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A Novel Feature Detection Method Using Multi-Dimensional Image Fusion for Automated Optical Inspection on Critical Dimension

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Keywords: Automated optical inspection (AOI), object segmentation, image fusion, point clouds, critical dimension (CD).

ABSTRACT

This paper presents a novel approach which is based on multi-dimension image fusion to effective extraction and segmentation of edge features for accurately measuring critical dimension on objects having complicated surface patterns or random reflectance. In the approach, coarse estimation of edge points is firstly performed by using the 3D edge detector to identify correct image regions of interest (ROI) for object segmentation. 2D image processing algorithms are performed on the ROI to segment the precise object edges for critical dimension (CD) measurement. To verify the effectiveness of the strategy, the developed method has been verified through measurement of aerospace composite parts for its edge detection and critical dimension accuracy. The measurement repeatability error of this critical dimension can be kept below 1.1% of the measured CD while the standard deviation can be kept less than 0.137 mm. Experimental results have demonstrated the feasibility and applicability of the developed method.

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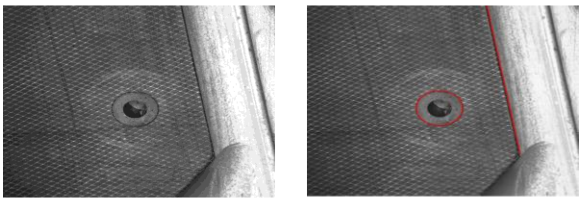
INTRODUCTION

Feature detectors have been an essential part of many vision systems, which are often the most vital yet most difficult step in automated optical inspection (AOI). The main task involved in feature detection is to precisely detect object features with critical dimension (CD) in the image. The result of the feature detection usually determines eventual success of subsequent operations regarding important product quality assurance. For example, Figure 1(a) and (b) show a 2D image of an aerospace composite part and its expected feature detection results which are one straight line as the aerospace composite part's boundary and the outer circle of the machined hole. The measurement accuracy of critical dimension such as the distance between the aerospace composite part's edge and the hole is determined by the correctness of feature detection on these geometric features on the part surface.

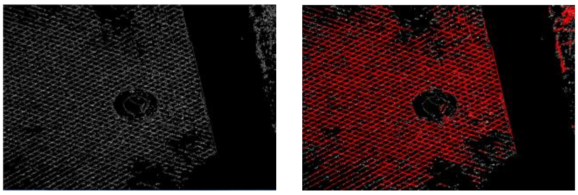
In the evolution of modern image processing techniques, a huge variety of feature detection techniques have been developed to satisfy demanding tasks in AOI. Most existing approaches in AOI are mainly performed in three steps: image smoothing, feature extraction and differentiation and object recognition and classification as presented in surveys (Basu, 2002; Davis, 1975; Senthilkumaran et al., 2009).



(a) (b)

Figure 1. An example of feature detection. (**a**) the original image; (**b**) expected result.

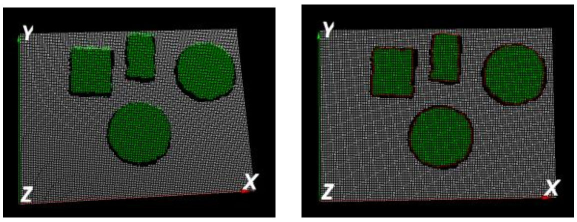
However, one of remaining difficulties in 2D image feature segmentation and extraction is effective segmentation of feature images from an inspecting image having complicated surface patterns. The surface complexity could easily lead to an undesired segmentation result that misses the detecting important object features. When even applying some advanced 2D image segmentation techniques to an aerospace machined part of composite materials for feature segmentation, satisfactory and robust segmenting result cannot be guaranteed. Figure 2(a)-(b) show that the edges of the image were detected by using a Canny detector (Canny, 1986), and then the expected line is detected by applying Hough Line Transform (Matas et al., 2000). Obviously, the matrix fibers on the part surface have seriously disturbed its effective detection on the machined hole and the part surface boundary. The undesired segmentation result shown in this example, clearly demonstrates the technical challenge to be tackled for establishing an effective method to extract important features for critical dimension measurement from an object having complicated surface features.



(a) (b)

Figure 2. Example of image segmentation result using conventional image processing techniques: (**a**) using Canny edge detection; (**b**) using Hough line transform.

