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Review of Defect Detection Methods for Thin-Walled Parts Based on Point Cloud Data Processing

Yuan Cao[1, a], Yongxiang Jiang[1, b], Chaofan Hong[1, c], Yanxi Guo[1, d], Yuanlong Xu[1, e], Jiayi Li[1, f]

[1]School of Mechanical Engineering, Tianjin University of Technology and Education, Tianjin 300350, China

[a]3238330442@qq.com, [b]214579510@qq.com, [c]1919742227@qq.com, [d]1244420211@qq.com, [e]3094943674@qq.com, [f]3343707068@qq.com

Abstract

Thin-walled parts are widely used in various fields of industrial production, but their inherent characteristics, such as low stiffness and susceptibility to deformation, make them prone to various defects during use. Thin-walled covering parts, which serve as thin shells or covers to protect other components, are extensively utilized in aerospace, automotive, and shipbuilding industries. The condition of these parts is directly related to the structural integrity, performance stability, and operational safety of the associated components and equipment. Due to their direct exposure to external environments, thin-walled covering parts are vulnerable to damage. Traditional defect detection methods, such as manual visual inspection and 2D imaging, have limitations in addressing these challenges. To improve the speed and accuracy of damage detection in thin-walled covering parts, this paper proposes a defect detection method based on point cloud data processing. This approach involves collecting point cloud data of the thin-walled parts, applying preprocessing techniques to remove noise, and utilizing feature extraction and machine learning algorithms to achieve automatic detection and classification of defects. The research results demonstrate that this method offers high accuracy and efficiency, effectively meeting the quality inspection needs for thin-walled parts in industrial production.

Keywords

Point Cloud Data Processing; Thin-Walled Parts; Defect Detection; Machine Learning.

1. Introduction

In recent years, with the rapid development of manufacturing and industrial automation, defect detection for thin-walled covering parts has become an indispensable aspect of industrial inspection. Thin-walled covering parts may suffer from various types of damage during use, such as dents. These dents can lead to severe stress concentration at the damaged areas, weakening the fatigue resistance of the parts and causing the damaged area to expand further, thereby having a significant impact on the thin-walled covering parts. Accurate detection of surface defects in thin-walled covering parts is therefore crucial for subsequent repairs.

2. Existing Defect Detection Technologies

Machine vision technology for defect detection can be categorized into two major types: the one is 2D Image Detection Methods, these are suitable for detecting common defects such as scratches, printing character defects, and texture loss. However, these methods cannot capture depth information about the defects. The other is 3D Vision Detection Technology, and this

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method involves scanning the object under inspection and then analyzing the point cloud data obtained from the scan to identify and extract defect areas. It can capture significant 3D features of the object, such as depth and height, and can accurately reflect the shape and structure of the defects.

The 3D measurement technology can be divided into two categories currently: contact and non-contact methods, as shown in Fig. 1.

