Application of Weighted Object Variance Algorithm in Metal Surface Defect Detection

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Abstract. In the process of metal surface defect detection, it is difficult to detect and segment small defects. In order to solve this problem, this paper uses weighted object variance algorithm to detect metal surface defects. Then the feature of defect area is extracted and the defect classification model based on support vector machine is trained. In order to verify the effectiveness of the method, this paper takes the metal surface of bearing cylindrical roller as the specific research object. The experimental results show that the method meets the production requirements.

Key words: weighted object variance; Bearing Cylindrical Roller; Defect Segmentation and classification; SVM.

1. Introduction
In the field of metal surface defect detection, it is difficult to detect small defects. The defects of cylindrical roller of metal bearing in production process have the characteristics of small and irregular shape. At the same time, bearing, as a basic component, has a very high research value. Therefore, taking the metal surface of bearing cylindrical roller as the specific research object, it is of great significance to study the metal surface defects. At present, most bearing cylindrical roller manufacturers still use the traditional manual visual inspection method to detect the surface defects of bearing roller, which has the problems of low detection efficiency and high false detection rate. With the increasing requirement of detection efficiency and accuracy, many automatic non-destructive testing schemes have been widely studied. The existing non-destructive testing schemes, such as ultrasonic and eddy current, have the disadvantages of complex operation and low detection efficiency. Machine vision inspection method has the advantages of high accuracy, fast speed and objective detection results, and has been widely used in various fields of industrial inspection [1].

Machine vision combines digital image processing, pattern recognition, computer science and other technologies. Based on image processing technology, under the action of CCD camera, lens, light source and so on, image acquisition and image transmission are carried out for the inspected workpiece. Then the related image processing methods are used to complete the image preprocessing, segmentation,
recognition, classification and other operations. Among them, defect area segmentation is one of the most important and challenging stages in surface defect detection. Excellent defect segmentation algorithm should make the surface defect area and background area have a good separation, which is very important for the extraction of surface defect features. Threshold-based segmentation algorithm has become an important tool in the field of image segmentation because of its intuitive and efficient characteristics. Classical threshold-based segmentation algorithms include histogram-based methods, clustering-based methods, attribute similarity-based methods, etc. Among them, Otsu algorithm is widely used because of its simplicity and efficiency.

Otsu[2] By selecting threshold values of the maximum between-class variance or the minimum within-class variance from the image histogram, the Otsu method can obtain a satisfied segmentation when the object and image background have the similar variance, however, the method fails if sizes of the object and image background are great difference. Many scholars have studied the problem that defect segmentation cannot accurately segment weak target images with the Otsu algorithm. Ng[3] proposed VE and Fan[4] proposed NVE algorithm, but these two algorithms did not completely solve the threshold segmentation problem of small defect or defect-free image[5]. Yuan[5] proposes a weighted adjustment Otsu algorithm, named the weighted object variance (WOV). WOV algorithm has been widely used because it improves the segmentation effect of Otsu algorithm on images with small defect area or defect-free. The object of this paper is the bearing roller surface. In the actual detection process, most of product surfaces have no defects or the defect is much smaller than its background areas. Based on this feature, this paper uses WOV method to segment bearing roller surface defects, and trains SVM classification model to extract features from the defect areas, and then classifies and identifies the defects.

In order to verify the validity of this method, the cylindrical surface of bearing cylindrical roller is used as the object of defect detection. The bearing cylindrical roller surface images mentioned below are all the cylindrical surface of bearing cylindrical roller. The experimental results show that the surface defect detection accuracy of bearing roller based on WOV method can meet the actual industrial production needs.

2. THE weighted object variance
The WOV method for selecting an image threshold is briefly introduced firstly in this section. Because WOV algorithm is based on the improvement of Otsu algorithm, we first review of Otsu algorithm.

2.1. Review of Otsu Method
Otsu method is based on the variance between classes to segment the object and background in the image. Variance is a measure of the uniformity of gray distribution. The greater the variance between classes, the greater the difference between the object and the background in the image. Therefore, a good Otsu binary segmentation method should be able to find a threshold. According to this threshold, the target and background parts of the image are segmented to maximize the variance between the two parts. The specific principles of Otsu method are as follows:

An image can be described as $f(x, y)$ with a gray level range from 0 to $L-1$, where $L$ is the number of distinct gray levels. In an image, the number of pixels per gray level $i$ is $N_i$, and the total number of pixels is $N$. The probability of occurrence of the gray level $i$ is defined as follows:

$$p_i = \frac{N_i}{N}, \quad i \in [0, L-1]$$

If an image is divided into two classes, object($B_1$) and background($B_2$), by a threshold $T$, $B_1$ consists of pixels with levels $[0, T]$, and $B_2$ consists of pixels with levels $[T+1, L-1]$. Let $w_1$ and $w_2$ denote the cumulative probabilities, $u_1$ and $u_2$ denote the mean levels of $B_1$ and $B_2$ classes, respectively.