The limitations of the 2D image processing methods available nowadays are mainly caused by limited information of 2D image in form of light intensity, its distribution and spatial spectrum map. To resolve more sophisticated image processing problems, computer vision scientists have developed many delicate algorithms in which computation efficiency and case depending characteristics are trade off in AOI. In recent years, it has become evident that the use of 3D image technique can be of great advantages, especially in overcoming the intrinsic weakness of the 2D approaches. In general, 3D data can describe an observed object without depending on light illumination or the viewpoint and can retain more geometric information about object features (Fuchs et al., 2010; Sansoni et al., 2014; Schnabel et al., 2008; Skalski et al., 2012; Skotheim et al., 2010). However, the measured 3D data from many modern 3D machine vision technologies may easily lose some high-frequency geometric information at critical surface boundary or edges because of optical diffraction disturbances around the edges. The measurement errors can reduce the accuracy of edge feature detection from the estimation of 3D point clouds generated by the 3D vision techniques. For example, Figure 3(a) shows point cloud of the scene captured from the optical probe developed at NTU (National Taiwan University). The red points displayed in Figure 3(b) is the edge points detected by the proposed 3D edge detector. The red regions represent the missing edges from the 3-D detection.



(a) (b)

Figure 3. The outputs of 3D image feature detection: (**a**) point cloud being detected by 3D vision technique; (**b**) missing object edges being marked Red due to optical diffraction disturbance.

Therefore, a novel method for feature detection is proposed to deal with the difficulties faced by modern 2D or 3D machine vision technologies in measuring objects having complicated surface patterns for critical dimension to be accurately determined. The proposed approach enables the vision system to achieve accurate real-time operation and it is highly effective to accommodate the variation of surface light reflectance. Our approach is aimed to achieve effective segmentation of object features, so critical dimension of these geometric features regarding important manufacturing properties can be accurately determined. In the developed method, coarse estimation of edge points based on the proposed 3D edge detectors can first narrow down regions of interest (ROI), so complicated surface patterns can be avoided. By referring to the correspondence map, 3D points belonging to these regions are merged into 2D image (Besl et al., 1992; Chen et al., 2016; Corney et al., 2002; Gafar et al., 2010; Germann et al., 2007; Ohbuchi et al., 2002; Osada et al., 2001; Paquet et al., 2000; Zhang et al., 2001). Finally, the 2D image processing algorithms are performed to achieve expected results.

This paper is organized in the following manner. Section 2 presents the workflow and main algorithms of the proposed multi-dimensional image edge merging approach. Section 3 presents and analyzes experimental results to determine the feasibility of the developed method. Finally, Section 4 draws conclusions.

MULTI-DIMENSIONAL EDGE MERGING ALGORITHM

Principle Concept and Flow Chart Diagram of the Edge Merging Algorithm.

To make the proposed method clear in its operation procedure, the flowchart shown in Figure 4 is used to describe the proposed method in its five main steps. The photos of the Figure 4 are the results of each step which are labeled with the identical numbers as their corresponding step.

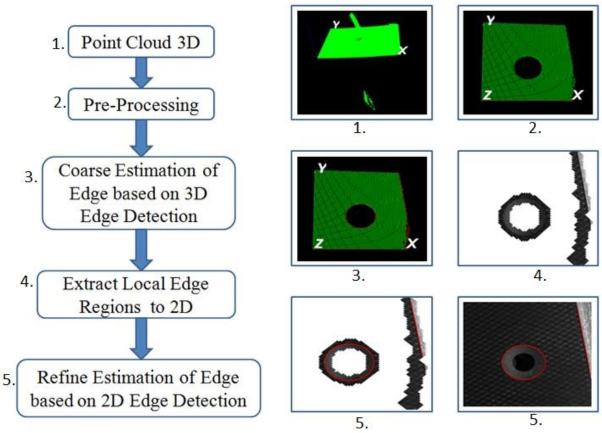


Figure 4. Flowchart of proposed multi-dimensional image fusion algorithm for feature detection.

