

Machine Vision-Based Chamfer Detection for Metal Parts

Shangying Han^{1*}, Kaili Guo¹, Yanzi Kong¹, Yanliang Gong¹, Junjin Chen², Ce Bian³, Mengfan Zhang³

¹ *Tianjin University of Science and Technology, Tianjin, China*

² *SMC (Beijing) Manufacturing Co., LTD., China*

³ *Tianjin Tianke Intelligent Manufacture Technology Co., LTD., China*

E-mail: * hsy_011023@163.com

Abstract

This paper introduces a detection system specifically designed for chamfering in metal holes, aimed at achieving precise detection of the chamfers. Chamfering, as a process of beveling the edges or corners of metal parts, plays a crucial role in the subsequent machining and assembly stages. Through multiple experimental validations, this paper employs an industrial camera with a telecentric lens to capture images of the metal chamfers, achieving optimal results. This paper utilizes computer vision techniques to accurately identify the location of the chamfers and delineate their dimensions. A comprehensive analysis of the chamfer radius effectively determines the presence of defects.

Keywords: visual inspection, machine learning, image segmentation, contour curve

1. Introduction

Metal, as one of the main raw materials for industrial products, inevitably develops various defects during the manufacturing process, such as scratches, dents, thread hole residues, and lack of chamfering [1, 2]. These defects not only affect the appearance of the product, but more importantly, they also impact its performance. Therefore, defect detection of parts during industrial production is essential [3]. Traditional manual inspection methods are prone to missing or incorrect detections, and they are inefficient and costly, which does not meet the demand for automated and rapid inspection [4, 5]. Thus, this paper employs machine learning to process captured images for automated defect detection.

This paper explores the fundamental methods for automated chamfer defect detection. The approach involves capturing images using a light source and an industrial camera under varying angles and light intensity conditions to determine the optimal imaging setup. Computer software, combined with machine vision technology, is employed to segment the acquired images. Defect features within the region of interest are extracted, and the outer contour of the features is fitted into a circular shape. The radius of the feature circle is used to precisely determine whether the chamfer is defective. This ensures efficient and accurate automated detection [6].

Based The content of this paper is organized as follows. The second section introduces the methods for image acquisition and the main theories of image processing. The third section describes the three stages of this project: data acquisition, image processing, and data validation. The fourth section provides a summary and conclusion of the main content of the paper.

2. Methods

For camera preparation, the selection of the camera type must consider both practical engineering requirements and economic efficiency. In this project, the RS-A2300-GM60-M10 model was carefully chosen based on the required chamfer size range and defect depth specifications. This camera meets technical requirements with its suitable resolution and depth of field. As a CMOS camera, it also aligns with economic considerations. It provides high-quality image data for subsequent image processing and analysis, ensuring the accuracy and reliability of defect detection [7].

When selecting a light source, it is essential to enhance the contrast between defects and their surroundings to highlight target features. A clear distinction should be created between the inspected and non-inspected parts of the object to improve contrast. The chosen light source must provide sufficient brightness and stability when illuminating the object. Additionally, the effects of light source color, camera type, and light source position on image acquisition must be considered [8-10]. Based on multiple experimental tests, a white ring light source (XHJ-R-35-90-W) was selected for this study. The detailed placement method is shown in Fig.1.

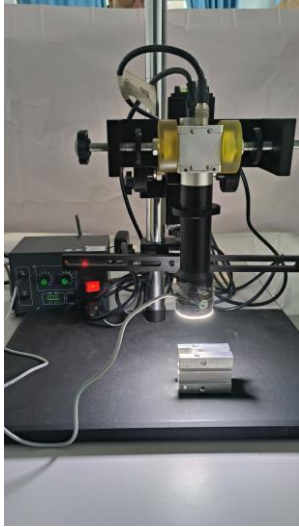


Fig.1 Photographic setup

In the chamfer inspection process, the core objective is to determine whether the target hole has undergone chamfering. Through photographic observation and analysis, it was found that the presence or absence of chamfering leads to significant differences in the radius of the outer contour circle. Holes with chamfering exhibit an increased outer contour circle radius. Based on this feature, various technical methods can be applied to accurately extract the radius data of the outer contour circle. By analyzing the size of this radius, it is possible to accurately determine whether the hole has been chamfered.

2.1. Region of interest (ROI) selection

In the field of machine vision and image processing, the critical area of interest within an image, defined by a rectangle, circle, ellipse, or irregular polygon, is referred to as the ROI. By explicitly specifying the image area to be processed, the ROI effectively reduces the amount of data handled by algorithms, significantly enhancing detection speed and efficiency. Focusing on specific areas also eliminates interference from irrelevant signals in the image, improving detection accuracy and reducing errors. In chamfer detection, creating ROI regions for key positions not only accelerates the detection process but also minimizes the influence of unrelated factors, making the detection process more efficient and precise.

