Optical metrology for digital manufacturing: a review

Sofia Catalucci1 · Adam Thompson1 · Samanta Piano1 · David T. Branson III1 · Richard Leach1

Received: 27 July 2021 / Accepted: 21 March 2022 / Published online: 1 April 2022 © The Author(s) 2022

Abstract

With the increasing adoption of Industry 4.0, optical metrology has experienced a significant boom in its implementation, as an ever-increasing number of manufacturing processes are overhauled for in-process measurement and control. As such, optical metrology for digital manufacturing is currently a hot topic in manufacturing research. Whilst contact coordinate measurement solutions have been adopted for many years, the current trend is to increasingly exploit the advantages given by optical measurement technologies. Smart automated non-contact inspection devices allow for faster cycle times, reducing the inspection time and having a continuous monitoring of process quality. In this paper, a review for the state of the art in optical metrology is presented, highlighting the advantages and impacts of the integration of optical coordinate and surface texture measurement technologies in digital manufacturing processes. Also, the range of current software and hardware technologies for digital manufacturing metrology is discussed, as well as strategies for zero-defect manufacturing for greater sustainability, including examples and in-depth discussions of additive manufacturing applications. Finally, key current challenges are identified relating to measurement speed and data-processing bottlenecks; geometric complexity, part size and surface texture; user-dependent constraints, harsh environments and uncertainty evaluation.

Keywords Optical metrology · Digital manufacturing · Industry 4.0 · Measurement uncertainty

1 Introduction

The latest industrial revolution is characterised by the transformation of individual activities (such as design, manufacturing, assembly, quality control and supply) into advanced, interconnected, highly efficient, flexible and automated production flows. In this setting, digital manufacturing refers to the application of integrated computer-based systems for the design and realisation of high-value products, as well as the management of complex manufacturing operations [1]. The last decade has seen a transformation of manufacturing industries, with a move towards the digitisation of routine tasks within their processes, and integration of such operations with external partners along the value chain [2]. Manufacturing activities are moving from conventional methods towards knowledge-driven processes, utilising information sharing and digital technologies, and innovative infrastructures that link systems across all areas of production [3]. The transformation into digitisation applies across many high-value sectors, including aerospace, automotive, medical instrumentation, precision optics and, more recently, construction. Productivity and quality are enhanced via the adoption of adaptive sensors and advanced technologies, by which all aspects of the manufacturing process (i.e. the whole life cycle of a product, from its design, manufacturing, assembly, testing and maintenance) are modelled, simulated and stored [4]. Due to these numerous innovations, the role of metrology (i.e. the science of measurement and its application [5]) within the manufacturing process chain has changed significantly. The use of optical measurement technologies for automation in research and on the manufacturing shop floor has been considered since significantly prior to the advent of the fourth industrial revolution. However, Industry 4.0 has allowed for the creation of optimised measurement procedures allow for quality control operations of every product by targeting critical measurements and metrological analyses to run in real-time. However, there is still a lack of confidence in the data that is captured and managed within those processes. As for any existing manufacturing infrastructure, confidence in data is the key enable for adoption of novel Industry 4.0 methodologies in manufacturing.
Good data enables right-first-time manufacture, reduces waste, scrap and energy consumption; and facilitates effective business decisions. Through metrological traceability, metrology solutions can be used to establish such confidence [6], reducing unnecessary scrap rates, inefficient processes and wasted production time.

1.1 Contents of the review

There are numerous existing reviews on manufacturing within the context of Industry 4.0 [7–11], mainly focused on related technologies that respond to the fundamental challenges of modern factory automation and their future framework and perspectives. Based on the principles presented in [2], with a greater focus into the implications of optical metrology within the context of digital manufacturing, the following research questions were posed:

1. Has the role of metrology (specifically optical co-ordinate and surface texture metrology) changed significantly inside the manufacturing flow over the last few years?
2. What are the major challenges given by the integration of metrology in digital manufacturing?
3. What are the latest trends for uncertainty and traceability, especially in the context of a digital manufacturing setup?

To answer those questions, an overview of coordinate and surface texture measurement solutions integrated into manufacturing processes is presented, alongside the challenges and limitations encountered when implementing these solutions. Here, the focus on coordinate and surface texture metrology is based on several considerations. Particularly, surface texture and coordinate measurement are perhaps the most critical parameter contributing to the quality and functionality of a manufactured part and the measurement of shape and surface texture represents a significant challenge for current measurement technologies.

Challenges include speed and data bottlenecks associated with software and hardware solutions; complexities resulting from variation in the size, shape, and texture of fabricated products; the user-dependency limitation of numerous quality inspection and verification processes; and issues that occur when measuring in harsh environments. The review ends with implications for uncertainty in measurement, particularly addressing the latest developments in methods for the uncertainty evaluation of optical instruments (for example, development of virtual instruments) and the uncertainty associated with three-dimensional (3D) point clouds and surface texture measurements.

