A Machine Vision System for Inspecting Mechanical Parts

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Abstract Computer vision-based inspection has become widely used in manufacturing industries for part identification, dimensional inspection, and guiding material handling systems. Defect-free production cannot be achieved with sampling inspection methods; therefore, a 100 percentage inspection approach is mandatory to meet the zero-defect goals of manufacturing industries. Achieving this is possible with advanced technologies, such as vision-based inspection systems. In this study, a vision-based inspection system is proposed for part identification, defect detection, and dimensional measurement. The system is validated using machined parts, including a Druck plate, Pressure plate, and Retainer. A part identification algorithm is developed based on a geometry search approach. The inspection algorithm classifies parts based on edge relationships, utilizing edge detection techniques to identify each part's geometric features. Surface defects are identified by analyzing the pixel intensity gradients within defective regions. The system measures part dimensions using a vision system, with results comparable to those obtained from a coordinate measuring machine.

Keywords: machine vision, part identifications, dimensional inspections, template matching, coordinate measuring machine.

1. Introduction

The rapid advancement of digital metrology is transforming monitoring, assembly, and inspection activities in manufacturing. Technologies like machine vision-based inspection systems streamline manufacturing processes by enabling online process monitoring and 100 percentage part inspection. These systems, equipped with vision sensors, outperform traditional gauges in efficiency and precision, particularly for tasks such as part identification, flaw detection, and dimensional measurement.

Several studies illustrate the utility of machine vision in quality control. Aswar [1] developed an automated system using edge detection and Hough transform for mechanical parts. Di et al. [2] introduced a vision system for real-time monitoring of electromechanical components, achieving reliable defect detection within set tolerances, while Shen et al. [16] applied image processing to inspect bearing defects. Sills et al. [17] demonstrated defect identification on specular surfaces by examining light reflections, crucial for inspecting automotive parts. Karimi and Asemani [7] compared surface defect detection techniques for ceramic tiles, analyzing co-occurrence matrices and histogram curves for optimal performance.

For complex, translucent materials, Huang and Pan [5] developed a vision-based inspection system tailored to the semiconductor industry, while Park et al. [12] implemented a Convolutional Neural Network (CNN)-based system to identify surface issues. Additionally, Li [8] improved part identification using image stitching algorithms for precise dimensional measurement. Convolutional neural networks (CNNs) have emerged as a popular and powerful tool for image classification tasks, with applications extending across various fields, including medical diagnostics, autonomous driving, and industrial inspection [3, 4, 13, 15]. Recent advancements include Liu et al. [9] carried out extensive review of machine vision for condition monitoring and fault diagnosis in machining, which contributes a theoretical basis for Machine Vision-Based Condition Monitoring and Fault Diagnosis of Machine Tools (MVCMFD-MTs). Moru et al. [11] presented a machine vision algorithm for gear inspection with subpixel precision, and Javaid et al. [6] highlighted the importance of machine vision in the quality assurance landscape of Industry 4.0. Ren et al. [14] emphasized the role of deep learning in defect classification.

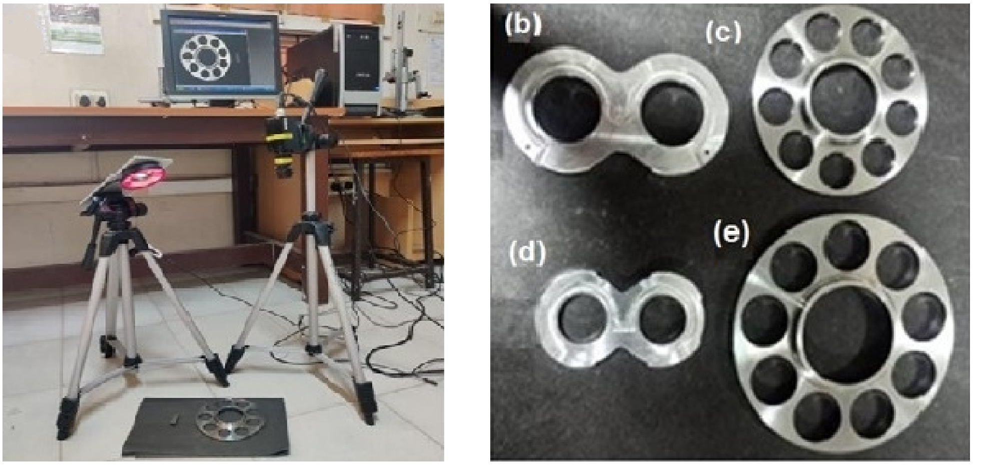
It is evident from the literature that research in vision-based inspection is rapidly advancing alongside technological trends. Techniques like edge detection and template matching are widely used for part identification and dimensional measurement. The findings emphasize that automated vision-based inspection systems significantly assist quality control engineers in qualifying numerous objects while reducing manual labour, inspection time, and quality control costs. Therefore, a vision-based inspection system is proposed for typical automotive component manufacturing industry to identify parts, surface defects and perform dimensional measurements.