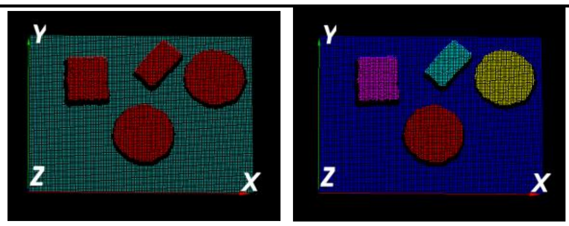
In Step 1, the digital image and 3D point cloud of the scene are acquired simultaneously at the same viewpoint by the probe for 2D object imaging. Because of possible measurement errors, the point clouds acquired from scene may potentially contain undesired sparse outliers. Therefore, outlier removal is performed through the computation of the distribution of the mean distance from a query point to its nearest neighbors in Step 2 (Pre-Processing) (Chen et al., 2015). Furthermore, since the speed of data processing strongly depends on the number of points in data set, down-sampling operation is an efficient solution to reduce the size of point clouds. Following this, coarse estimation of edge points based on the proposed 3D edge detection algorithm is performed (Chen et al., 2015, 2016, 2016). From the edge points obtained in the previous stage, regions of interest (ROI) are narrowed down and mapped to its corresponding 2D image. Finally, the 2D image processing algorithms are performed to achieve expected results.

3D Edge Detection Algorithms

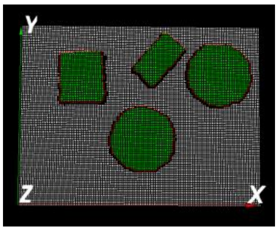
Edge points in point cloud provide important geometric information since they correspond to changes in the depth information of objects in the scene. The object edges correspond to significant variations in the depth of object surfaces. The types of depth variation considered in this research are step edges and ramp edges. A step 3D edge point involves a transition between two depth levels occurring between neighboring points. An example of the developed 3D step edge detector is shown in Figure 5. Meanwhile, the ramp 3D edge points can occur in depth ramp profile, such as the one shown in Figure 6.

The 3D step edge detector described in Algorithm 1 is developed to define the borders of the object in 3D point cloud by using geometric transition from foreground to background.

Algorithm 1: 3D Step Edge Detector.	
Input: Measured point cloud $P=\{P_i, i=0, 1, .., n\}$.	
Output: Edge points $E=\{E_i, i=0, 1, ..., m\}$.	
1	***Pre-processing***: Reduce the dense of point cloud P by using down sampling with certain lateral resolution; Remove noisy points (Noise removal) and segment scene point cloud into individual object point clouds (Object segmentation).
2	***Orthographic projection***: To generate the orthogonal projected points map from the 3D point clouds, every 3D processed point, $\boldsymbol{p}_i$, is projected onto a plane α, which is perpendicular to the optical imaging axis of 3D sensor.
3	***Neighbors Relationship***: Find neighbors of each point being projected onto a plane α, then calculate the sum of two dimensional vectors from the query point to its neighboring object points.
4	***Criteria of Edge Points***: Set a query point to be an edge point if its sum of vectors in step 3 is not equal to zero.
5	***Map to 3D Space***: All edge points detected from step 4 on plane α will be mapped to the corresponding points in 3D point P.



(a) (b)



(c)

Figure 5. An example of the 3D step edge detector. (**a**) point cloud of the scene; (**b**) the segmented objects in point cloud; (**c**) results of the 3D step edge detector.

For the edges, it should be recalled that the purpose of 3D edge detection is to localize variations of the depth level. Differentiation is the computation of the necessary derivatives to localize these 3D edge points. The differentiation operator is characterized by its order, its invariance to rotation and its linearity. The order of the differentiation operator is defined by the order of its partial derivatives. The most commonly used operators are the gradient and the Laplacian. The gradient is a first-order operator for depth function z=*f(x,y)* defined as the vector $\left(\frac{\partial f(x,y)}{\partial x}, \frac{\partial f(x,y)}{\partial y}\right)$. Meanwhile, the Laplacian for depth function z=*f(x,y)* of two variable is defined as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (1)$$

In the x-direction, we define the second-order derivative of *f(x,y)* as difference:

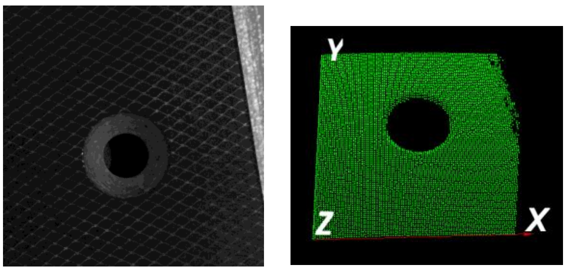
$$\frac{\partial^2 f}{\partial x^2} = f(x+1, y) + f(x-1, y) - 2f(x, y) \quad (2)$$

and, similarly, in the y-direction we have:

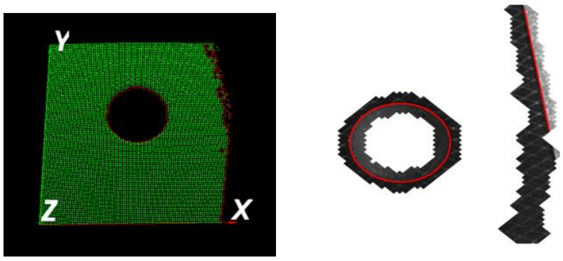
$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y) \quad (3)$$

Therefore, it follows from the preceding three equations that the discrete Laplacian of two variables is:

$$\nabla^2 f(x,y) = f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y) \quad (4)$$



(a) (b)



(c) (d)

Figure 6. An example of the 3D edge detector using Laplacian. (a) original image; (b) point cloud of scene ; (c) results of the 3D edge detector using Laplacian; (d) result of mapping 3D edge points to 2D image.

EXPERIMENTAL RESULTS AND ANALYSES

The machined plates are used as flying wings in airplanes, which are made of composite materials with many glass fibers synthesized within the materials. The plates are having a high complexity of surface patterns, which are extremely difficult to be measured by conventional AOI techniques. Thus, the plates are taken as examples to test the feasibility of the propose method.

To measure the plates, the NTU-developed 3D optical probe was used to capture images of the aerospace composite parts. The kernel components of the developed probe include projector and photoelectric sensor. The projector projects sinusoidal structured blue-band light onto the measured surface to implement the phase shift algorithm. As the surface profile of the measured object points can be presented as different optical path differences (OPD), shown in Figure 7(a), the light intensity information captured by the photoelectric sensor can be transferred to the depths of the measured object points. Using the Digital Micromirror Device (DMD) to project a fringe strip structure light onto the surface of the measured object. The phase intensity of the deformed stripe is captured by the charge couple device (CCD), and the phase information is reconstructed by phase wrapping and phase unwrapping procedures. The phase image of the fullfield is obtained, and the phase image is further transformed to be the 3D profile of the object. Figure 7(b) shows that the structured light is projected onto the measured surface for 3D reconstruction and a 2D image can be captured simultaneously. A mini pc which is equipped with 3.1GHz i7-5557U processor and 4GB RAM is integrated with developed optical probe to perform the feature detection. The free-form 3D profile of the whole measured field of view (FOV) surface can be reconstructed by the developed method as shown in Figure 7(c). The 2D image is used to identify the accurate edge location of the feature objects, so that the diffractive measurement problem of the 3D edge detection will not impact the accurate measurement of crucial dimension of critical components on the inspecting part. This is the most important advantage of the proposed multi-dimensional image fusion method.

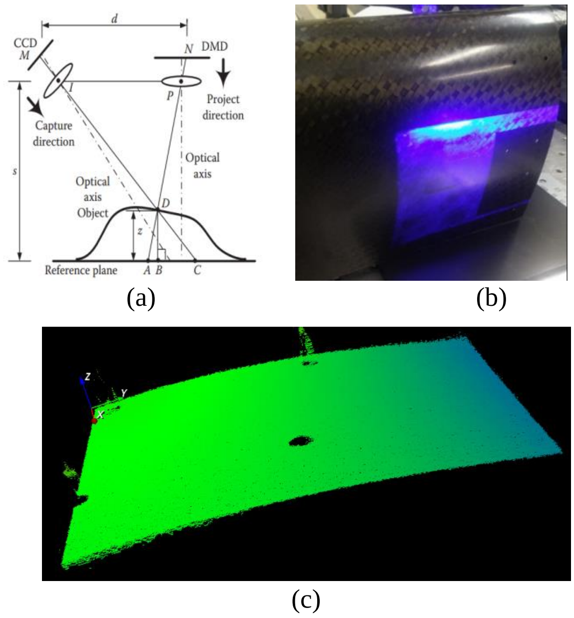


Figure 7. (a) optical configuration in 3D measurement; (b) actual measurement of the aerospace composite part; (c) 3D point cloud being reconstructed.