This literature review was performed using the main scientific databases (Scopus, Google Scholar). A comprehensive initial search for extracting literature on the themes of optical metrology in digital manufacturing and its integration into Industry 4.0 context included publications from 2000 through 2021. Due to the high volume of available contents, the focus of the review targeted specific keywords such as “optical metrology”, “digital manufacturing”, “industry 4.0”, “zero-defect manufacturing”, “measurement uncertainty”. Moreover, selected publication ranged from 2015 through 2021, with only a few examples from the early 2000s. Papers were primarily selected if the contents of the study contributed towards answering any of the above questions through a three-stage evaluation process: (a) literature search based on specific keywords, (b) literature analysis and synthesis based on title/abstract screening, and (c) full-text screening of selected articles. The result of this process is a systematically collected set of sources that were then processed into the discussion presented throughout this paper.

Among 145 of the selected studies for review, 118 articles are journal publications, 17 papers are taken from conference and symposia proceedings, ten are books and book chapters; and eight publications are international standard certifications and good practice guides. Of these publications, 20 are dated between 2000 and 2014, nine in 2015, twelve in 2016, 20 in 2017, 27 in 2018, 16 in 2019, 31 in 2020 and ten in 2021.

2 Integrated metrology for Industry 4.0

In recent decades, due to innovations such as smart multisensor systems, virtual metrology and metrology-driven operations, the role of metrology inside the manufacturing flow has significantly changed. Previously, measurement solutions were generally employed for quality checks as the final step of a product’s conformity verifications, typically operating as post-processing activities. As a result of the latest “industrial revolution”, a large variety of measured data required for management, monitoring and diagnostic activities is now available in real-time and can be used to facilitate inspections and analysis [2, 7]. Highly digitised factories continuously collect and share data through inter-connected devices, machines, and production processes. In this environment, in-process metrology solutions and non-contact optical measurement systems, often mounted on industrial robots, offer fully automated and fast control and verification solutions. Optical metrology solutions easily fit into Industry 4.0 processes and metrology can promote true data-driven production. Image processing and vision systems, operating next to assembly and production cells, are able to acquire inspection data during/alongside the assembly/verification processes, automatically storing information associated with each manufactured product. As such, all relevant knowledge regarding the quality of a workpiece can be obtained.
while the part is being measured. Feedback-based control solutions are then performed using intelligent connection mechanisms linked to a central manufacturing system [12]. The practice of concentrating multiple production tasks in a single, connected, smart, automated and data-driven process infrastructure is known as “closed-loop manufacturing” [13]. Closed-loop manufacturing can deliver high production performances, reducing costs and improving product quality through the combination of digital technologies, manufacturing and measuring operations based on inspection and consumer feedback. The schematic workflow of this concept is presented in Fig. 1.

### 2.1 Data connectivity

Closed-loop manufacturing is linked to the concept of data connectivity, which represents the foundation of digital manufacturing [8, 9]. In closed-loop operation, data is collected, turned into usable information and shared to promote fast and reliable action [10]. For information to flow in real-time, current measuring instruments are linked together using cyber networks (i.e. instruments are integrated as cyber-physical systems, defined as “systems which link real – physical – objects and processes to information-processing – virtual – objects and processes via open, partly global information networks which can be connected together at any time” [2, 14]).

![Diagram of the production workflow](image)

**Fig. 1** The production workflow starts from the design and manufacturing of products employing digital technologies, followed by measuring operations and inspection. The data collected from the consumer feedback is then linked back to product development departments, allowing rapid enhancement of the product design.

Due to the adoption of new enabling technologies, such as cloud data management, measuring machines can act as their own interfaces, directly connecting and communicating with each other and to external actors. As an interconnected virtual architecture, cloud data management provides intelligent organisational capabilities and services to the manufacturing line. Cloud data management allows the line to become a networked unit of implemented tools for continuous communication of processes and machines [4]. Additionally, to enable real-time decision-making mechanisms, data is directly shared across companies and supply chains [15]. Enhanced connectivity increases the visibility of shop-floor processes, while simultaneously maximising production efficiency.