2.2. Extraction method of detection images

The image is initially processed using a thresholding method, where the grayscale features of the image are used to calculate grayscale segmentation thresholds to segment the image. The theory involves comparing the grayscale value of each pixel with the threshold, and based on this comparison, the image is segmented. In this experiment, two fixed thresholds, T_1 and T_2 , are used to binarize the image.

$$Out(x, y) = \begin{cases} 255 & T_1 \leq p(x, y) \leq T_2 \\ 0 & \end{cases} \quad (1)$$

Grayscale inversion is a widely used technique in image processing that effectively changes the light and dark

distribution patterns of an image. Through this operation, the bright areas of the image are transformed into dark regions, while the originally dark areas become bright [11]. Implementing grayscale inversion not only helps to more clearly highlight the ROI, but also provides significant convenience for subsequent image segmentation and morphological processing steps.

$$Out(x, y) = 255 - p(x, y) \quad (2)$$

The image domain reduction operation limits the content of the input image to a specified ROI. It reduces the domain of the input image to the portion that intersects with the defined ROI, without changing the actual size or matrix dimensions of the image. This allows processing to focus on the target area while ignoring irrelevant elements, thus improving processing efficiency. By excluding the background region, it reduces the influence of background noise and focuses on the foreground area, which helps to enhance the accuracy of the algorithm.

$$I_{reduced}(x, y) = \begin{cases} I(x, y), & \text{if } R(x, y) = 1 \\ 0, & \text{if } R(x, y) = 0 \end{cases} \quad (3)$$

2.3. Chamfer contour extraction method

In the algebraic method for circle fitting based on XLD contours, the contour of the circle is fitted by minimizing the algebraic distance between the contour points and the fitted circle. This process aims to find the best circle and output its radius and center coordinates [12]. The algebraic distance refers to the squared difference between a contour point and the corresponding point on the fitted circle. The method iteratively adjusts the circle's center coordinates and radius, optimizing the fitting process. This optimization minimizes the sum of the algebraic distances from all contour points to the fitted circle, resulting in the best circle fit. The radius of the fitted circle represents the radius of the chamfered contour. By evaluating the size of this radius, it is possible to detect whether the chamfer is present. The formula for the algebraic distance is as follows:

$$L_i = (x_i - a)^2 + (y_i - b)^2 - R^2 \quad (4)$$

To find the minimum value, an iterative method is used. The values of a , b , and R (representing the circle's center coordinates and radius) are continuously adjusted until the target value becomes sufficiently small or converges to a stable solution. This iterative process refines the circle's parameters by minimizing the algebraic distance, ensuring an optimal fit. The algorithm proceeds until the change in the parameters is negligible or the stopping criterion is met, resulting in the most accurate circle fitting for the given contour.

$$F(a, b, R) = \sum_{i=1}^n [(x_i - a)^2 + (y_i - b)^2 - R^2]^2 \quad (5)$$

3. Experimental Data and Experimental Procedure

This project consists of three core stages: the data acquisition stage, the image processing stage, and the data validation stage.

3.1. Experimental data collection

In this study, the RS-A2300-GM60-M10 industrial camera, along with a ring light source, was used to perform multiple systematic image acquisition tasks on various types of workpieces. The captured image data were immediately transmitted to the computer system for in-depth analysis and processing using Halcon machine vision software. Through comprehensive comparison and analysis of the datasets obtained under different shooting conditions, the optimal experimental data were selected. The purpose of this process was to adjust the shooting parameters and find the optimal position, providing a foundation for subsequent image processing.

3.2. Image processing steps

After the image is captured by the camera (Fig.2), it is transmitted to the computer for processing. The image is then analyzed using code to detect any defects.

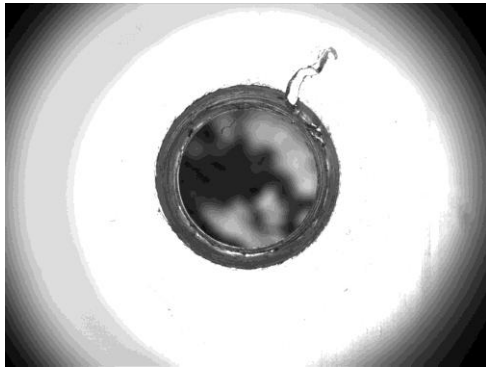


Fig.2. Captured image example

The specific flowchart is as follows (Fig.3):

