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Automated assessment of measurement quality in optical coordinate metrology of complex freeform parts

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Abstract

The measurement of complex freeform geometries represents a fundamental challenge for quality assurance in the production of high value-added parts, in particular when additive manufacturing technologies are involved. In addition, the increasing advances towards automation and integration in industrial production hint at the possibility of developing intelligent coordinate measuring systems, capable of autonomously planning a measurement process and assessing measurement performance while the inspection task is in progress. In this context, optical measurement technologies appear as ideal candidates, featuring high sampling densities, relatively short measurement times and capablity to access complex surfaces. In this work, the ongoing development of algorithmic solutions dedicated to the automated assessment of measurement quality is discussed. The solutions are designed to be embedded in smart and autonomous coordinate measuring systems, and need only the acquired point clouds and knowledge of the nominal geometry (CAD model) to operate. At the core of the algorithmic solutions, point cloud analysis and spatial statistics are used to assess measurement uncertainty and part coverage, the latter referring to the capability to sample hidden surfaces and hollow features, as typically found in additively manufactured parts. The algorithmic solutions are illustrated and validated through application to a test case of industrial relevance, generated via additive manufacturing.

Optical measurement technologies, point cloud analysis, quality indicators, part coverage, measurement uncertainty

1. Introduction

In conventional manufacturing, the fabrication of highly complex and freeform components is often difficult, and geometric complexity is achieved through assembly [1,2]. Additive manufacturing (AM) technologies, on the contrary, offer opportunities for increased freedom in the design and fabrication of more complex parts, reducing the need for assembly, but increasing the challenge of metrological inspection [2–4]. The process of identifying optimal measurement set-ups must be repeated for the inspection of each new, geometrically complex, AM part, which implies the selection of the most suitable measurement technology and related measurement process parameters, maximisation of part coverage, optimisation of fixturing and optimal pose selection [5]. Given the pressing need in several industrial sectors (including automotive, aerospace and biomedical [6]) to adopt optimised solutions for checking product quality, and at the same time, reduce the manufacturing times and costs, novel means for the optimisation of the measuring process are needed.

In this context, measurement systems can be defined as "smart" when capable of merging the advantages of the underlying measurement technologies with increased capability of self-adaptation and flexibility [7] to the inspection of manufactured components. In particular, flexibility is defined in the roadmap "Manufacturing Metrology 2020" (VDI/VDE-GMA [8,9]) as the "adaptation to changes in measurement tasks", i.e. being able to respond flexibly to changes in measurement requirements, and being able to inspect different features and new components in a fully-automated way. At the same time, the assessment of measurement performance accomplished in real-time is in high demand [10]. Therefore, based on the resultant feedback and outputs from the measuring procedure, smart systems will be able to assess quality in-process (i.e. while the measurement is being performed), correcting themselves and streamlining the additional measurements required in order to increase the quality of the results [5,10].

The work presented in this paper focuses on the preliminary development of a set of algorithmic solutions for the automated computation of measurement quality indicators. These solutions are designed to be integrated into optical instruments, guiding them towards future full automation of part inspection and intelligent measurement planning.

2. Methodology

In this work, measurement quality indicators are defined, aiming at assessing the quality of high-density point clouds produced by optical technologies and registered to the underlying CAD model available in form of triangle mesh [11]. As a central aspect in the computation of the quality indicators, measured points are analysed in relation to where they fall within the triangle mesh (i.e. within which individual triangle facet). Therefore, a cloud-to-mesh association strategy is implemented at the core of the algorithmic solutions. In addition, the use of a triangle mesh allows definition of spatial maps of local measurement requirements (for example, coverage specifications and repeatability of critical areas) through triangle tagging (see schematic triangle tagging example in Figure 1). This in turn allows the evaluation of local measurement performance of the point cloud.

