An Integrated Image Processing Approach for Micro-Defect Detection

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Abstract

The continuous growth in the remanufacturing industry requires advanced processing of components, and autonomous surface scanning and defect identification is its integral part. The 3D free-form surface can be reconstructed with a point cloud obtained from the scanning. Laser line triangulation-based surface scanning is a promising method for generating a 3D point cloud of the component surface. In this paper, a robotic defect scanning system developed using *py_openshowvar*, an open-source cross-platform communication interface is presented. For effective scanning of micro-scale features with minimal noise, it is crucial to optimize the scanning parameters. The scanner parameters such as exposure time and stand-off distance have been optimized for accurate feature detection. The scanning of some surfaces with fabricated micro-defects has been performed, and an integrated image processing-based defect identification technique is presented. Detected micro-defects are characterized using image processing techniques. The geometries obtained from the presented technique were validated, and the results are in good agreement with actual defect geometry, and the measurement error is below 9%.

Keywords: 3D Surface Scanning, Parameter Optimization, py_openshowvar, Image Processing, Defect Detection

1. Introduction

In industry, the high-value components are prone to develop the micro-defects after a certain number of production cycles. Therefore, periodic restoration of these components is required. In order to have adequate restoration of components, the assessment of the component surface needs to be automated. The laser line triangulation (LLT) based scanning a promising technique for the non-contact, non-destructive 3D surface assessment [1]. There has been various applications of the technique in the inspection of gears [2], pipes [3], plates [4] and weld blanks [5]. LLT based scanners provide good accuracy and a high scanning rate. However, the accuracy is highly dependent on the scanner parameters, and unoptimized scanning parameters result in undesired noise in the acquired data. Hence, it becomes imperative to optimize scanner parameters for accurate scanning. Manorathna et al. [6] evaluated the performance of the laser line scanner under different operating conditions to minimize any unambiguity in measurements. Secil et al. [7] proposed a framework for data collection and visualization of geometric objects using a robot and laser profile sensor. The raw data often contains noise associated with it, which needs to be removed prior to surface analysis. Peng et al. [8] presented a denoising technique for geometric data based on locally adaptive Wiener filtering.

The robotic 3D scanning system consists of a laser line scanner and a robotic manipulator. For complete surface scanning and reconstruction, complex mathematical tools are required, which is not supported by robotic languages such as *Kuka Robot Language* (KRL). These specific robotic languages have limited expressiveness and lack of extensibility [9]. For processing complex 3D dataset, an external more robust language have to be employed. Sanfilippo et al. [10] presented the case studies to demonstrate the potential of the *JOpenShowVar* (an open-source framework) with the KRL program. Cross communication between a user program and the Kuka robot can be established to accomplish the desired positioning of the robot using the *KUKAVARPROXY* server [11]. The micro-defect present in the components is required to be detected from the point cloud data. Ye et al. [12] proposed defect-detection algorithms such as depth gradient, face-normal gradient. In another work [13], a study on feature extraction of a weld joint using a laser scanner was carried out, and the authors proposed an algorithm for feature detection using a 2D cross-sectional profile.

In this paper, a 3D scanning system developed in the Machine Tools Lab, IIT Bombay, is presented. The effect of exposure time and the stand-off distance on the micro-defect profiles. The optimization of scanner parameters has been performed to avoid any undesired noise arising because of wrong parameter selection. An integrated image processing approach is presented to detect the defects present on the surface. 3D scanning of some artificially developed micro-scale defects has also been conducted in order to assess the efficacy of the developed technique.

