Intelligent automation aiding rapid surface feature quantification in 3D

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Intelligent Automation Aiding Rapid Surface Defect 
Quantification in 3D

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Abstract—Automatic small surface feature inspection of high-precision components requires superior measurement and automated analysis systems. Early identification and quantification (depth, area and volume) is a key aspect in quality assurance in order to check the health of the manufactured part. Human visual analysis of surface feature inspection is qualitative, subjective and time consuming. Three-dimensional (3D) robotic inspection should provide a more robust and systematic quantitative approach for surface defect measurement. 3D measuring instruments typically generate point cloud data as an output, although via different principles. Data processing of point cloud data is often subject to repeatability issues causing significant concern with data confidence. This research is concerned with the measurement of novel traceable sub-millimetric surface defects and the development of a novel, robust, repeatable and mathematical solution for automatic defect detection and quantification. This is then extended to a surface defect on a plain bearing measured in real-time using a 3D measuring instrument mounted on a 6-axis robot and quantified using the novel algorithm. The results show that the new surface defect measurement and quantification is more robust, efficient, and repeatable than existing solutions.

I. INTRODUCTION

In industry, surface topography is one of the significant factors in performance of high precision components. Surface topography is normally recognized as comprising of different surface components, i.e. roughness, waviness, form, and surface suspicious features. Whilst separation of roughness, waviness and form components is usually conducted by the application of filters [1], discrete detection of surface suspicious features is also crucial because they may significantly influence the functional performance of a component. Inspection of such surface features is an important task for manufacturing industries, in terms of product quality, production efficiency, and performance efficiency. Any feature detected requires assessment in terms of a pass / fail criterion.

Automatic detection of process-induced features (e.g. indentations and scratches), is an important issue in machine vision. Detection of defects in 2D and 3D has been reported for various applications in different industries. Examples include; the real-time detection of defects on rail surfaces [2], highly reflected curve surfaces [3], the robust and automated detection of tooling defects for polished stone [4], along with a computer-aided visual inspection system for surface defect detection in ceramic capacitor chips [5]. Once such special features have been identified, it is important to accurately extract the defect from the surface. Several algorithms have been developed and published for defect detection in images [6-8] as well as different filtration techniques set out in the ISO 16610 series of standards [9] to aid the characterization of surface features [1][10]. This can also be adopted to detect surface defects. Once a defect is detected and ideally isolated, it then becomes important to quantify the defect geometry (such as depth, area and volume). Although, significant work has been reported in detecting surface defects using various optical methods, robust, traceable and importantly, automatic methods for volume measurement in 3D, is less well explored.

ISO 8785 [11] gives the definition of types of surface defects but currently standards are not available to isolate and quantify defects. Currently ISO 25178-2 [12] is available to quantify aspects of surface volume of materials, which can and has been adopted to measure the volume of defects. Commercial analysis software are also available that allow a user to identify a defect manually and consequently quantify defects. However visually driven manual delimiting of a defect is always subjective and qualitative, leading to repeatability/reproducibility issues and errors of quantification. Moreover, there is an issue of reliability of data representation due to the lack of traceable surface defect comparators and defect soft-gauges.

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In this research, standard, repeatable and traceable defect artefacts have been generated and a novel algorithm has been developed to quantify defects automatically and rapidly in 3D.

II. DEFECT ARTEFACT

A. Artefact Generation

There is no significant evidence of standard surface defect comparators commercially available and hence there is a need to generate standard and traceable surface defect artefacts. Indentations have been produced on a 6 axis Fanuc industrial robot approximately 8.0 mm in diameter with a lateral resolution of approximately 2.4 mm x 2.4 mm including ground and polished surfaces, step edges and large scale form. These are nominally 300.0 µm, 250.0 µm, 180.0 µm and 40.0 µm in depth. Typical sets of indentations have been produced on four different flat plates which have roughness values ($Rq$) in a range of 0.06 µm to 1.27 µm. Fig. 1 shows the four different sizes of Rockwell indentations on a flat plate ($Rq = 1.27$ µm).