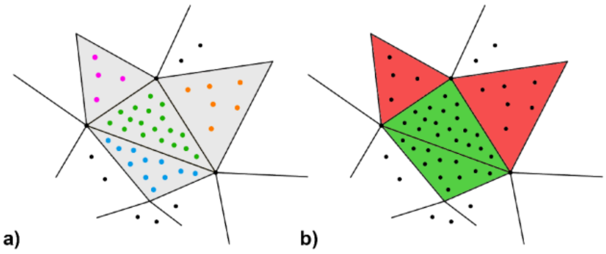

Figure 1. Schematic representation of triangle tagging: a triangle mesh with overlaid colour maps. a) Point-to-triangle associations (points associated to each specific triangle are illustrated with different colours), and b) coverage specifications (covered triangles are indicated in green, while uncovered ones are indicated in red)

2.1. Selected test case and experimental set-up

In this work, a metal bracket featuring a complex hollow geometry is selected as a test case for computation of the measurement quality indicators. The test case features approximate dimensions of (125 × 45 × 8) mm (size of the enclosing envelope). It was fabricated at the University of Nottingham by laser powder bed fusion (LPBF) using stainless steel 316L. The test case was selected as suitable to assess the performance of the measurement quality indicators as it presents regions of surface with different functional importance; furthermore, the part contains some of the typical, complex features found in AM components (e.g. high slope angles and hollow features).

The experimental set-up for the measurement of the test case part was based on the combination of a commercial measurement fringe projection system (blue-light technology GOM ATOS Core 300) and algorithms developed in MATLAB (measurement set-up and test sample shown in Figure 2).

Measurements were made in the Manufacturing Metrology Team (MMT) laboratory at the University of Nottingham, where temperature was controlled to (20 ± 0.5) °C. The part was placed on a rotary table and scanned at 360° for a total of five repeats (performed in repeatability and reproducibility conditions). The acquired data were stitched in real-time into five complete 3D point clouds using the GOM Scan software, with the support of reference point markers of 0.4 mm adhered to the surfaces of the part.

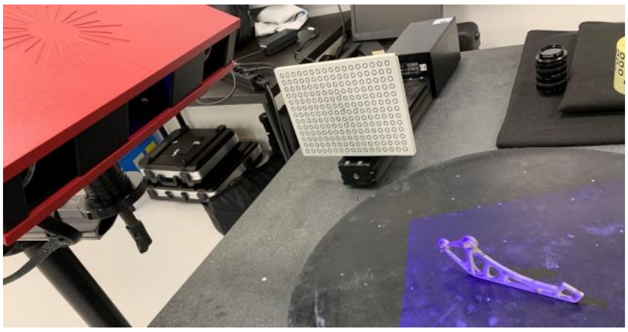

Figure 2. The optical fringe projection measurement system GOM Atos Core 300 while measuring the selected test part

Data processing for the measured datasets involved manual removal of points belonging to the background surfaces surrounding the part, application of a noise filter based on outlier detection and deletion of isolated points [11,12].

2.2. Registration and cloud-to-mesh association

The registration of the measured point clouds to the underlying reference geometry representing the part (available in the form of a STL triangle mesh) is a fundamental step in the measurement pipeline. Registration was performed based on landmark matching (i.e. local curvature). A detailed discussion of the registration approach adopted is given elsewhere [13].

Once the registration of the datasets was completed, a cloud-to-mesh association pipeline was applied to identify the triangle facets associated with each point within each measurement repeat (point-to-triangle association). The procedure is as follows:

- computation of the normal vector for each point in the cloud, via principal component analysis (PCA) [14];
- ray casting of the normal onto the triangle mesh to identify the intersection point, and thus the triangle facet associated to the point [15];
- assessment of the validity of the association based on point-to-triangle distance [12], using either:
  a) a hardcoded threshold on maximum permissible distance;
  b) outlier rejection ($\mu \pm 3\sigma$) with respect to the population of distances.

A colour map representation of the associations can be used to visually assess the point-to-triangle association (Figure 3).