Some holes on the free-form surface of the plates are machined to provide necessary binding function in assembly of airplane wings. These holes have to be machined accurately on the curved surfaces and keep an accurate CD between the hole center and the plate surface boundary to ensure the sufficient strength of the wing assembly. This is extremely critical to the safety of the airplane operation. As mentioned above, the modern 2D image segmentation techniques fail to segment and extract the circle features of these machined holes. Thus, the proposed method was employed to resolve this critical issue.

In the test, the hole neighboring area is the region of interest (ROI) to be first detected by the developed 3D edge detection algorithm. An example of the whole view of 3D point clouds is shown in Figure 8(a). By using the developed method, the ROI of 3D point cloud of was initially identified and segmented from the whole point clouds. 3D edge detection algorithm was used to detect the circle edge of the hole on the composited material part, which is displayed in Figure 8(b). With this, the 3D edge points were mapped to the 2D image within the inspected field of view, and then the estimation of accurate edge was refined by Canny detector and Hough transform, which is shown in Figure 8(c). The result of the accurate circle edge is presented in Figure 8(d). With accurate locations of the identified machined hole and part boundary, the CD between the hole and part boundary can be further determined by finding the minimum distance between the hole center and the boundary line.

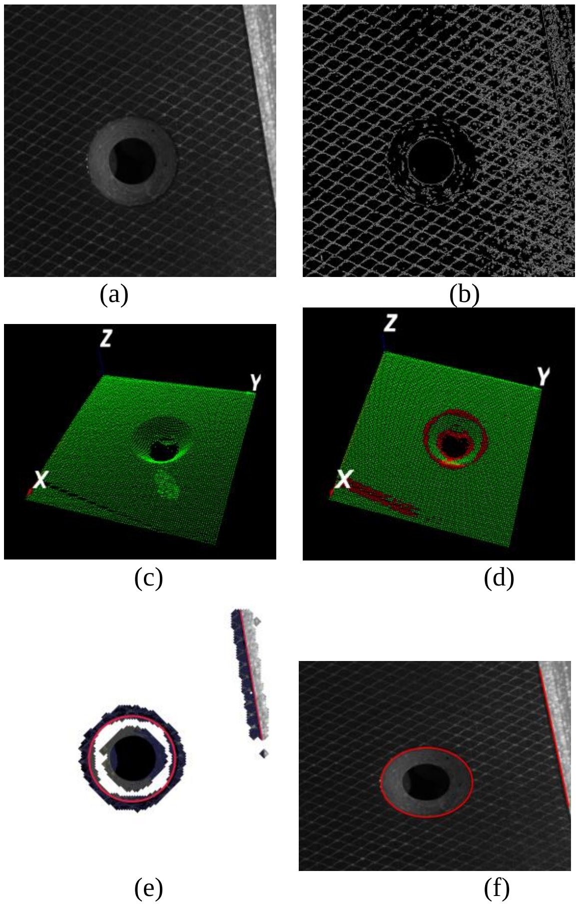


Figure 8. (a) original image; (b) result of Canny edge detection; (c) point cloud of ROI ; (d) result of the 3D edge detector; (e) result of 2D feature detectors performed on the extracted edge regions; (f) the final result of developed method.

Figure 9 shows the final detection result of the hole whose diameter is 2.5 mm under a 30-times repeatability test. The mean value of the hole diameter is 2.528 mm as the standard deviation is 0.018 mm. The center of hole is determined accurately based on the circle detection. Finally, the critical dimension which is the spacing from center of hole to the part boundary is 12.636 mm. The measurement repeatability error of this critical dimension can be kept below 1.1% of the measured CD while the standard deviation can be kept less than 0.137 mm.

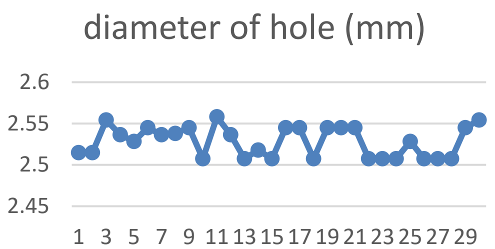


Figure 9. 30-times diameter measurement result of machined hole.

