Real-Time Detection Method for Surface Defects of Stamping Parts Based on Template Matching*

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Abstract. A defect detection method based on template matching is proposed in the environment of detection of stamping parts in industrial manufacturing. Contours of the part can be obtained by the edge detection algorithm, therefore, we can calculate the deviation matrix of the input image and the standard image by establishing the template feature library of these contours. Then, Compare the deviation matrix and the feature of the contour in the defect position which is confirmed by using two threshold filters to realize the automatic detection of the surface defect of the part. In addition, algorithms include filtering noise reduction and curve fitting are used to improve the overall quality of this detection method. Experiment results show that the surface defect detection method based on template matching has advantages of high adaptability and low time complexity. The accuracy rate of the optimized algorithm can reach over 95\% in case that the number of templates is sufficient. The algorithm is suitable for real-time detection of industrial assembly line manufacture.

1. Introduction

With the popularization of computer technology, the use of machine vision technology to detect the defect of products is playing an increasingly important role in industrial production. At present, domestic technology in this aspect has a great gap with foreign countries no matter depth and breadth. The domestic experiment of defect detection is mainly based on mathematical morphology. For example, the sub-pixel edge detection method is used to detect burrs, cracks, etc. of parts. This method has the advantage that it has high precision and can find defect which is difficult to be observed by naked eyes, and is suitable for accurate detection; however, its disadvantage is that the algorithm has high time complexity and requires long detection time. There is also the use of closed operations in morphology to detect burrs and breakage at the edge of the part. Although this method is more efficient than the former, it is susceptible to environmental. Furthermore, this method is still in the stage of experimental demonstration, and not verify algorithm on the production line. Consequently, this paper proposes a new method based on contour feature matching to detect surface defects such as leakage, whole deformation and defects in stamping parts in real time.
2. Pre-process of the digital image

Before detecting the surface defect of stamping parts, it is necessary to pre-process input original images by graying, de-noising, edge detecting, etc. Pre-processing plays a crucial role in improving the accuracy of defect recognition. For example, we use the canny edge extraction algorithm to the original input image (Figure 1.(a)) directly and found a large amount of noise around edges (Figure 1.(b)). The reason for this phenomenon is that the surface of the stamping part is contaminated with a lot of oil in the industrial site. Moreover, there are also some dents and textures on the surface of the test belt. Figure 1. (c) shows the result of canny edge extraction after using Gaussian filtering algorithm. It can be seen from the figure that the effect of the edge extraction is good, and basically had no noise around edges.

![Figure 1](image1.png)

**Figure. 1** Comparison of edge extraction effects after image preprocessing: (a) the original image. (b) Edge image extracted without noise reduction. (c) edge image extracted after noise reduction.

Some pictures (Figure 2. (a)), even after Gaussian noise reduction processing, will produce noise of different sizes and unequal numbers after the edge extraction (Figure 2.(b)). Therefore, it is necessary to eliminate the influence of the background noise of the picture. This article uses a noise reduction method that removes the foreground by edge filling.

![Figure 2](image2.png)

**Figure. 2** Background with more serious interference: (a) original image. (b) contour image after Gaussian noise reduction.

To eliminate the effects of noise completely, a black filling (0) is required inside the largest contour of the stamped part. Then compare the grayscale image with the filled image: If the pixel value of a point in the filled image is not 0, the pixel value of the corresponding position is set to 255 (white) in the grayscale image. This method eliminates out-of-contour noise (Figure 3).

![Figure 3](image3.png)

**Figure. 3** The process of eliminating background noise: (a) grayscale image. (b) filled image. (c) noise reduction image.