B. Measurement of artefact

Artefacts have been measured in 3D using a parallel optical coherence tomography (pOCT) instrument. The 3D optical sensor is capable of measuring different surface types, including ground and polished surfaces, steps and films. The instrument produces 3D datasets with a field of view of approximately 2.4 mm x 2.4 mm with a lateral resolution of approximately 8.0 µm. The measuring instrument is mounted on a 6 axis Fanuc industrial robot-Mate 200ic. This robot is chosen for typical inspection tasks due to its finer repeatability (0.02 mm) compared to other commercial industrial robots.

III. NOVEL ALGORITHM

The novel algorithm to quantify the defect automatically has been created using MATLAB R2012b and is briefly illustrated in Fig. 2. The 3D measuring instrument provides point cloud data as the output of the measured surface. Fig. 3 illustrates 3D data of the measured surface that contains conical defect 2 (as shown in Fig. 1).

Measurement noise, for instance spurious spikes, is always present in acquired data from any 3D optical instruments and it is important to remove such noise for better qualitative assessment otherwise it could lead to incorrect quantification. A low pass 2D Gaussian filter is implemented to remove such noise. Moreover, 3D datasets also contain geometric form (typically in the millimetric) scale that needs to be removed for better assessment of the defect. If this is not achieved, large scale form would mask smaller scale defect information. By generating the mean surface using an advanced robust Gaussian regression filter, form can be removed thus a residual surface can be obtained.

After the filtration process, it is important to isolate the defect from the residual surface. The purpose of this process is to locate the defect region and 3D data portions for later defect quantification. For defect isolation, edge detection of the defect is essential. An edge of the defect is defined as an abrupt change in surface height on the 3D data. There are various image processing techniques available for edge detection, such as gradient operators and thresholding. Due to embedded surface roughness, gradient operators for edge detection were found too complex and hence a local thresholding method considering surface texture was adopted to isolate the defect.
Once a defect is isolated, it is relatively straightforward to derive the boundary of the defect in 3D as shown in Fig. 4, as a blue circumferential line outlining the brim of the defect region.

A reference plane is generated using the least squares method to fit into the defect boundary data points. In a given field of view, the algorithm tries to find the minimum point. Once the minimum point is obtained then the perpendicular distance from the minimum point to the generated least square plane can be calculated using a simple mathematical equation which is effectively depth information of the defect. To evaluate an area of the defect, the total number of pixels encapsulated in the defect boundary region is considered. To compute the volume of a defect, the algorithm calculates the perpendicular distance from each defect point (pixel) to the least square plane. Considering an area of a pixel, the sum of all the perpendicular distances from each pixel to the reference plane is ultimately the volume of the defect.

The area of a pixel is defined by the lateral resolution of the measuring instrument. This process is applied to various defect artefacts of different sizes and embedded in different roughness substrates, as explained in Section II A, and the results are discussed as follows.

IV. ARTEFACT ANALYSIS

Automatic defect quantification of the different sizes of defect artefacts using the algorithm is shown in Table 1. In this example, artefacts shown in Fig. 1 were measured five times repetitively. It can be seen that the relative standard deviation in calculating geometrical quantities (depth, area and volume) is observed to be less than 0.4 % in defects above 178.0 µm in depth.

However, the algorithm computes the depth, area and volume of the smallest defect (39.0 µm in depth) with slightly higher relative standard deviation (1.0 % to 3.0 %) than the rest of the other defects. The higher variation observed in measuring the smallest defect may be due to uncertainties associated with the measuring instrument, robot and generation of defect artefacts. Fig. 5 is a graphical representation of the geometric parameters of the four different size defects on a logarithmic scale.

A key element of this research work is to identify how effective the developed automated process is when dealing with defects embedded in substrates of various roughness. Table 2 shows a comparison of defect quantifications of a defect (depth of 250.0 µm) embedded in flat plate with roughness values ($R_q$) of 0.06 µm, 0.16 µm, 0.78 µm and 1.27 µm. It is observed that the algorithm copes well with all four rough substrates in finding the geometrical quantities of defects. The relative standard deviation is observed to be less than 1.0 % in all cases. To show this more effectively, depth, area and volume of defects are graphically shown in Fig. 6 on a logarithmic scale.