2. Experimental framework for image acquisition

The image acquisition system comprises a Uniq Vision UM-201 monochromatic camera (752×582 pixels) [20], a red LED ring light, a 50 mm lens, a PC2-Vision frame grabber [18] with a CPU interface and Sherlock v6.3 image processing software [19]. Figure 1a illustrates the setup for the image acquisition and lighting systems. A two-dimensional image of the parts is captured by the monochromatic camera with 8-bit grayscale levels, and a high-frequency red LED ring light enhances image quality. This study includes various components such as Pressure Plate, Druck Plate, and Retainer (in two sizes) to validate the vision-based inspection system. Figures 1b-e display images of these components.

3. Inspection algorithms

In this study, the Sherlock v6.3 image processing software was used to develop algorithms for part identification, defect detection, and dimensional measurement. Images of the machined parts were captured using a vision sensor, and a dataset containing both defective and non-defective parts was created to train the inspection algorithm. Figure 2



a b-e

Fig. 1. (**a**) Experimental framework for image acquisition, (**b**) Pressure plate, (**c**) Retainers (small), (**d**) Druck plate, and (**e**) Retainers (big).

presents sample images from this dataset, which were used to build the inspection algorithms.

3.1. Part identification algorithm

The captured datasets of the parts were used to train part identification algorithms. Parts were identified based on their geometric edges, which were extracted and stored as templates using an edge detection technique. Each part type was assigned a variable ranging from ‘0’ to ‘100’, with variables ‘A’, ‘B’, and ‘C’ representing the Retainer, Pressure Plate, and Druck Plate respectively. The value of each variable indicates the geometric similarity to the trained images, where a value of ‘100’ represents a complete match, and ‘0’ indicates no similarity. Considering the intensity variations in the images caused by changes in ambient lighting, a threshold value of ‘92’ was established for classifying the parts. For instance, if the value of variable ‘A’ exceeds the threshold, the part is classified as a Retainer. Similarly, other parts are identified based on their respective variable values exceeding the threshold.

3.2. Defect identification algorithms

Defects on the machined surfaces, such as scratches, blowholes, and cracks were detected by analyzing pixel intensity variations. These defects cause discontinuities in pixel intensity distribution, represented in a histogram. Comparing histograms of defect-free