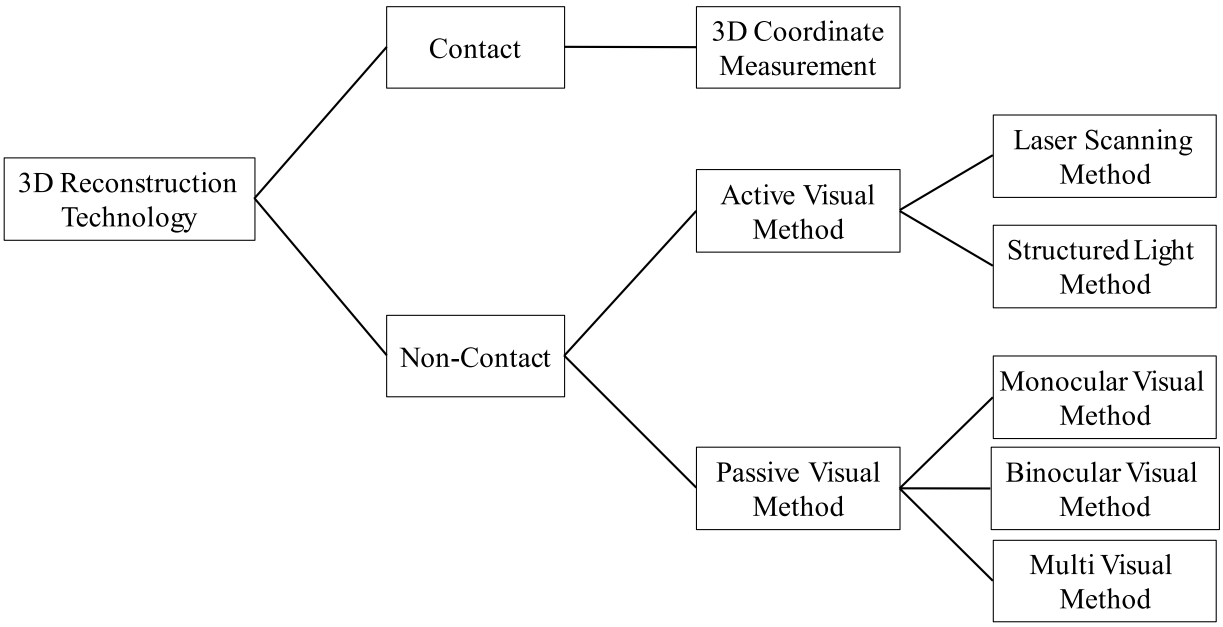

Figure 1. Measurement Methods Classification

2.1. Contact measurement method

Traditional contact measurement methods are influenced by the surface shape of the object being measured and can only detect specific measurement points. This makes it difficult to comprehensively reflect the overall dimensional errors of the object, which limits the effectiveness of using the dimensional data in subsequent processing stages and can lead to inaccurate measurement results. The coordinate measuring machine (CMM), which offers relatively high precision among contact measurement methods, operates by moving a probe along the X, Y, and Z axes and calculating dimensional information based on the coordinate data. However, this method requires strict control of the operating environment, which limits its application in 3D measurement.

2.2. Non-contact measurement method

Non-contact measurement technology involves using sensors or devices that interact with the object being measured through methods such as optical, laser, ultrasonic, or electromagnetic waves to obtain measurement data related to the object's dimensions, shape, or surface characteristics. This technology is characterized by its speed, high precision, and stability, significantly overcoming the drawbacks of contact measurement methods, and it has been widely adopted in many application fields.

Currently, the most commonly used non-contact measurement methods are optical-based, which can be further categorized into two main types: active visual methods and passive visual methods.

(1) Active visual method

Active visual methods involve using specially projected light sources to achieve detection. These methods work by capturing the light that is reflected or scattered between the workpiece

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and its environment, enhancing the 3D information of the workpiece's surface and analyzing the light's characteristics to achieve detection. Active vision methods generally include laser scanning and structured light methods.

a) Laser scanning method: this technique obtains the 3D shape and spatial position of the target object by emitting and receiving laser beams and applying principles of time or phase measurement. It has the advantage of fast detection speed but comes with high equipment costs and requires complex data processing and analysis.

b) Structured light method: the principle behind this method involves setting up a detection system composed of the object being measured, a projector, and a camera. The system projects an encoded structured light pattern onto the surface of the workpiece. The camera then captures the structured light information from the workpiece’s surface, and by calculating this information, the depth of each point on the workpiece’s surface can be derived. In early research on structured light, Takeda[1] incorporated Fourier calculations into the spatial frequency information of the gratings used, improving measurement resolution.

(2) Passive visual method

Passive visual methods involve using visual sensors to capture images of a workpiece under natural lighting conditions without the need for additional light sources. These images are analyzed to extract various features, and appropriate algorithms are used to obtain 3D information about the object being measured. Based on the number of cameras used, passive vision methods can be classified into three categories: monocular, binocular, and multi-view vision methods.

a) Monocular visual method: this method uses a single camera to capture information about the workpiece, such as brightness and contours, and then calculates the 3D depth data of the workpiece based on these features.

b) Binocular visual method:this approach involves a vision system composed of two cameras (left and right), which simulates human binocular vision to capture more depth information. The two cameras simultaneously capture images of the workpiece from different angles, allowing for the measurement of 3D data. In the field of computer vision, in 2010, Zhao[2] and colleagues developed a binocular vision measurement system capable of simultaneously measuring the surface perimeter of several 3D workpieces. Experiments measuring the curved surface perimeter of four workpieces demonstrated that the system could achieve an accuracy of 0.7 millimeters. However, binocular cameras can be easily affected by the ambient lighting conditions during operation, and they do not perform well when measuring workpieces with repetitive textures.

c) Multi visual method: this method addresses issues encountered in binocular vision systems by adding one or more additional cameras, allowing the system to capture images from multiple angles. While this approach can enhance detection capabilities, it also increases the complexity of hardware setup and makes calibration algorithms more challenging. Consequently, multi-view systems are less commonly used in practical applications.

3. Defect Processing Methods Based on Point Cloud Data

3.1. Defect Detection in Point Cloud Data Processing

With the rapid development of computer vision technology, image processing can capture information similar to what the human eye perceives and facilitate target detection. However, there are significant drawbacks when using images for object detection. First, the quality of images is easily influenced by factors such as lighting and material properties. Second, 2D images only provide brightness information and the object's contour features, making it impossible to capture depth information. As a result, 2D images struggle to effectively represent

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3D defect information, and this method performs poorly in detecting defects, especially dents and other surface deformations.