3. Establishment of the Template Library

In this paper, the surface defect detection is based on the template matching method. Therefore, it is necessary to establish a standard template library with features of stamping parts.
3.1. The construction process of the template library

The purpose of the template library is to analyze a number of standard stampings in real time, we need to calculate the whole feature values and other parameters of these stamping parts, and store them in the database for later use. The flow chart is as follows:

![Flowchart of establishing the template library.](image)

**Step1**: Parameter initialization.

The parameters are divided into two classes: One class of parameters are basic parameters, including the number of stamping parts, the number of contours (N), and the number of stamping parts used to build the template library (M). The other type of parameters is eigenvalue required to construct the template library, including the area (a) perimeter (l) circularity (c) of the contour. And they are stored in the form of matrices as $A = (a_{ij})_{m \times n}$, $L = (l_{ij})_{m \times n}$, and $C = (c_{ij})_{m \times n}$. The circularity is defined as follows:

$$c = \frac{4\pi S}{l^2}$$

It can be known from the definition of circularity that a circle has a circularity of 1, and a square has a circularity of $\pi/4$. Consequently, the use of the circularity as the third eigenvalue can distinguish the circular contour well from the other contours.

**Step2**: Calculate the eigenvalues of all the contours of the stamped part and number the contours.

To facilitate matching, all contours are numbered in increasing order of perimeter. Then read the next picture and repeat the above steps.

3.2. Statistical analysis of eigenvalue

Eigenvalues of contours change as its position in the field of view changes. We can use the mean value and standard deviation to eliminate the data with large deviation and get the error range of the eigenvalue required for detection. Thus, we need to analyze the data as follows:

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The mean matrix \( \overline{X} \) and the standard deviation matrix \( \sigma \) of corresponding eigenvalues are obtained for each contour of stamping parts. Where

\[
\overline{X}_n = (\overline{x}_n)_{nx1}, \quad \sigma_n = (\sigma_n)_{nx1}
\]

\[
\overline{X}_l = (\overline{x}_l)_{nx1}, \quad \sigma_l = (\sigma_l)_{nx1}
\]

\[
\overline{X}_c = (\overline{x}_c)_{nx1}, \quad \sigma_c = (\sigma_c)_{nx1}
\]

Set the error range matrix \( \Delta \) and filter the feature values twice. We choose \( \Delta = \overline{X} + 4\sigma \) for the error range. Then, starting from the number of the stamping part \( (m=1) \), sequentially judge whether the corresponding eigenvalue is within the range of \( \Delta \) until \( m = M \). If it is out of the error range, the value is rejected. The process is repeated twice to get the final range matrix and used as a reference range in defect detection.

4. Surface defect detection

We need different methods for different types of defects (such as stamping-missing, Hole deformation) detection and judgment. This section discusses the framework and internal modules of the specific detection method. This detection method is also applicable to defect detection of other similar objects. It has good applicability and expandability, which is the core of this paper. The defect detection algorithm is mainly divided into two steps.

4.1. Preliminary screening

Preliminary screening is mainly to solve the problem of leakage punching. The process is as follows:

If the number of contours is smaller than the number of contours of the template \( (n < N) \), it is judged that the defect is stamping-missing, and no subsequent calculation is needed, then output the result directly. If the number of contours is greater or equal to the number of contours of the template \( (n \geq N) \), then we should analyze the contours one by one through template matching and enter the next step to find the problem contour.

4.2. Contour analysis and template matching

In order to match the contour number of the stamped part to be tested with the contour number in the template library, we use the same method (see 2.1) to number the contours.

For a test stamping part \( sp_1 \) (Figure 5), calculate the eigenvalue of each contour. The analyses of its contours as follows:

![Figure 5](image)

**Figure. 5** Test part \( sp_1 \): (a) original image. (b) contour image.

| Contour   | \( a \)     | \( b \)     | \( c \)     |
|-----------|-------------|-------------|-------------|
| Contour1  | 872.500     | 110.326     | 0.900       |
| Contour2  | 991.000     | 118.569     | 0.813       |
| Contour3  | 991.000     | 119.397     | 0.874       |
| Contour4  | 1069.500    | 122.811     | 0.891       |
| Contour5  | 1113.000    | 125.397     | 0.889       |
| Contour6  | 3400.000    | 950.975     | 0.047       |
| Contour7  | 187104.000  | 1183.890    | 0.781       |