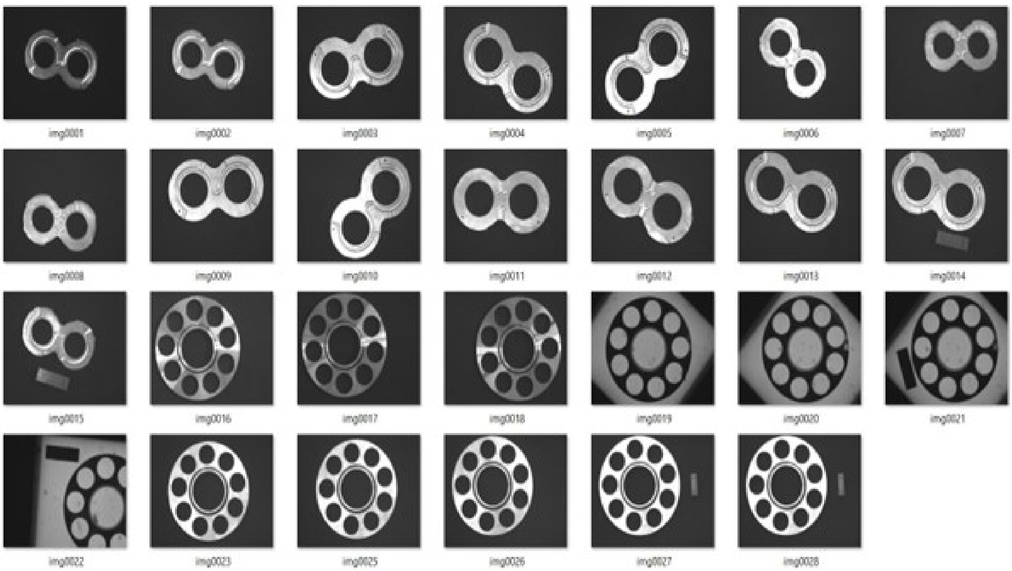


Fig. 2. Image data set used for inspection algorithm.

and defective parts reveals intensity distribution changes that indicate surface defects. Additionally, the shape of the histogram reflects the image's contrast levels.

3.3. Dimensional measurement

The part images were converted into binary images using a thresholding technique. In a binary image, pixel intensities are represented as either '1' or '0,' resulting in sharp edges that are essential for measuring part dimensions. The dimensions to be measured for the pressure plate and retainer parts are illustrated in Figs 3a and b. For the pressure plate, the diameter of the two holes and the centre-to-centre distance between the holes were measured. For the retainer, the pitch circle diameter of the small holes, the diameter of the small holes, and the inner circle diameter were measured. The diameter and position of the circle can be determined by identifying a minimum of three points on its circumference.

The equations for calculating the radius and locating the centre of the circle are provided below. (x_1, y_1), (x_2, y_2), and (x_3, y_3) represent three points on the circumference of the circle, and (x_0, y_0) denote the centre of the circle. These points are expressed in matrix form as shown in equation (1)

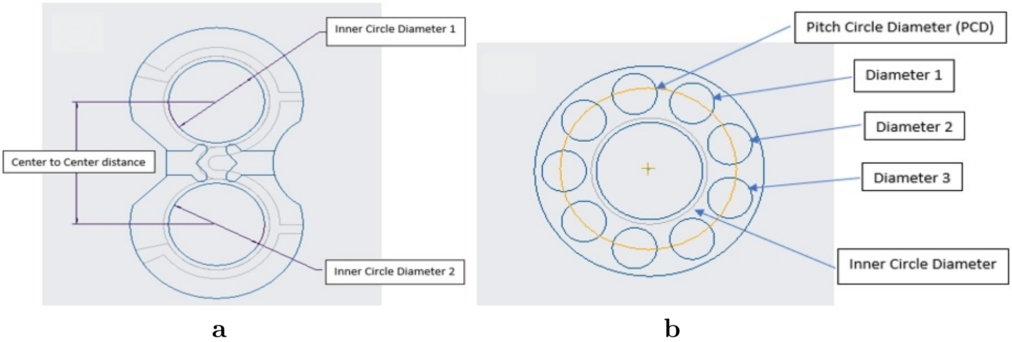


Fig. 3. Measurement of Part Dimensions: (**a**) Pressure plate and (**b**) Retainer.

$$A = \begin{bmatrix} x^2+y^2 & x & y & 1 \\ x_1^2+y_1^2 & x_1 & y_1 & 1 \\ x_2^2+y_2^2 & x_2 & y_2 & 1 \\ x_3^2+y_3^2 & x_3 & y_3 & 1 \end{bmatrix} . \tag{1}$$

The centre of the circle (x_0, y_0) is located using the relations given in equation (2)

$$x_0 = \frac{1}{2} \cdot \frac{M_{12}}{M_{11}} , \quad y_0 = \frac{1}{2} \cdot \frac{M_{13}}{M_{11}} . \tag{2}$$

The radius of the circle is calculated using the relation given in equation (3)

$$r^2 = x_0^2 + y_0^2 + \frac{M_{14}}{M_{11}} , \tag{3}$$

where $M_{ij}(A)$ is the determinant of A without row i and column j.

