Research on Defect Classification and Detection Technology of Image Processing Collected by Computer

Xiaojing Luo and Guangxing Cai*
School of Science, Hubei University of Technology, Wuhan 430064, China
*Corresponding author: xiaojingluo@hbut.edu.cn

Abstract. The paper uses median filter computer algorithms to detect and classify machine component image defects using image processing, pattern recognition and machine vision theories. In the experiment, automatic extraction of defect images and minimization of defect images are completed to reduce processing volume and storage space requirements, and automatically determine defect categories. The article processes the collected defect images, and the experimental results prove that the method can correctly realize the detection of track surface defects and has certain applicability.

1. Introduction
Image processing and visual inspection is an image engineering technology that has developed rapidly in recent years, and has been widely used in various fields of industrial production. In advanced automated production, image inspection technology plays an important role. At present, most bearing factories' machines Component inspection is still dominated by manual inspection, which not only consumes a lot of manpower and material resources, but also cannot ensure the quality of machine components [1]. The traditional detection method for surface defects is manual visual inspection, such as mobile phone covers and casings, and the outer surface of soft-packed lithium batteries. Mobile phone backlight module, LCD screen cell and module semi-finished surface, etc. Based on this research background, the thesis conducts in-depth research on machine component defect detection algorithms based on the characteristics of machine component defect images, adopts image reprocessing methods, uses median filter algorithm to extract defect features and classifies and recognizes, and improves the accuracy of machine component defect detection. And speed, has a certain practical value.

2. The main colour model of the colour image of machine components
Most colour models in use today are hardware-oriented or application-oriented. In image processing, the most common hardware-oriented model in practice is the RGB (red, green, basket) model. The HIS (Hue, Brightness, Saturation) model is more in line with the way people describe and interpret colours. The HIS model and the RGB model can be converted mutually [2]. The following is the calculation formula for converting RGB to HIS:

\[ I = \frac{R + G + B}{3} \]  

(1)
3. Classification of component image defects based on median filter algorithm

The median filter algorithm is the simplest method of defect classification and detection. The transfer function of the degraded system is reversed to achieve defect detection [3]. Its main principle: first understand the degenerate function $H(u,v)$, and then use the degenerate function and the Fourier transform $(G(u,v))$ of the degraded image to calculate the Fourier transform estimate $\hat{F}(u,v)$ of the original image:

$$\hat{F}(u,v) = \frac{G(u,v)}{H(u,v)}$$

(4)

The formula (4) is the so-called inverse filtering. This formula is valid in the absence of any noise, but the observed image is actually noisy, so formula (4) should be changed to formula (5). Where $N(u,v)$ is additive noise.

$$\hat{F}(u,v) = F(u,v) + \frac{N(u,v)}{H(u,v)}$$

(5)

From formula (5), we can get:

$$F(u,v) = \hat{F}(u,v) - \frac{N(u,v)}{H(u,v)}$$

(6)

From equation (6), we can see that if $G(u,v)$, $H(u,v)$, $N(u,v)$ are known, $F(u,v)$ can be obtained, and $F(u,v)$ can be inversely Fourier transformed to get $f(x,y)$, which is the defect classification detection image we want. The above process is the basic processing process of the inverse filtering algorithm. From equation (6), we can see that when $H(u,v)$ is very small, $N(u,v)/H(u,v)$ will become very large, which is equivalent to amplifying the noise a lot, making the effect of defect classification and detection images very poor. In addition, if $H(u,v)$ has a zero point, then at the zero point of $H(u,v)$, $N(u,v)/H(u,v)$ will become infinite, so the image cannot be correctly classified and detected at these points.

As shown in Figure 1, the inverse filter can perform defect classification and detection for the image without adding noise, but the result of the defect classification and detection point spread function must be accurately set. The point spread function of the defect classification detection has the
same parameters as the point spread function of the blurred original image, so the defect classification detection effect is good [4]. If the estimation of the motion parameters is not accurate, the defect classification detection results will be affected. However, after moving pictures with noise are passed through the median filter algorithm, the defect classification detection results are significantly reduced.

Figure 1. Machine component image defect classification detection results under the inverse filtering algorithm

In 1967, Helstrom improved the median filter algorithm and proposed the Wiener filter defect classification detection method, also known as the Wiener filter. It uses the product of a complex quantity and its conjugate equal to the square of the magnitude of the complex quantity [5]. The basic idea of Wiener filtering is to find the demobilization method when the average square error of the original image \( f(x, y) \) and the demobilized image \( \hat{f}(x, y) \) is the smallest. The error is calculated as:

\[
e^2 = E\{(f - \hat{f})^2\}
\]  

(7)

It can be expressed by the following formula:

\[
\hat{F}(u, v) = \left[ \frac{H(u, v)}{|H(u, v)|^2 + \gamma} \right] \cdot G(u, v)
\]

(8)

The steps of the defect classification and detection process using Wiener filter are shown in Figure 2 below.