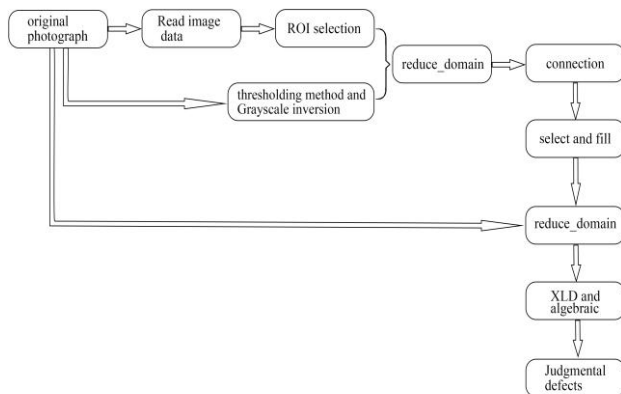


Fig.3. Image processing flowchart

(1) Selection of ROI.

The image is imported into dedicated software for subsequent precise analysis and processing. The first step is to extract the basic properties of the image, namely its size, which is represented by the total number of pixels. This step is crucial for positioning and setting the scale for the following operations. After determining the optimal shooting position, a circular ROI with a fixed radius is defined, centered on the middle of the image. This selection of the ROI not only simplifies the analysis but also focuses on the most informative part of the image, thereby improving the accuracy and efficiency of the analysis. Next, the image domain is reduced using the domain reduction operation, and the image (Fig.2) is cropped to the previously selected ROI. This effectively removes background or redundant information unrelated to the subsequent analysis, making the process more focused and efficient. The extraction result is shown in Fig.4.

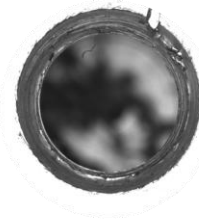


Fig.4. ROI extraction

(2) ROI Processing

After extracting the ROI, the next step is to further process this area. In the initial stage, since the selected radius is relatively large, it is necessary to remove unnecessary parts within the ROI to effectively eliminate potential interference. A thresholding operation is applied to the image (Fig.2) to identify and select the threshold range corresponding to the parts unrelated to the ROI. This step helps to distinguish the unrelated areas from the ROI. Next, a grayscale inversion is applied to the image. The purpose of this operation is to invert the grayscale values, which facilitates a subtractive effect during the subsequent domain reduction operation. This makes it easier to separate the ROI from surrounding unrelated parts more clearly. Finally, the grayscale-inverted area is combined with the original ROI for domain reduction. This step essentially performs an initial processing of the ROI. By reducing the domain, the interference from irrelevant areas surrounding the ROI is effectively removed, allowing for precise extraction and purification of the ROI. The result is shown in Fig.5.

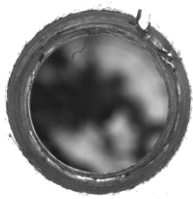


Fig.5. Captured image example

(3) Contour extraction preparation

After the initial processing of the Region of Interest (ROI), a connection region operation was applied to further process the image, separating the sub-regions within the ROI. This allowed each region to be processed individually (Fig.6). The area of each region was then calculated and sorted based on size. The area calculation not only provides information about the scale of each region but also serves as a basis for subsequent feature selection. To effectively exclude interference from unrelated areas, the top five regions were selected based on their area size as feature items (Fig.6). To facilitate the following contour extraction and feature analysis, the selected top five regions were filled and merged into a single unified region (Fig.6). This step not only simplifies the contour extraction process but also enhances the accuracy and efficiency of feature extraction. Finally, a domain reduction operation was applied again, reducing the domain of the image (Fig.2) and the filled regions. This allowed the features of the processed ROI to be extracted efficiently (Fig.6).

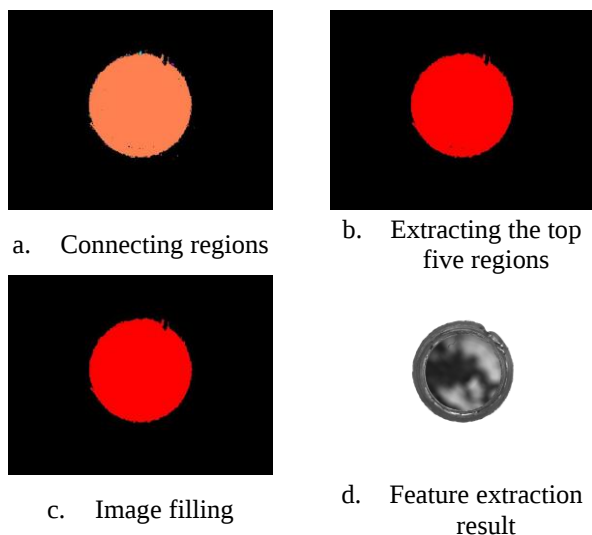


Fig.6. Preparation process

(4) Contour extraction

After the features are extracted, the next step is to obtain the boundary of the inner region. The boundary region is then used to define the contour points by selecting the outermost boundary pixels. An XLD contour is created based on these boundary points. Finally, an algebraic

method is applied to fit a circle to the contour (Fig.7), and the relevant values of the fitted circle, such as the radius, are used as key parameters to determine whether the chamfer has any defects.