Another measured part made of composited material with a shiny surface was also measured. The shiny surface will normally cause difficulty in feature extraction and positioning. By using the developed method, Figure 10 illustrates that the positioning of the hole edge and the part boundary can be clearly extracted and identified. The experimental results indicate that the feature segmentation and edge positioning can be accurately performed to determine critical dimension without suffering of random surface light reflectance.

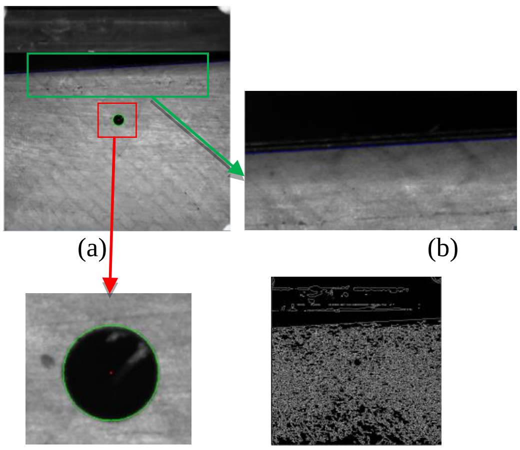
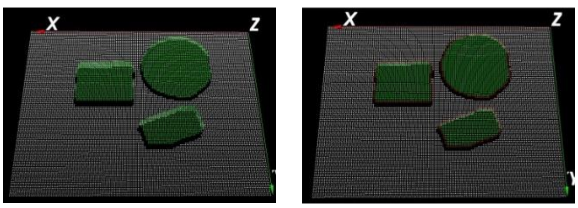
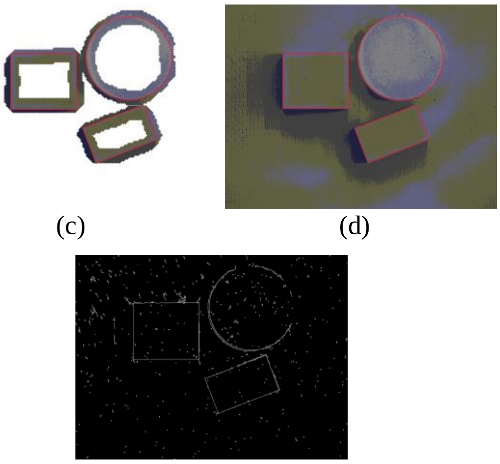


Figure 10. (a) feature detection of a shiny surface; (b) zoom of edge line; (c) zoom of circle; (d) result of Canny edge detection.

Furthermore, two rectangle gauges and one pre-calibrated circle block were used as the third example to test the developed method. The edges and boundary lines of the measured parts can be also extracted and identified, shown in Figure 11.



(a) (b)



(e)

Figure 11. (a) 3D point cloud; (b) results of the 3D step edge detector; (c) results of 2D feature detectors performed on the extracted edge regions; (d) the extracted features of the measured parts; (e) result of Canny edge detection.

CONCLUSIONS

An innovative feature detection method has been developed to realize accurate CD measurement for precision manufacturing. By using multi-dimensional fusion, the developed method makes a breakthrough in measuring critical dimension on machined parts having complicated surface patterns. The developed technique provides a feasible solution to overcome the difficult problems faced by some of the modern image processing techniques. The experimental result shows the measured repeatability is less than 1.1% of the overall measuring range and the standard deviation below 1%. The experimental results can demonstrates that the developed method can be further developed to be an *in-situ* automated optical inspection system for precision manufacturing.

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適用於關鍵尺寸自動光學檢測的創新多維融合圖像特徵偵測方法

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摘要

本文提出一個結合三維點雲提取邊緣和二維精確圖像特徵偵測的方法。先以量測件表面深度進行三維邊緣偵測可克服二維影像光強變異及量測面花紋的等困難，三維邊緣偵測結果映射至同步擷取的二維影像，再以二維圖像特徵法則可得到量測件的圖像特徵。航空複合材料工件上的關鍵尺寸量測重複度小於1.1%，証實發展方法具有潛力可以發展而應用於精密製造。