$$w_1 = \sum_{i=0}^{T} P_i, \quad w_2 = \sum_{i=T+1}^{L-1} P_i = 1 - w_1, \quad u_1 = \frac{\sum_{i=0}^{T} i^* P_i}{w_1}, \quad u_2 = \frac{\sum_{i=T+1}^{L-1} i^* P_i}{w_2}$$
The mean levels of the image \( f(x,y) \) can be computed as:

\[
u = w_1 u_1 + w_2 u_2 \quad (3)
\]

For a threshold \( T \), Otsu shows that the between-class variance \( \sigma^2 \) of \( B_1 \) and \( B_2 \) is as follows:

\[
\sigma^2 = w_1 (u_1 - u)^2 + w_2 (u_2 - u)^2 \quad (4)
\]

The optimal threshold \( T^* \) of Otsu method can be determined as:

\[
T^* = \arg \max(\sigma^2(T)), \quad 0 \leq T^* \leq L - 1
\]

After obtaining the threshold \( T^* \), binary image can be computed as:

\[
g(x,y) = \begin{cases} 
1, & f(x,y) > T^* \\
0, & f(x,y) \leq T^*
\end{cases} \quad (6)
\]

The Otsu method, provides satisfactory results for thresholding an image with a histogram of bimodal distribution. This method, however, fails if the histogram is unimodal or close to unimodal[6]. For bearing cylindrical roller defect detection applications, roller surface defects can range from no defect to small or large defects, which means that the gray-level distributions range from unimodal to bimodal. It is necessary to select an improved threshold segmentation method for bearing roller surface defect segmentation.

### 2.2. The WOV Method

The main improvement of WOV algorithm to Otsu algorithm is that WOV algorithm adjusts the formula of calculating the variance between classes (formula 4) of Otsu algorithm by weight, as follows:

\[
\sigma_n^2 = \rho w_1 (u_1 - u)^2 + w_2 (u_2 - u)^2 \quad (7)
\]

The weight \( \rho \) is used to control the influence of the target area (defect area in this paper) on the variance calculation process. When there is no defect in the image or the image defect is small, the proportion of the target area in the calculation of variance should be reduced. When the defect increases in the image, the proportion of the defect area in the calculation of variance should increase. \( \rho \) should be adjusted adaptively according to the size of defect area, and then a reasonable segmentation threshold can be obtained. In WOV algorithm, \( \rho = w_1 \), \( \rho \) varies with the proportion of defect areas to meet the needs of adaptive adjustment, as follows:

\[
\sigma_n^2 = \rho w_1 (u_1 - u)^2 + w_2 (u_2 - u)^2 \quad (8)
\]

The Otsu method and WOV method were applied to the bearing cylindrical roller surface image, the effect is shown in Figure 1 (defect areas are marked with red circles). Figure 2 is the gray histogram of the original image and the threshold obtained by Otsu and WOV methods. Through Fig. 1 and Fig. 2, it can be seen that Otsu obtains obviously too large thresholds, and classifies more background into defect areas, while WOV method obtains much smaller thresholds, which can more accurately segment defect areas.

![Figure 1](image1.png)

**Figure 1.** Segmentation results of defective: (a) original image with a small defect; (b) Otsu thresholding result; (c) WOV thresholding result.
3. Surface Defect Detection Based on WOV Method

Through the above mentioned, WOV method can effectively solve the problem of defect area segmentation in the process of bearing cylindrical roller surface defect detection. In this paper designs a process of bearing roller surface defect detection based on WOV method. The process includes image acquisition, image preprocessing, defect segmentation, defect classification and so on. The flow chart of surface defect detection for bearing cylindrical roller designed in this paper is shown in the figure 3.

The specific process is described as follows:

3.1. Image Acquisition

In this paper, the bearing cylindrical rollers are rotated by the rotary table, and the lateral expansion of the bearing rollers is obtained by linear CCD camera and linear LED light source. The schematic diagram of the acquisition device is shown in the figure 4(a), and the original image acquired is shown in the figure 4(b).

3.2. Image Preprocessing

Preprocessing of bearing cylindrical roller surface image mainly includes two steps: roller area extraction and image denoising.

1. roller area extraction: The original image collected contains a certain size of non-roller area. In order to reduce the computational load of subsequent image processing, the bearing roller area should be segmented from the original image. The extraction of roller area can follow the following steps: a) Because the overall gray value of bearing roller area is high, the image segmentation threshold can be calculated based on WOV algorithm, and the binary image can be generated; b) The largest white area in the binary image is the bearing roller area, and the bearing roller image is segmented from the original image. The segmented image is shown in the figure 4(c).