**Table. 1** Contour information of \( sp_1 \).
The information in the error table of the template library matching the stamping \( sp_1 \) is as follows:

**Table. 2 The error range of \( sp_1 \).**

| Contour1 | … | Contour7 |
|----------|---|----------|
| a | l | c | … | a | l | c |
| Min | 872.145 | 108.938 | 0.882 | … | 86852 | 1055 | 0.766 |
| Max | 874.333 | 111.751 | 0.907 | … | 89014 | 1397 | 0.789 |

The detection algorithm judges eigenvalues of each contour, in turn, to determine whether they are between the minimum and maximum values. For example, the perimeter of the contour 1 is 110.325, which satisfies \( 108.938 \leq 110.325 \leq 111.751 \), thus the algorithm confirms that the perimeter of the contour No. 1 has no problem. The circularity of the contour 2 is 0.813, smaller than 0.878 in error table. At this time, the algorithm finds that there is a problem with the contour 2, and \( sp_1 \) is judged to be defective.

The algorithm requires a simple classification of these contours. When the stamped part detects defects, it is necessary to output the type of defect contour.

From the data analysis of \( sp_1 \), the contour 7 has the largest perimeter, so it is the edge contour, and the contour 6 has the smallest circularity and is less than 0.1, which is the least like a circle, so it is judged to be the curved contour in the middle. The contour 1, contour 2, contour 3, contour 5, and contour 6 have little difference in perimeter, area, and circularity, so these five are circle contours. Contours are classified according to the following criteria.

**Table. 3 Classification of contours.**

| Type            | Judgment conditions                        |
|-----------------|--------------------------------------------|
| Circular contour| Area less than 1300 and circularity greater than 0.8 |
| Edge contour     | Area greater than 75000                    |
| Curved contour   | Circularity less than 0.1                  |

In the experiment, we use 50 and 100 standard templates to initialize and use 30, 50 and 100 test parts. The results are as follows:

**Table. 4 50 standard templates (unoptimized).**

| Number of test parts | Correct | Error | Accuracy |
|----------------------|---------|-------|----------|
| 30                   | 24      | 6     | 80.0%    |
| 50                   | 39      | 11    | 78.0%    |
| 100                  | 82      | 18    | 82.0%    |

**Table. 5 100 standard templates (unoptimized).**

| Number of test parts | Correct | Error | Accuracy |
|----------------------|---------|-------|----------|
| 30                   | 26      | 4     | 86.7%    |
| 50                   | 44      | 6     | 88.0%    |
| 100                  | 87      | 13    | 87.0%    |

After analyzing the results, we find that the more numbers of standard templates, the higher accuracy. The reason is that with the increase of the standard data, the error range is becoming more reasonable, and have the stronger anti-interference ability. However, due to the large error in the contour matching process of the circular hole, the accuracy is not higher than 90%.
5. Experiment analysis

5.1. Improvement of Defect Detection Algorithm

Although the program has realized the function of detecting defects, after the automatic online inspection process test, we found that in the actual situation, stamping parts will rotate at any angle in the image, or flip. This results in a large variation range of the eigenvalue of each circular contour, hence the small defects are difficult to identify that misjudgment may occur. In particular, several circular contours that the sizes are similar are located at different positions of the stamping parts, so the influence of the deformation of stamping parts at different positions in the image is large. Therefore, we need to improve the above issues as follows:

We use the circular fitting method to fit the circular contour in the stamping parts. Firstly, the effective contour point is selected by the standard parameter \(\text{mean} + 4 \times \text{variance}\), and the circular fitting algorithm repeat twice, the second fitting use new standard parameter \(4 \times \text{means}\) to select the point. The detailed steps are as follows:

- Use least squares circle fitting algorithm on all contour points of the circular contour;
- Calculate the distance \(d\) from each contour point to the center of the circle and calculate the difference \(\Delta\) between the distance \(d\) and the radius \(R\):
  \[
  \Delta = |R - d|
  \]
- Calculate the mean \(\bar{x}\) and the variance \(S^2\) of \(\Delta\), and set the contour points that smaller than the threshold \((\bar{x} + 1.55^2)\) as the valid points;
- Use least squares circle fitting algorithm a second time on all valid contour points;
- Calculate the distance from all contour points to the quadratic circle \(d_2\) and calculate the difference \(\Delta_2\) between the distance \(d_2\) and the radius \(R_2\):
  \[
  \Delta_2 = |R_2 - d_2|
  \]
- Calculate the mean \(\bar{x}_2\) of \(\Delta_2\), and determine the contour points that larger than the threshold \(4\bar{x}_2\) as a defect and mark it;

The detection algorithm can effectively identify the whole defect after optimization. Furthermore, it can avoid the misjudgment because of the elliptical holes. The effect is as follows:

![Figure 6 Fitting of circular contour.](image)

5.2. Analysis of experimental results

The environment of the experiment is: Windows XP, 4GB memory with CPU Core i5 6500, 3.2GHz. A circular fitting detection part is added to the defect detection algorithm. The test results are as follows:

| Number of test parts | Correct | Error | Accuracy |
|----------------------|---------|-------|----------|
| 30                   | 28      | 2     | 93.3%    |
| 50                   | 46      | 4     | 92.0%    |
| 100                  | 95      | 5     | 95.0%    |
Table. 7 100 standard templates (optimized)

| Number of test parts | Correct | Error | Accuracy |
|----------------------|---------|-------|----------|
| 30                   | 29      | 1     | 96.7%    |
| 50                   | 48      | 2     | 96.0%    |
| 100                  | 96      | 4     | 96.0%    |

The comparison between the optimized accuracy and the unoptimized is as follows:

Table. 8 Effect of optimization.

| Number of test parts | Unoptimized 50 templates | Unoptimized 100 templates | Optimized 50 templates | Optimized 100 templates |
|----------------------|---------------------------|---------------------------|------------------------|-------------------------|
| 30                   | 80.0%                     | 90.0%                     | 93.1%                  | 96.5%                   |
| 50                   | 79.1%                     | 88.7%                     | 91.8%                  | 95.7%                   |
| 100                  | 81.4%                     | 88.5%                     | 94.8%                  | 95.8%                   |

The optimization effect of the algorithm is obvious. Whether using 50 or 100 templates for initialization, the accuracy of the final detection is above 90%. However, there are still misdetections. The two main reasons are: (1) some test parts are close to the edge of the field so that the captured image is dark, this causes the reduction of the edge extraction accuracy, and the obtained data has a large error with the actual. (2) Some parts will have a large deformation because they are too far from the field. Therefore, the circular contours will become elliptical, which causes the circularity of the hole to be greatly different from the template. False defects occur even with a circular fitting.

6. Conclusion

This algorithm is not mature that the detection rate hardly reaches 100%. In the process of detection, false detection, missed detection will happen. The main reason for these problems is that the mechanical structure of the experimental device is unstable, and the environment of the industrial site is rather harsh, which makes it difficult to position the stamping parts in the field to be the same every time. On the other hand, the detection algorithm is not perfect enough, the accuracy of detection needs to be improved. The improvement direction in future is mainly to improve the algorithm, to design a more stable algorithm that can detect more subtle defects with high accuracy. In addition, we can start from the bottom layer that considers using multi-threaded computing to improve the speed of the detection system. Especially for those industrial environments of pipeline production, the improvement of the detection efficiency undoubtedly greatly increases the production efficiency, thereby improving the practicability of the system.

The design of this defect detection method has applied computer vision technology to industrial production. At the same time, it can also be used in similar fields, such as industrially produced screws and nuts and has a good application prospect as well.

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