66.37	68.75	41.55	47.26	82.82	60.62
RF	17.47	91.19	72.23	83.83	8.73	66.67	70.93	60.18
GBDT	43.90	94.78	91.21	82.15	40.34	68.34	86.49	74.63
XGBT	44.87	95.56	91.21	82.32	41.21	67.89	86.00	74.79

It can be seen from Table 1 that different classifiers have different recognition effects on different defects. From the average recognition rate of 7 kinds of defects, KNN classifier, GBDT classifier and XGBT classifier have the highest recognition accuracy. In order to further improve the accuracy and robustness of defect recognition, 10 kinds of classifiers are randomly combined into the framework of section 2.1 in this paper according to three groups to form a fusion classifier. Finally, the top three groups are listed in Table 2:

Table 2

Three groups of classifiers with the best fusion effect

Method	Precision	Recall
XGBT+KNN+RF	94.52%	95.19%
XGBT+KNN+NB	92.03%	93.71%
XGBT+KNN+SVM	85.85%	86.48%

It can be seen from Table 2 that XGBT classifier and KNN classifier are among the three best fusion models. This is also related to the best classification effect of these two types of classifiers. The fusion of XGBT+KNN+RF classifiers has achieved the best results in defect recognition accuracy and recall rate. The above three sets of classifier fusion models are further given, and the recognition accuracy of seven types of mechanical parts defects is compared. The results are shown in Table 3.

Table 3

The recognition accuracy of three sets of fusion classifier models for seven types of mechanical parts defects (%)

Method	defect 1	defect 2	defect 3	defect 4	defect 5	defect 6	defect 7	average
XGBT+KNN+RF	90.52	92.36	95.38	94.21	95.23	96.84	97.11	94.52
XGBT+KNN+NB	81.32	96.53	88.61	92.35	98.53	95.63	91.25	92.03
XGBT+KNN+SVM	82.19	81.23	84.28	88.51	86.36	87.07	91.28	85.85

In order to facilitate the comparison of defect identification accuracy in Table 3, the data in Table 3 is drawn into curve form, as shown in Figure 5.

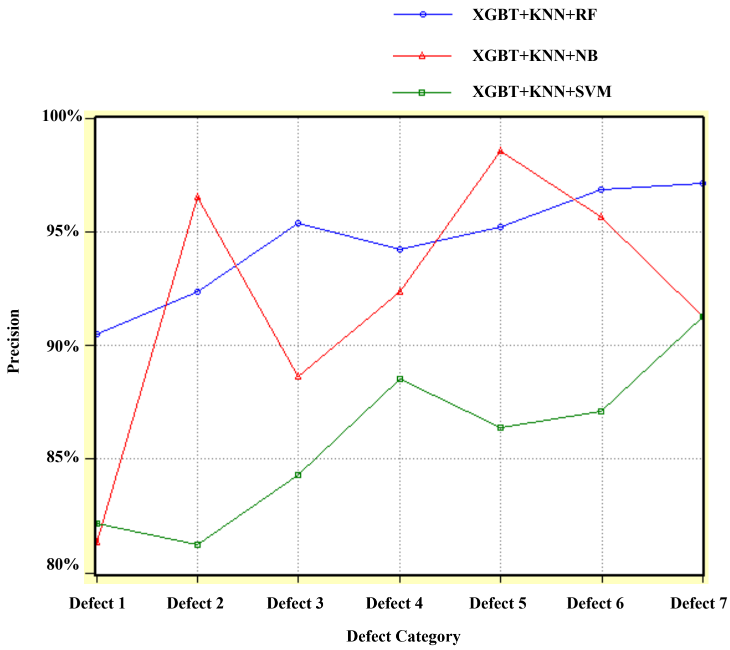


Fig.5 Recognition accuracy curve of seven types of mechanical parts defects by three groups of classifiers fusion model

From the results in Table 3 and Fig. 5, it can be seen that after the fusion of three groups of classifiers, XGBT+KNN+RF, XGBT+KNN+NB, XGBT+KNN+SVM, the accuracy of defect recognition for seven types of mechanical parts is significantly higher than that of a single classifier. From the comparison results of these three sets of fusion classifiers, XGBT+KNN+RF not only has high recognition accuracy, but also has a relatively stable recognition accuracy curve for seven types of mechanical parts defects, with the best robustness. In comparison, the average recognition accuracy of XGBT+KNN+NB is also relatively high, but the curve fluctuation is large, showing that there are obvious differences in different defect recognition effects.

4. Conclusions

Aiming at the problem of automatic recognition and classification of mechanical parts defects, this paper constructs a method based on machine vision and multi-classifier fusion. In this method, a variety of different classifiers will be fused together to form the fusion judgment results of mechanical parts defects. The basis for each classifier to identify defects comes from the image features obtained by machine vision. Here, the improved morphological method of multi-element structure is used for image enhancement to improve the contrast of mechanical parts image. Further, wavelet transform and two-dimensional Ostu segmentation are used to obtain the features of the mechanical part image as the input of the classifier. During the experiment, 10 kinds of classifiers were used to identify 7 kinds of mechanical parts defects. Through the test, XGBT+KNN+RF, XGBT+KNN+NB, XGBT+KNN+SVM have the best fusion recognition effect. Among them, XGBT+KNN+RF fusion classifier not only has high recognition accuracy, but also has good robustness to 7 types of mechanical parts defects.

In the future research work, we can further try the practical application effect of the combination of other classifiers for mechanical parts defect recognition. At the same time, on the basis of ensuring the recognition accuracy, further improving the recognition speed is also the focus of future research.

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