2. Experimental setup

The experimental setup for surface scanning and defect detection is developed at Machine Tools Lab, IIT Bombay. It consists of a compact laser line triangulation scanner (model: ScanCONTROL 2900-50, make: Micro-Epsilon). The scanner offers a vertical resolution of 4 µm and thus can be utilized for micro-scale defect detection. As it is a line scanner, it provides a 2D height profile (Z direction) along the projected laser line (X direction) in order to scan the complete 3D surface, multiple parallel profiles along Y direction at regular intervals. This can be achieved with a positioning system. In the current setup scanner is mounted on an industrial 6-axis robotic manipulator (model: KR 20-3, make: KUKA). This manipulator not only facilitates data acquisition along Y direction but also enables scanning of large components which are beyond the range of the standalone scanner. The experimental setup is shown in Fig. 1.

The controller used by the robot does not provide the required flexibility and versatility to incorporate the laser line scanner to perform all mathematical operations associated with data processing and visualization. Therefore, a custom program is written in Python programming language, which can be run on any external computer. Both robot and laser line scanner have been integrated through the developed Python program.

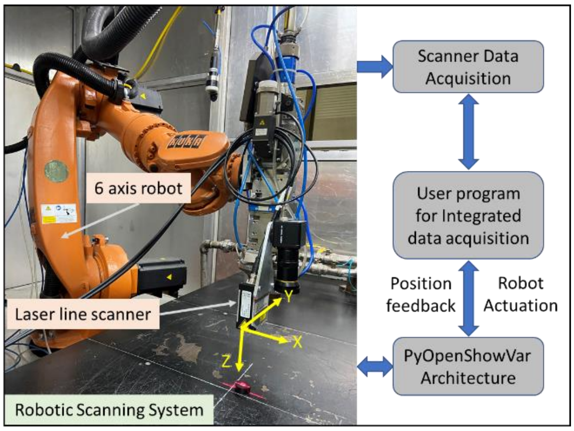

Fig. 1 Experimental setup

The program script for the scanner has been written based on the standard development tool kit supplied by the manufacturer, which is compatible with Python. The developed program offers a trigger to acquire a line profile as per requirement and also a provision to adjust the scanner parameters. As opposed to the scanner, controlling a robot from an external computer is a bit complex in nature. An open-source cross-platform communication interface named *py_openshowvar* has been used in the current setup. This establishes a proxy server (*KUKAVARPROXY*) inside the robot controller and acts as a middleware between the user program and the robot controller. The system variables of the robot can be read and written through this proxy server, which facilitates position feedback from the robot as well as actuation.

3. Scanner parameter optimization

The laser line scanner uses a CMOS sensor to acquire the relative depth of the surface. The surface data scanned from the scanner highly depends upon the scanner parameters, such as exposure time and stand-off distance. These scanner parameters need to be optimized for minimal errors in the measurements. The effect of both of these parameters on the profile form deviation has been studied.

3.1 Effect of exposure time

The exposure time is one of the critical parameters for a laser line scanner. In order to understand the effect of exposure time, multiple defect profiles are acquired at different exposure times. The defect profiles obtained after tilt removal at exposure times of 0.5 ms, 0.75 ms, 1 ms, 1.5 ms, and 2 ms are shown in Fig. 2. The true profile of the defect obtained from the Alicona® focus variation microscope is also shown in Fig. 2 for better comparison. Deviations from true defect profile at various exposure times can be clearly seen in Fig. 2. The mean square error (MSE) is calculated to optimize the exposure time between the scanned 2D profile, and the true profile scanned from the Alicona® focus variation microscope.