1. Step 1: Calculate the two-dimensional discrete Fourier transform of image \( g(x, y) \) to obtain \( G(u, v) \);

2. Step 2: Calculate the two-dimensional discrete Fourier transform of the point spread function \( h(x, y) \);

3. Step 3: Estimate the power spectral density \( P_f \) and noise spectral density \( P_n \) of the image;

4. Step 4: Calculate the estimated value \( \hat{F}(u, v) \) of the image by formula (8);

5. Step 5: Calculate the inverse Fourier transform of \( \hat{F}(u, v) \) to obtain the restored image \( \hat{f}(x, y) \).
We use Wiener filtering to restore dynamic blurred images. Usually, we don’t know the power of the signal and noise, but $\gamma$ can be replaced by a constant. When $\gamma = 0$, the Wiener filter is transformed into a standard inverse filter [6]. When $\gamma$ is not equal to 0, although the expansion of noise can be suppressed, the model of defect classification detection is not as accurate as the deconvolution filter, which results in distortion of defect classification detection. The larger $\gamma$ is, the better the effect of suppressing noise, but the defect classification detection is not accurate. From the phenomenon point of view, the image after defect classification detection is blurry. The smaller the $\gamma$, the more accurate the defect classification and detection, but the noise suppression effect is not good. Therefore, the selection principle of $\gamma$ is: if the noise is large, $\gamma$ is appropriately increased, and if the noise is small, $\gamma$ is appropriately reduced. Generally, it is between 0.1 and 0.001, depending on the specific situation. Compared with inverse filtering, Wiener filtering can automatically suppress noise to a certain extent. In the defect classification and detection of dynamic blurred images with noise, Wiener filtering has a better effect. Figure 3 is a comparison diagram of a noisy dynamic blurred image after inverse filtering and Wiener filtering. The Wiener filtering defect classification detection result is obviously better than the inverse filtering.
4. Experimental Design

4.1. Data set
The experimental data set in this article comes from the circuit images taken by industrial cameras on the industrial production line. First, the reference image and the image to be tested are differentially operated to segment the defective areas of the machine components as the data set. Since these machine component defect images are of different sizes, adjust all the image is 100×100pixels. The data set contains 10 types of defects, including breakouts, leaks, defects, open circuits, holes, short circuits, burrs, excess copper, insufficient etching, and wrong punching. Each type contains 184 samples and a total of 1840 images [7]. The entire data set is divided into two subsets, 1480 machine component defect pictures for training and 360 machine component defect pictures for testing.

4.2. Experimental design and comparative analysis
In order to verify the effectiveness of the algorithm in this paper, the method was compared with the recognition methods based on the combination of histogram of directional gradient (HOG), SIFT and SVM, which are commonly used on the production line. The HOG+SVM algorithm divides the normalized 64×32pixels image into 16×16pixels cell units, and divides the gradient direction into 9 intervals. In each unit, the gradient direction of all pixels is in each direction. Histogram statistics are performed on the interval. 2×2 cells form an overlap-shaped block, each block has 16×9-dimensional features, and each picture is represented as 4608-dimensional features, and SVM is used to classify the features [8]. The SIFT+SVM algorithm uses the SIFT algorithm to extract the feature points of the machine component defect image, then uses K-means clustering to obtain the feature vector describing the image, and finally uses SVM to classify it. It can be seen from Table 1 that the HOG+SVM and SIFT+BOW+SVM algorithms currently used on the production line have low recognition accuracy for multiple types of defects and require manual design of machine component defect features. The correct recognition rate obtained by this method is at 96.67%, the accuracy rate has increased by at least 20%. In addition, the feature extraction process does not require manual intervention and is highly adaptive. Experimental results show that the method in this paper is more effective in identifying defects in machine components.
Table 1. Test results of different algorithms

| Type of defect          | HOG+SVM | SIFT+BOW+SVM | Median filter algorithm |
|-------------------------|---------|--------------|-------------------------|
| 0-hole position offset  | 0.5833  | 0.5833       | 0.9167                  |
| 1 leak                  | 0.5833  | 0.75         | 1                       |
| 2 gaps                  | 0.4167  | 0.5833       | 0.9722                  |
| 3 open circuit          | 0.6667  | 0.9167       | 1                       |
| 4 holes                 | 0.1667  | 0.9167       | 0.9167                  |
| 5 short circuit         | 0.8333  | 0.9722       | 0.9722                  |
| 6 glitches              | 0.3333  | 0.5833       | 0.9167                  |
| More than 7 copper      | 0.4167  | 1            | 1                       |
| 8 Insufficient etching  | 0.6667  | 0.75         | 1                       |
| 9 wrong hole punch      | 0.8333  | 0.5833       | 0.9722                  |
| Total correct rate      | 0.55    | 0.7639       | 0.9667                  |

5. Conclusion
The paper designs a median filter algorithm for machine component defect recognition. The experimental results show that the detection method proposed in this paper has a correct recognition rate of 96.67% for the type of machine component defects. Compared with the traditional method, the recognition accuracy rate is greatly improved. This method has good adaptability and real-time performance, provides an effective solution for the on-line detection of machine component image defects, and has broad application prospects.

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