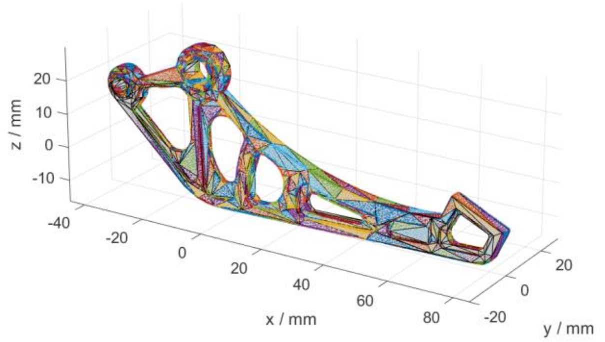

Figure 3. Example rendering of point-to-triangle association. Points mapped to each specific triangle are shown in different colour

3. Measurement quality indicators: definitions and results

Once all the points have been processed (i.e. associated with a triangle), the number of points paired to each triangle can be computed, which in turn leads to a first assessment of coverage. In addition, the point-to-triangle distance related to each individual association (signed, considering the orientation of the triangle facet normal and assumed as pointing outwards) can be recorded. From the stored information, measurement quality indicators are derived addressing e.g., sampling density (number of points associated to each triangle), accessibility of hidden regions (triangles with no or too few points), local point scatter and bias with respect to the surface (signed distances of the points associated to each triangle). Detailed definitions of the indicators and computation methods are presented elsewhere [16].

Example results of the computation of measurement quality indicators on the test part are shown in Figure 4 (colour maps of coverage ratio, sampling density, and point dispersion in panels a), b) and c) respectively) as locally mapped to the underlying, registered geometry. Mesh triangles were colour-coded according to the indicator results. The threshold value for the classification of covered and uncovered facets for each triangle was set at 75% of the maximum computed sampling density. In order to obtain a visually clearer distribution of the results shown via colour map, the values recorded for the sampling densities and point dispersion were normalised by division with their respective maximum value recorded across the repeats. Boxplots for the coverage ratio and the coverage area ratio indicators are shown in Figure 5. From the five repeated measurements, approximately 92% of the triangles resulted as sufficiently covered (coverage ratio) and approximately 86.5% of the part area resulted as sufficiently covered (coverage area ratio).

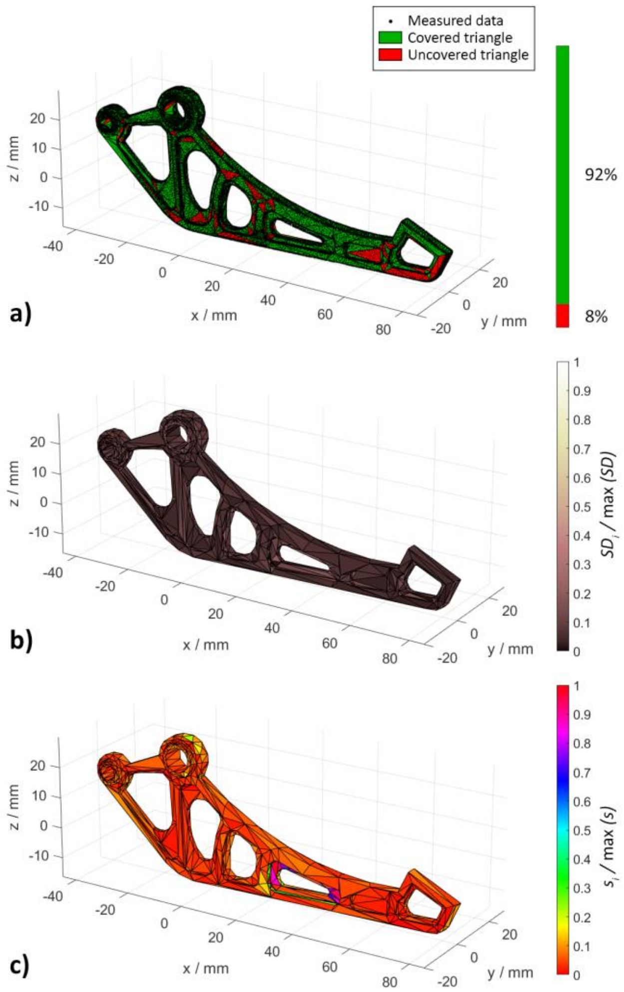

Figure 4. Example of indicators results in form of customised colour maps: a) coverage ratio reporting covered and uncovered triangles rendered using binary colouring, b) sampling density overlaid to triangle mesh (shown in normalised form), c) mesh triangles coloured using the dispersion of signed point-to-surface distances (shown in normalised form)