The centre-to-centre distance between the two circles is the Euclidean distance between the two pixels. If the centres of the circles A and B are represented by coordinate points (x_a, y_a) and (x_b, y_b), respectively, then the Euclidean distance D between these points is given by equation (4)

$$D = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} . \tag{4}$$

Using equations (1) to (4), the location of the feature and the dimensions of the parts are measured.

4. Results and discussion

The objective of this machine vision-based inspection system is to identify components such as the Pressure Plate, Druck Plate, and Retainer from the captured images, detect defects like scratches, blowholes, and cracks on machined surfaces, and measure the dimensions of the Pressure Plate and Retainer. A dataset comprising both defective and non-defective parts was created to train the inspection algorithms. The results obtained from the vision-based inspection system are presented in this section.

4.1. Part identification

The template matching technique was used for part identification. Figures 4(a-c) illustrate the output of the part identification algorithm, showing the component names in the results window. The images of the pressure plate, the Druck plate and the retainer are captured in various orientations, resulting in a complete image dataset for all parts. Geometric features were extracted from the image data and stored as templates. This technique compares the template images with the captured images, with the percentage of matching expressed as a value ranging from '0' to '100'. A value of '0' indicates that there is no match between the template and the corresponding section of the original image, while a value of '100' signifies a complete match.

The geometry search algorithm assesses the geometric characteristics of the parts, identifying both the type of part and its orientation. The percentage of geometric similarity between the template and newly captured images ranges from 92% to 100%. Consequently, a similarity threshold of 92% was established for the identification of parts in the three parts considered in this study. This variation is attributed to fluctuations in ambient light intensity and noise during the image acquisition process. Controlling ambient light variations can significantly reduce errors in part identification. The part identification algorithm effectively recognizes all parts and displays their names in the results window.

4.2. Defect identification

The machined surface exhibit defects such as scratches and blowholes, which can be identified using a histogram technique. A histogram of an image provides a graphical representation of pixel intensity. To detect surface defects, the region of interest representing the machined surface was first extracted, followed by measuring the intensity difference between adjacent pixels, known as the pixel gradient, in the defect-free image. This intensity gradient was then compared with that of the captured images.

The intensity gradient of the defect-free areas was observed to be high only at the edges, while the gradient on the machined surface was significantly low. The surface texture and the glare of the light contribute to the minimal variation in the intensity