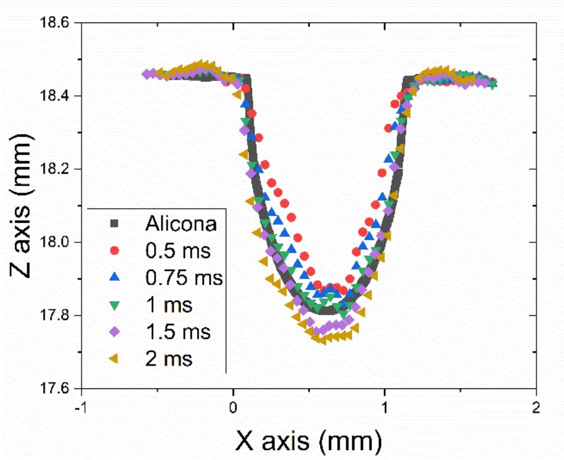

Fig. 2 Effect of exposure time on the profile form

The mean square errors obtained in the profiles generated at different exposure times are shown in Fig. 3. It can be seen from Fig. 3. that the mean square error first decreases then increases as the exposure time is increased. This is because, at low exposure time, the scanner misses some data points, and at high exposure time, substantial noise is introduced in the data. The minimum MSE is observed at an exposure time of 1 ms to 1.5 ms, which is considered as optimum range of exposure time.

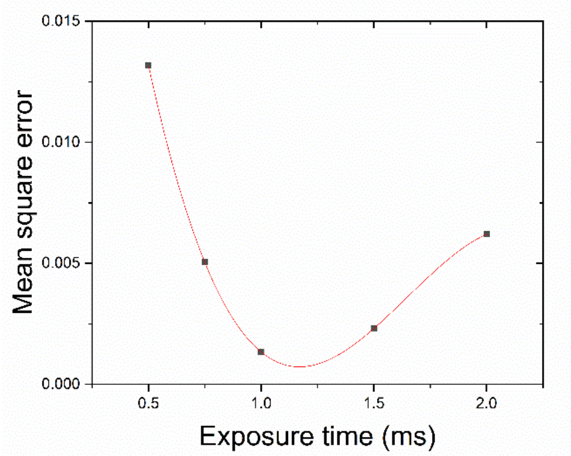

Fig. 3 Mean square error at various exposure times

3.2 Effect of stand-off distance

The stand-off distance is another important scanner parameter affecting the accuracy of data acquisition. Multiple defect profiles are acquired at different stand-off distances with an optimized exposure time of 1 ms. The stand-off distance was varied from 55 mm to 105 mm at intervals of 10 mm. The defect profiles obtained at these stand-off distances along with the true profile (obtained from Alicona®) are shown in Fig. 4. The deviation of profiles measured from the scanner from the true profile can be clearly observed from Fig. 4. The variation of MSE for different stand-off distances is shown in Fig. 5, which shows that the profile trough becomes shallower as the stand-off distance increases. This is because the scanning range of the scanner is in the form of a trapezoid, but the sensor size is fixed. At low stand-off distance, the resolution of the scanner is better and vice-versa. Fig. 5 shows that the stand-off distance of 55 mm to 85 mm optimal with low MSE values.