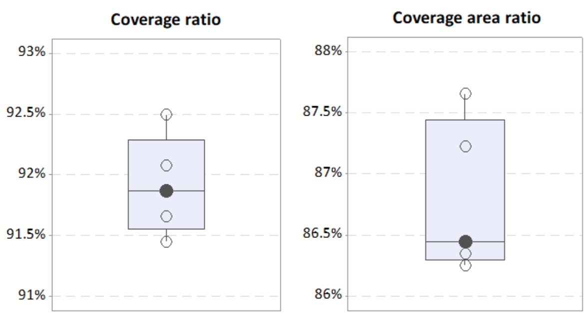

Figure 5. Indicators of part coverage (boxplots from five measurement repeats): coverage ratio, and coverage area ratio. The circles are the individual results for the indicator computed on each one of the five point cloud repeats, the black circle is the median

An example of the probability distribution of dispersion of signed distances is shown in Figure 6 (i.e. first measurement repeat indicated as s_1). The statistics computed from the probability distributions for the measurement repeats are reported in Table 1 (probability distributions indicated as s_1, s_2, s_3, s_4 and s_5 respectively).

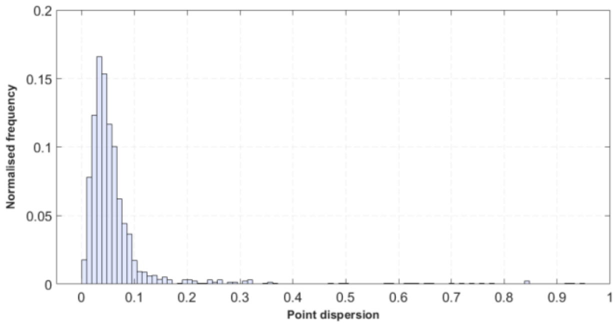

Figure 6. Example binned histogram of dispersion of signed point-to-surface distance values for the first measurement repeat (see the statistics reported in Table 1 indicated in column s_1). Dispersion is expressed in millimetres; normalised frequency (vertical axes) is the number of occurrences of the values in a bin, divided by the total number of occurrences

Table 1 Statistics of the distribution of dispersion of signed distances

	s_1	s_2	s_3	s_4	s_5	unit
mean	0.06	0.06	0.06	0.06	0.06	mm
st.dev	0.09	0.09	0.08	0.09	0.09	mm
range	0.00 - 0.95	0.00 - 0.93	0.00 - 0.90	0.00 - 0.98	0.00 - 0.96	mm

4. Conclusions and future work

The ability to capture hidden surfaces of the part geometry, maximise measurement coverage and produce high-density point clouds represent increasingly challenging requirements that must be fulfilled by measuring instruments, in particular when called on to inspect complex geometries, such as those produced by AM. The proposed work focuses on the preliminary development of sets of algorithmic solutions to automatically compute measurement quality indicators, designed to be embedded in future, smart optical measurement systems for the full automation of part inspection and intelligent measurement planning. The performance indicators, fed into the measuring pipeline, help optimising the measuring process investigating the relationships between the acquired point cloud and the reference geometry, automatically assessing coverage, sampling density and local dispersion of the measured points in relation to the individual surfaces of the measured part. The obtainable information can also support investigation on the performance and behaviour of optical measurement technologies, providing the foundation to further research towards the development of more advanced optical measuring instruments. The indicators represent novel quality assessment tools to guide instruments towards self-assessment of their own performance in-process (*i.e.,* while measuring), via adaptive optimisation and measurement re-planning. More specifically, thanks to feedback mechanisms instruments will be capable of planning the most suitable corrective actions, when quality issues are detected in the measurement result (for instance, insufficient degree of coverage, unacceptable measurement error).

In addition to the quality indicators, we have recently published a method for the evaluation of measurement uncertainty [17], offering a novel solution for the optimisation of the measurement process based on point cloud statistical model. We hope to present this work at future euspen events.

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