As 3D point cloud data acquisition technology has advanced, point cloud data has found great application in defect detection within the visual domain, offering several advantages. First, 3D data provides depth information about the object, allowing for more precise localization and description of defects. Second, 3D data can provide height information, which helps distinguish defects from surface textures more effectively. Additionally, by analyzing features such as shape and curvature from the 3D data, different types of defects can be more accurately identified and classified.

Experts and scholars both domestically and internationally have conducted extensive research on defect detection using 3D data. For example, Lin[3] et al. utilized point cloud data of blade profiles to analyze and detect defects on the blade's surface, successfully identifying and locating the defects. Zong[4] et al. proposed a method that involves using a vision system to capture point cloud data of surface defects and quantifying this data. By establishing a point-to-image mapping relationship between points on the object's surface and those in color images, they achieved precise segmentation of the defect areas and calculated the 3D feature data of the defects. Experimental results demonstrated that this detection system is highly reliable for 3D defect detection and assessment.

3.2. Defect detection method based on point cloud data

Based on traditional visual observation systems, a measurement method has emerged that combines binocular vision with structured light to obtain 3D point cloud data of the measured object. Xue[5] integrated encoded structured light with binocular vision technology, decoding the structured light pattern and utilizing the code consistency principle to locate corresponding points and acquire the object's point cloud data. This approach significantly improves the sparsity of point clouds caused by unclear features in binocular measurements. The method requires only the calibration of the binocular cameras, which reduces system complexity and enhances operability and flexibility.

The binocular structured light system offers high-density, high-precision, and strong adaptability for 3D point cloud data acquisition. Its operation is relatively simple, as it only requires the calibration of binocular cameras without the need for complex feature extraction and matching. This reduces the overall operational difficulty and greatly enhances the system's convenience. Therefore, this study employs binocular structured light equipment as the tool for research.

The raw point cloud data obtained through measurement technology is often vast and may contain noise and redundant or invalid information, making it unsuitable for direct use. Point cloud data preprocessing involves denoising and simplifying the point cloud data while maintaining its essential features. This allows a reduced set of points to replace the original, overly detailed point cloud, preparing the data for subsequent 3D point cloud analysis. Before preprocessing, it is typically necessary to construct a spatial topology for the point cloud data to enable rapid neighborhood queries of the sampled points. Common spatial indexing methods include the space cell method, BSP trees, KD-trees, and octrees, with KD-trees and octrees being the most commonly used structures.

Scholars both domestically and internationally have conducted extensive research on point cloud denoising. Desbrun[6] et al. developed a filtering algorithm based on mean curvature flow for regular point clouds. This method maps geometric feature changes of the measured object according to different mean curvatures, effectively suppressing noise points while preserving the target's contour. However, the process may cause some surface curvature on the object. Schall[7] et al. proposed a filtering algorithm that identifies noise from smooth surfaces and focuses on denoising. This algorithm assigns a likelihood measure to each point to obtain the

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probability of noise on the surface, allowing the detection of various noise amplitudes. Wu[8] divided point cloud data into two regions—flat and edge—using curvature feature weights, and applied specific filtering algorithms to denoise each region based on their characteristics.

Point cloud simplification aims to reduce the number of points in the data while retaining key features, improving the efficiency of data processing and analysis, and reducing storage costs. Scholars have conducted substantial research in the field of point cloud simplification. Chen[9] et al. used point cloud data to construct STL format files, converting each point in the point cloud into a triangle. By deleting or merging some triangular meshes in the generated STL file, they achieved point cloud data simplification. Liu[10] et al. proposed a method that simplifies point clouds based on curvature variations. In areas with significant curvature changes, important feature points can be retained. However, in areas with less curvature variation, this method may generate holes, affecting subsequent point cloud processing.

4. Conclusion

The binocular system-based point cloud data detection method is gradually becoming the mainstream approach for defect detection in thin-walled components. This technology, through high-precision imaging and 3D modeling, captures rich three-dimensional coordinate information, enabling the precise identification and localization of minute defects in thin-walled parts. Compared to traditional methods such as visual inspection and basic measurement tools, the binocular system significantly improves detection accuracy and precision. It also overcomes the limitations posed by the shape, material, and structural complexity, making it widely applicable to various thin-walled component inspections.

Moreover, the non-contact nature of point cloud data detection eliminates the risk of damage caused by physical contact while improving detection efficiency. Although the initial investment in equipment may be high and the system has certain environmental requirements, the broad application potential of binocular systems, along with their convenience in data storage and analysis, positions this technology as a critical tool for enhancing quality control and advancing manufacturing processes for thin-walled components.

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