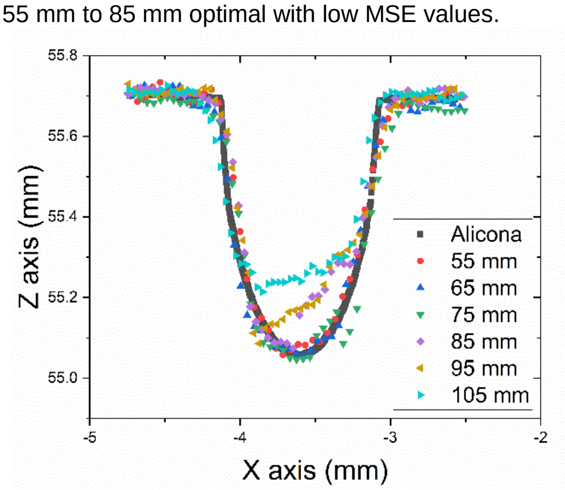

Fig. 4 Effect of Stand-off distance on the profile form

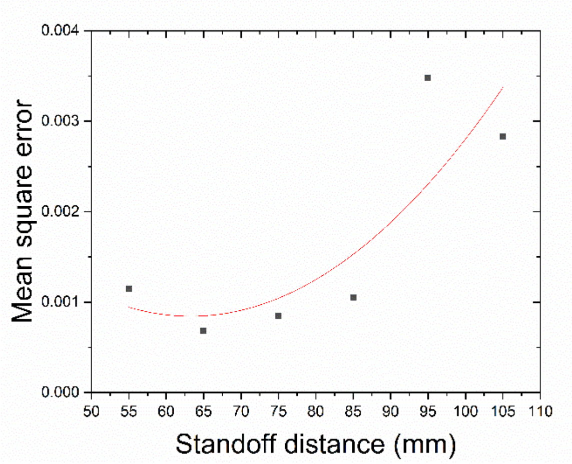

Fig. 5 Mean square error at various stand-off distances

4. Defect detection

The 3D point cloud of the surface is obtained by scanning the component using the developed system. For automatic defect detection, an image processing-based algorithm is used. The complete defect detection process is shown in Fig. 6.

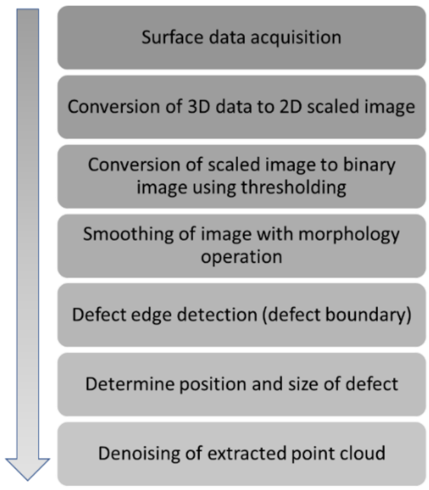

Fig. 6 Defect detection process

First, the 3D point cloud is leveled by removing the tilt. The 3D point cloud data obtained after levelling is then converted to a 2D greyscale image with Z axis data scaled from 0 to 255. A bilateral filter was applied to the greyscale image for denoising. This image is then converted into a binary image using thresholding. Then, the morphological closing operation is applied to make contours smooth. Subsequently, the Canny edge detection is applied to find the contours of the defect. Once the location and boundary of the defect are identified, the size of the defect can be assessed. An example of image processing for defect detection is shown in Fig. 7.

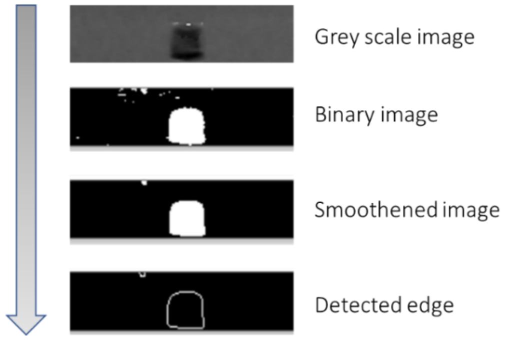

Fig. 7 Image processing base defect detection

The actual defect geometry and the point cloud of defects extracted from the developed approach are shown in Fig. 8. This point cloud data will then be used to plan the Laser Directed Energy Deposition (LDED).

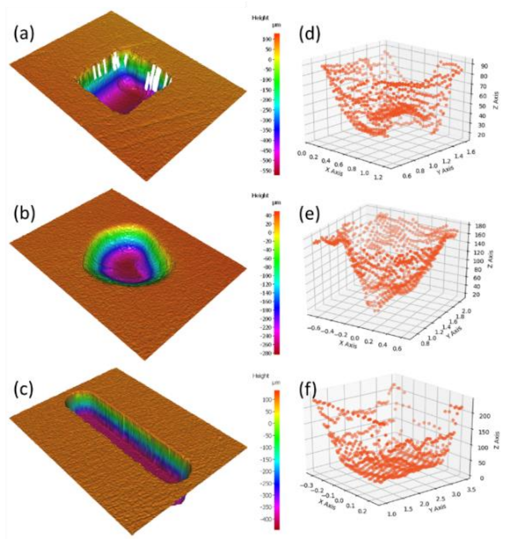

Fig. 8 The actual (a) Actual semi-ellipsoidal, (b) Actual micro-dimple, (c) Actual micro-slot, (d) Extracted semi-ellipsoidal, (e) Extracted micro-dimple, and (f) Extracted micro-slot

5. Defect validation

In order to check the efficacy of the scanning system and developed a defect detection algorithm, the validation of the results is necessary. Three geometric parameters, namely, length, width, and depth, were selected for validating the extracted defects. A comparison of these geometric parameters for all the three artificial defects, i.e., Ellipsoidal, micro-dimple, and micro-slot is shown in Figs. 9(a), (b), and (c), respectively.