2. image denoising: In the process of image acquisition and transmission, noise will inevitably occur due to the environmental impact and the reasons of its own equipment. The existence of noise will greatly affect the difficulty of image processing, so it is necessary to denoise the bearing roller image. Due to the diversity and complexity of noise types, image denoising methods are also varied. Considering the real-time requirement of industrial production, this paper chooses median filter for image denoising based on the principle of simplicity and efficiency. Roller image denoised by median filter is shown in the figure 4(d).
3.3. Defect area Segmentation Based on WOV Algorithm

Defect area segmentation is a key step in the surface defect detection of bearing cylindrical roller. The defect area segmentation results determine whether there is a defect on the surface. If the defect area can be accurately segmented, it will provide an important guarantee for subsequent defect feature extraction and defect classification. There are three kinds of defects in the surface image of bearing cylindrical roller detected in this paper: scratches, pits and spots. The original image of three kinds of defects and the effect of using WOV algorithm to segment defect areas are shown in the figure 5. The defect areas are marked with red circles. By analyzing the defect segmentation results of a large number of samples, WOV algorithm can accurately detect whether there are defects on the roller surface, and accurately segment the defect area.

3.4. Defect Classification

In the actual production process, in order to classify defective rollers for subsequent processing, and in order to effectively adjust the production links according to defect data. So it is necessary to classify the defect areas. In the research field of metal surface defect classification, the common research method is to train the defect classification model [7] according to the extracted defect features [8].

In this paper extracts 15-dimensional features from the defect areas, and the feature names are shown in Table 1. Then, the SVM [9] classifier is trained according to the extracted features to classify and recognize defects.
Table 1. Feature description.

| Feature number | Feature name                  | Feature number | Feature name                  | Feature number | Feature name                  |
|----------------|--------------------------------|----------------|--------------------------------|----------------|--------------------------------|
| 1              | Defect area                    | 2              | Ratio of length to width width | 3              | Roundness                     |
| 4              | Minimum circumferential circle diameter | 5              | Maximum inside circle diameter | 6              | Minimum circumscribed rectangular area |
| 7              | Perimeter                      | 8              | Minimum gray level             | 9              | Maximum gray level deviation   |
| 10             | Gray scale                     | 11             | Gray mean                      | 12             | Gray scale deviation           |
| 13             | Gray entropy                   | 14             | Anisotropy                     | 15             | Relevance                      |

4. Experimental results and analysis

In order to verify the validity of the surface defect detection method of bearing cylindrical roller designed in this paper, the defect detection experiment is carried out by collecting the surface image of bearing cylindrical roller. The experiment is divided into two parts: defect segmentation experiment and defect classification experiment.

4.1. Defect Segmentation Experiment

The samples used in the experiment consist of four types: defect-free, pit defect, scratch defect and spot defect. Each type has 300 samples, totaling 1200 samples. According to the detection process designed in Chapter 3, the steps of bearing roller area extraction, noise reduction and defect area detection are carried out.

According to the WOV algorithm, after completing the defect area segmentation step, the statistical analysis of the segmentation results shows that the WOV algorithm can completely and accurately identify the defect-free samples in 1200 experimental samples, and can accurately segment the defect area of the defect samples. The experiment shows that the method meets the requirements of actual industrial production.

4.2. Defect Classification Experiment

Firstly, according to the feature names in Table 1, feature data were extracted from 900 defect samples.

Then, this paper building a defect classification model based on SVM algorithm, which is divided into three stages: sample set partition, training and testing. The following is a detailed description:

1. Sample set partition: 200 samples were randomly selected for each type of defect, so 600 samples constituted the training set. 50 samples were randomly selected for each type of defect. So 150 samples constituted the validation set. The remaining 150 samples constitute the test set.

2. Training: This paper chooses the ‘one vs all’ way to train multi-class SVM model. The model uses RBF kernel function, and the parameters of the model are determined by grid search and cross validation. Through many experiments, the parameters of the model are determined as follows: $\gamma = 0.1$, $C = 100$.

3. Testing: The performance of the trained defect classification model is tested. After statistics of the test results, the recognition rate of scratches and spots is 99%, and that of pits is 98%. The classification recognition rate of the three kinds of defects can meet the needs of industrial applications.

5. Conclusion

Experiments show that the method of bearing roller surface defect detection based on WOV algorithm designed in this paper can divide defective samples and defect-free samples completely and correctly, and in the subsequent defect sample classification and recognition, it also achieves the accuracy of industrial application. The next research should further improve the classification accuracy of pits, which are relatively small defects. And, in order to improve the robustness of the method proposed in
this paper, the surface defect detection and recognition of bearing cylindrical roller under complex illumination environment should also be studied.

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