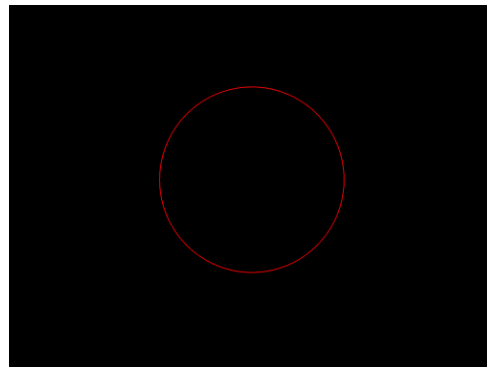


Fig.7. Captured image example

3.3. Extensive experimental data validation

After the code development was completed, it was crucial to validate its correctness and reliability. To ensure the comprehensiveness and rigor of the experiment, a large amount of experimental data was used for verification. The actual radius of the workpiece holes captured in the experiment was 2.8 mm (including the chamfer, Approx. pixels 302), with images taken using the RS-A2300-GM60-M10 camera at a resolution of 1600×1200 pixels. A subset of metal hole images was selected as test samples to assess the performance of the code in real-world applications. The experimental data used is detailed in Table 1, which provides an overview of the test samples

Table 1. Overview of selected experiments

Image	Theoretical Contour Radius (in Pixels)	Detected Contour Radius (in Pixels)	Chamfer Detection Results
	302	270.243	Without Chamfer
	302	267.669	Without Chamfer
	302	267.838	Without Chamfer
	302	265.173	Without Chamfer
	302	319.672	With Chamfer
	302	318.11	With Chamfer
	302	323.58	With Chamfer
	302	319.137	With Chamfer

4. Conclusion

This study explores the use of industrial cameras and ring light source technology to capture clearer images of chamfer defects. Advanced machine vision processing methods are then applied to these images for detailed analysis. By precisely defining the ROI, utilizing appropriate threshold settings and grayscale inversion techniques, key information is effectively extracted from the images. Finally, an accurate circle fitting algorithm is used to calculate the outer contour radius of the metal holes. This key parameter provides important support for determining whether chamfer defects are present.

This research holds significant practical value in the field of industrial vision inspection. It not only improves the accuracy and efficiency of chamfer defect detection but also provides strong technical support for the quality control of industrial products. By continuously optimizing the image acquisition and processing workflow, a more intelligent and automated industrial inspection system is expected to be achieved in the future, contributing to the transformation and upgrading of the manufacturing industry.

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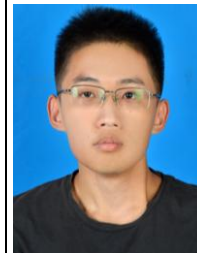
Authors Introduction

Mr. Shangying Han



He is currently a university student in Tianjin University of Science and Technology. His research area is about mechanical learning and image processing.

Mr. Kaili Guo



He is currently a university student in Tianjin University of Science and Technology, studying mechanical automation and related fields. His research areas are machine vision and image processing.

Ms. Yanzi Kong



She is a lecturer at Tianjin University of Science and Technology. She received her PhD from the University of Chinese Academy of Sciences. Her primary research interests lie in machine vision and active perception.

Mr. Yanliang Gong



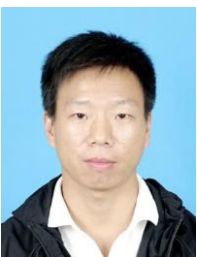
He is currently a university student at Tianjin University of Science and Technology, with an interest in the field of robotics. His current research areas are machine vision and image processing.

Mr. Junjin Chen



He received his bachelor's degree in Mechanical Design, Manufacturing and Automation from Beijing Union University in 2014. His research interests are industrial automation and robotics. From 2005 to 2007, he worked at Beijing Aeronautical Manufacturing Engineering Research Institute. Since September 2007, he has been working at SMC (Beijing) Manufacturing Co., LTD., China.

Mr. Ce Bian



He received his master's degree in control engineering from Tianjin University of Science and Technology in 2019, focusing on machine vision technology. Since 2017, he has been working in Tianjin Tianke Intelligent Manufacture Technology Co., LTD., serving as the general manager.

Ms. Mengfan Zhang



She received her bachelor's degree in financial management from Zhengzhou College of Commerce in 2019. She specializes in machine vision technology. Since 2019, she has been working as a visual engineer in Tianjin Tianke Intelligent Manufacture Technology Co., LTD., China.