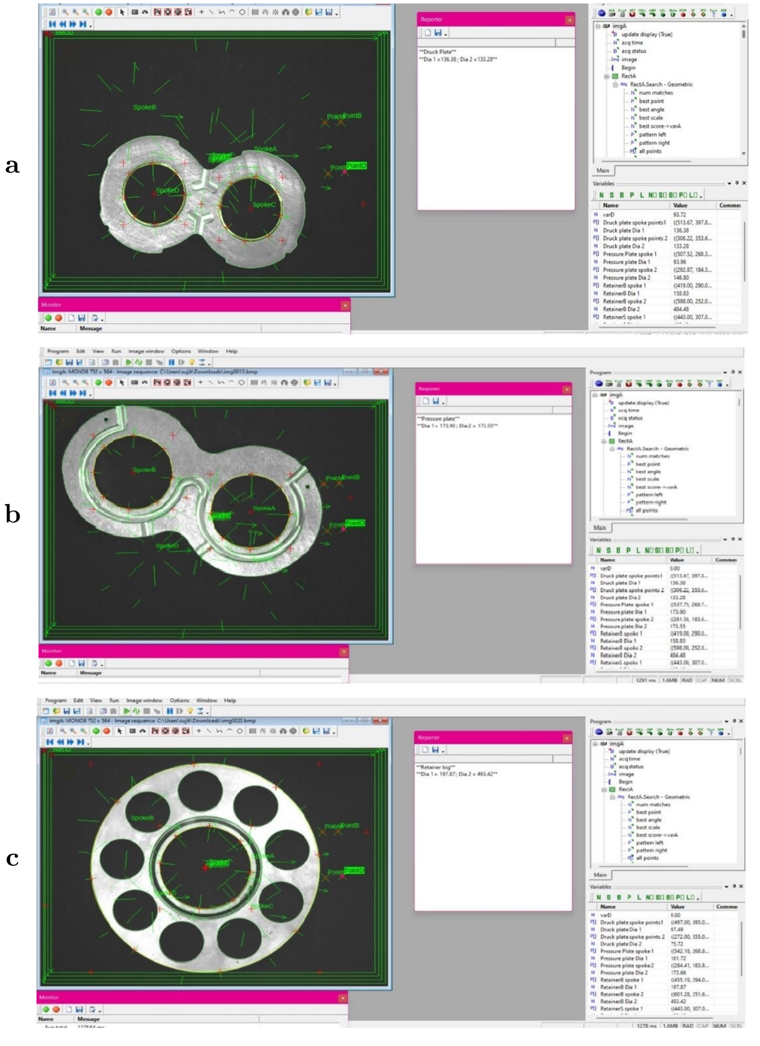


Fig. 4. Results of the part identification algorithm (**a**) Druck plate, (**b**) Pressure plate and (**c**) Retainer.

gradient. In contrast, images containing surface defects show a pronounced intensity gradient across the machined surfaces. The presence of these defects alters the reflection of light rays, resulting in a higher intensity gradient of pixels in images with defects. Figures 5a and b illustrate the histograms of the pressure plate without defect and with a

b

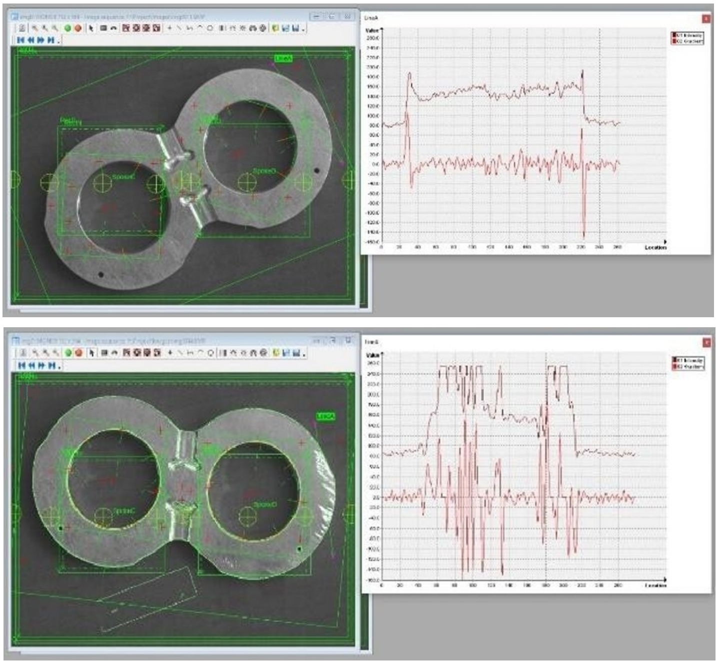


Fig. 5. Histogram of the Pressure plate (**a**) without defect and (**b**) with defects.

defects, respectively. Similarly, Figures 6a and b present the histograms for the retainer without defect and with defects.

4.3. Dimensions of the parts

After identifying the parts as the pressure plate, retainer, and Druck plate, a specific dimensional measurement algorithm was applied to determine their dimensions. For the pressure plate, measurements include the diameter of the holes and the centre-to-centre distance between them. In the case of the retainer, the measurements consist of the diameter of the inner circle, the diameter of small circles, and the diameter of pitch circle of the small holes. The dimensional measurement algorithm identifies the circumference of each hole and selects eight points along this circumference. The hole's location was computed using Equation (2), while the hole dimensions were calculated with Equation (3) and the centre-to-centre distance between holes was derived from Equation (4), as discussed in Section 3.3.