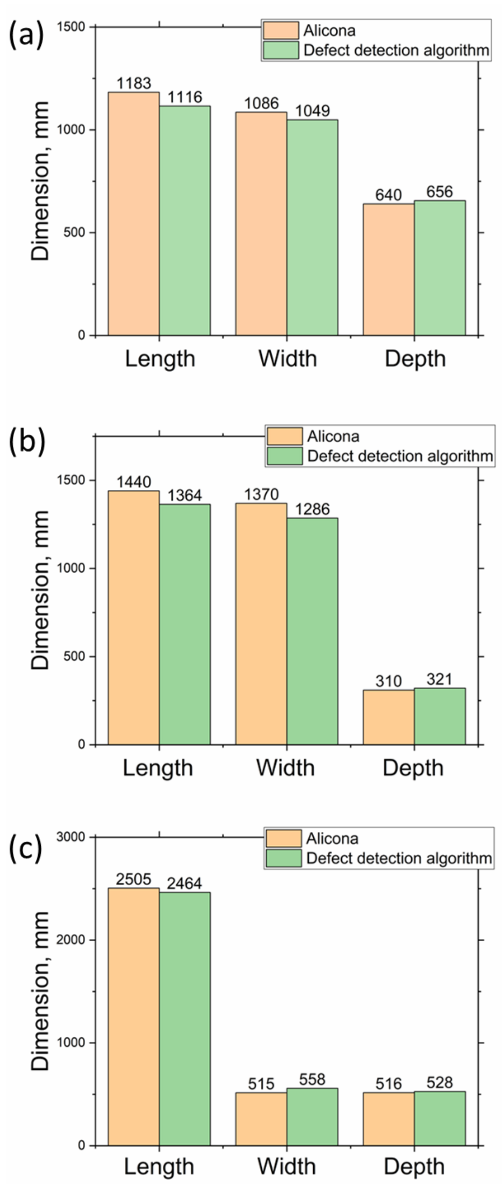

Fig. 9 Validation of extracted defects with actual defect size (Alicona) for (a) Semi-ellipsoidal, (b) Micro-dimple, and (c) Micro-slot

It can be observed from Figs. 9(a) through 9(c) that the extracted defect geometry is in good agreement with the measured geometry. There is slight underestimation of the lateral dimensions due to the noise arising at the edges and image smoothening. For all three defect geometries, the errors in length, width, and depth range between 2% to 8%. Hence, it can be inferred that the defect identification approach presented in this paper yields acceptable results.

6. Conclusions

This paper focuses on the development of a robotic surface scanning system equipped with an autonomous defect detection algorithm. This work presents an autonomous defect detection technique, which can be extended for online monitoring and closed loop processing. The following conclusions can be drawn from this paper:

- A robotic scanning system comprising a six-axis KUKA manipulator and laser line scanner is developed using an open-source cross-platform communication interface.
- It is observed that the accuracy of measurement through laser line scanner depends on the scanner parameters, such as exposure time and stand-off distance.
- The values of exposure time and stand-off distance are optimized, and the optimum ranges are 1 ms to 1.5 ms and 55 mm to 85 mm, respectively.
- The developed image processing-based defect detection approach is able to extract the defect geometry accurately for various defect geometries.
- The geometric parameters of the extracted defect geometries were validated, and the prediction errors range between 2% to 8% across all test cases.

Acknowledgments

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