<table>
<thead>
<tr>
<th>Defect</th>
<th>Measured Quantities</th>
<th>% Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Depth ($\mu$m)</td>
<td>Area ($\mu$m$^2$)</td>
</tr>
<tr>
<td>1</td>
<td>305</td>
<td>1426074</td>
</tr>
<tr>
<td>2</td>
<td>252</td>
<td>1281856</td>
</tr>
<tr>
<td>3</td>
<td>178</td>
<td>1135027</td>
</tr>
<tr>
<td>4</td>
<td>39</td>
<td>28603.2</td>
</tr>
</tbody>
</table>

Figure 3. Raw 3D data of a defect artefact

Figure 4. Residual surface with isolated defect
The results presented in Table 1 illustrate that the novel algorithm is very repeatable and effective for quantifying defect artefacts of different sizes. Likewise the results presented in Table 2 show the performance capability of the novel algorithm to detect the defect artefacts embedded in different roughness of substrates and to quantify defects automatically, is again very repeatable. However, whilst the novel algorithm is effective on artefacts which are of known size and controlled geometry it is very important to identify the effectiveness of the algorithm on real defects which are embedded in free form surfaces.

V. REAL DEFECT MEASUREMENT

The automotive industry may reject parts with defects in the manufacturing process, because even a minor defect in a manufactured part may result in a functional failure at a later in-service stage. Thus it is very important to detect, classify and quantify defects at an early stage because it is often a key parameter in quality assurance in order to determine pass/failure of the manufactured part.

Fig. 7 shows a suspicious region on a plain bearing. This defect is measured repetitively five times using the 3D measuring instrument. Fig. 8 shows the point cloud data of the measured suspicious region of the plain bearing. It can be clearly seen that the small defect is masked by the large scale of geometric form. It thus follows that the precise detection of the defect, isolation from the surrounding substrate, and its quantification, is very critical.

Measured 3D data of the defect on a plain bearing is processed using the novel algorithm explained in Section III. Fig. 9 illustrates the form-free residual surface with the highlighted defect region. The novel algorithm computed the maximum depth (height in this case) as 9.0 µm, area of 143560 µm² and volume being 589397 µm³ with a relative standard deviation of 2.0 %, 1.4 % and 3.9 % respectively.

TABLE 2. GEOMETRICAL QUANTITIES OF DIFFERENT DEFECT ARTEFACTS EMBEDDED IN VARIOUS ROUGH SUBSTRATES

<table>
<thead>
<tr>
<th>Rq (µm)</th>
<th>Measured Quantities</th>
<th>% Standard Deviation</th>
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<tbody>
<tr>
<td></td>
<td>Depth (µm)</td>
<td>Area (µm²)</td>
</tr>
<tr>
<td>0.06</td>
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<td>1270131</td>
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<tr>
<td>1.27</td>
<td>248</td>
<td>1217754</td>
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</tbody>
</table>

Figure 5. Comparison of measured quantities of different size defect artefacts

Figure 6. Comparison of measured quantities of defect artefacts in different roughness substrates

Figure 7. Defect on the concave side of the plain bearing
VI. CONCLUSIONS

The current research has identified the need for enhancing the functional capabilities and efficiency of 3D surface defect detection and quantification. To date, this research has developed and successfully demonstrated:

- Traceable and repeatable defect artefacts with different sizes and in a range of substrates with various roughness.
- Measurement of the defect using 3D instrument which uses the physical principle of parallel optical coherence tomography mounted on a 6-axis robot.
- Robust, rapid, automated measurement of defects using new MATLAB based algorithms, with high level of repeatability on the defect volume measurement.
- The application of the implemented algorithm on quantification of the defect on industrial components (plain bearings in this example).

Further work is currently involved with refining algorithm capability and speed, and exploring the applicability of this process to a broader group of real defects on a range of different operational surfaces, using different robotic systems.

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REFERENCES