The centroid of the part geometry, obtained from the geometry search algorithm, serves as the reference point for determining the orientation of features within the parts.

a

b

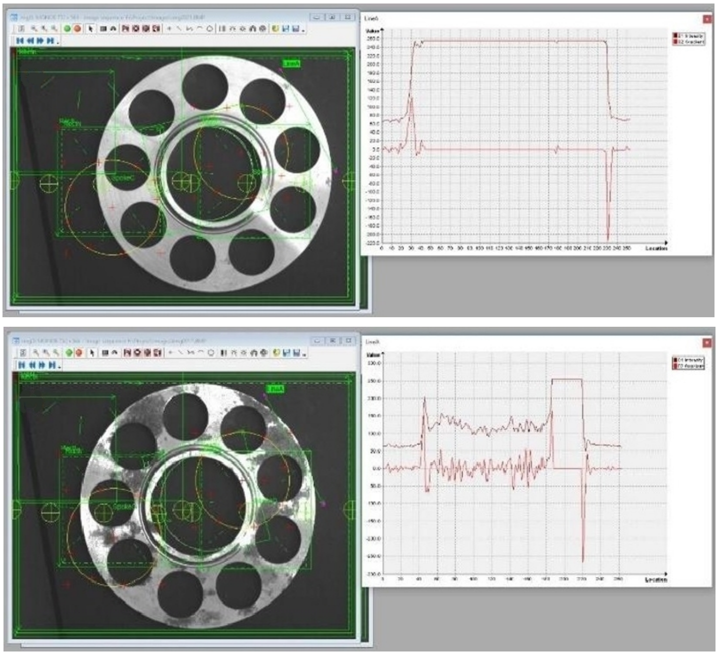


Fig. 6. Histogram of the Retainer (**a**) without defect and (**b**) with defects.

Initially, the dimensional measurement algorithm locates the part's orientation before measuring the required dimensions. This approach enables accurate dimension measurement even if the parts are positioned at different orientations within the field of view and eliminates the need for fixtures to position the parts during the inspection process.

To validate the accuracy of the results obtained from the vision-based inspection

Tab. 1. Comparison of Results: CMM and Machine Vision.

Component name	Features	Results of inspection algorithm [mm]	Results of CMM [mm]	Deviation [mm]	Deviation [%]
Pressure Plate	Diameter of inner circle 1	25.46	25.716	0.256	0.99
	Diameter of inner circle 2	25.54	25.721	0.181	0.70
	Centre to centre distance	40.17	40.653	0.483	1.18
Retainer	Inner circle diameter	43.85	43.421	0.429	0.98
	Diameter of smaller circle 1	17.97	17.958	0.012	0.07
	Diameter of smaller circle 2	17.58	17.955	0.375	2.09
	Diameter of smaller circle 3	17.85	17.963	0.113	0.63
	Pitch circle diameter	67.95	67.511	0.439	0.65

system, part dimensions are also measured using a CNC Coordinate Measuring Machine (CMM) (Make and Model: Mitutoyo CRYSTA-Apex S544 [10]). The efficiency of the dimensional measurement algorithm is assessed by comparing the measurement results with those obtained from the CMM. Table 1 presents a comparison of the dimensions of the pressure plate and retainer measured by both the algorithm and the CMM. The results demonstrate that the vision-based inspection system effectively measures part dimensions, producing a maximum measurement error of 2.09%. Further accuracy in measurement can be achieved by employing appropriate lighting techniques and utilizing a camera with higher spatial resolution.

5. Conclusion

A vision-based inspection system has been proposed to automate the inspection process and enable 100% inspection of machined parts. In this study, algorithms for part identification, defect identification, and dimensional measurement were developed for inspecting machined components such as pressure plates, retainers, and Druck plates. An image dataset was created using parts with and without defect, and the inspection algorithms were trained using this dataset. The part identification, defect identification, and dimensional measurement algorithms were implemented using Sherlock image processing software.

This inspection system captures an image, recognizes the part geometry, and compares the captured images with the trained images for accurate part identification. The pixel intensity distribution was analyzed for defect identification in both the pressure plates and retainers. The dimensional measurements obtained from the machine vision algorithm exhibited a maximum deviation of 2.09% compared to the results from the CMM. This deviation can potentially be minimized by employing a high-resolution camera and effective lighting techniques.

While the proposed vision-based inspection system currently measures and identifies two-dimensional part features, future work could expand its capabilities to measure and identify three-dimensional features of the parts. Additionally, artificial intelligence (AI) techniques could be integrated to enhance part and defect identification, enabling more accurate and automated detection of surface flaws and part classifications.

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