The sharing and exchange of data within communicating systems creates “on-demand” digital storage solutions and processing resources connected to a general digital industrial network, allowing for the trusted transmission of data, as well as traceability to cyber and physical reference standards to assure part provenance [16]. Essentially, every piece is connected, traced, tracked, measured and consequently improved, and every stage of the manufacturing line is controlled by self-monitoring mechanisms (i.e. built-in sensors integrated into machine operational functions). These intuitive components allow exchange of data between equipment, synchronising each task on the shop floor (for example, initiation of production, assembly, replacements and corrections) and improving decision-making through...
In-line measurements for zero-defect manufacturing

2.2 In-line measurements for zero-defect manufacturing

Digital manufacturing and smart measuring technologies enable the development of zero-defect manufacturing strategies, moving from off-line metrology and dedicated measuring equipment to in-line measurements and automated inspection systems (see the definitions of in-line and off-line metrology and classification, as discussed in [27, 28]). Measuring in-line presents several benefits over conventional, off-line methods, including the minimisation of the inspection time (removing some of the more time-consuming tasks), the continuous monitoring of process quality, faster cycle times and the creation of fully automated manufacturing cells [29]. Qualitative faults and imperfections that may affect functional properties or subsequent assembly operations are detected in advance, reducing the chances of potential reworks and delays and addressing the possible issues while the part is still being manufactured [30]. Further, measuring in-line requires that the technology/instrument employed must be feasible for the production line (where the measurement of dynamic objects is often required), whilst guaranteeing accurate results in short measurement times. As an example, the measurement system (either mounted on a robot-arm or placed in the measuring cell [11]) should be placed on a conveyor or roller table and moved along synchronously with the workpiece (i.e. the two coordinate reference frames must translate with one another).

In addition to robot-mounted measurement devices that can address a range of tasks autonomously, the latest trend has seen a majority of verification tasks concentrated into a single instrument performing on-machine or, more specifically, in-process inspection. The shape and surface texture information of a measured part are representative of the process characteristics and the actual performances of the machine tool employed. As such, as reported by Gao et al. [27], the integration of manufacturing and measuring operations is beneficial to the production process. Consequently, commercially available measurement instruments have seen a significant improvement in multiple manufacturing industries, not only in their intrinsic measurement performances, but also in terms of design and planning of measurement procedures [7, 9]. Numerous instrument suppliers are marketing their products for their specific use in quality control and in-process verification of machined parts, driven by the common objectives of covering customer's needs and meeting new market demands [2, 31]. Proprietary software platforms for virtual simulation of the measurement environment, i.e. virtual measuring room (VMR) and optical sensors mounted on industrial robotic-based systems or directly integrated within the machine tool, are increasingly employed as solutions for in-line manufacturing scenarios. At present, there are several commercial (or close to commercial) sensors that can be employed for integrated metrology with a list of current, manufacturer agnostic, software and hardware configurations for in-line (and off-line) measurements presented in Table 1. While these solutions are numerous, their full integration into digital manufacturing processes is still characterised by a large number of barriers yet to be overcome (see detailed discussion in Sect. 3).

In the following subsections, an overview of the latest measurement technologies for in-line integration into manufacturing processes is presented. Here, examples of geometrical and dimensional analysis of workpieces and detection of surface defects with a particular focus on in-process monitoring for additive manufacturing (AM) are included. While this paper is manufacturing process-agnostic, here,
the AM focus is provided because the wide variety of challenges present in AM part measurement broadly represent the set of challenges present in digital manufacturing, summarised as a series of appropriate case studies.

### 2.2.1 Geometrical and dimensional inspection

Currently, the majority of inspection devices for the measurement of geometrical and dimensional features available on the market for industrial applications (such as automotive assembly and aerospace inspections) use optical technologies, most commonly laser-based instruments. Kiraci et al. [32] developed an industrial demonstrator (Fig. 2a) used to assess the performances of a laser radar solution for in-line dimensional inspection in the context of body-in-white (BIW) automotive applications. The authors aimed to understand the effects of the robot re-positioning error by mounting the sensor on a robot-arm moving on a trail (shown in schematic form in Fig. 2b) and examining the measurement accuracy and repeatability, compared to contact measurements. The results showed a significant reduction in measurement cycle-time, allowing a rapid detection and correction of assembly defects in real-time.

Later, the same authors [33] evaluated the capability of three measurement systems (i.e. a contact co-ordinate measuring machine and a single-line laser triangulation as...
off-line measurement solutions; and laser radar as an in-line solution), determining their feature-specific suitability for automotive inspection. A calibrated artefact, representative of common automotive features, was selected as a test case. Kiraci et al. found that the laser radar provided results comparable to the off-line systems in terms of accuracy. Tran and Ha [34] proposed a high-resolution camera and a multi-line, laser-based sensor for the measurement of gap/flush in assembly of automotive vehicles (Fig. 3). The measurement system showed its capability for measuring complex surfaces at high speed within an in-line vehicle assembly environment. Zhou et al. [35] presented a method based on laser scanning technologies for the automated fast inspection of freeform shapes, with the aim of developing an instrument for in-line dimensional inspection in the automotive and aerospace sectors. Long et al. [36] proposed a framework for automatic gap/flush measurement based on unstructured point cloud analysis. The cross-sections needed for the analysis of the gap/flush profiles were extracted based on point cloud segmentation methods. The framework was tested using two commercial optical instruments: a laser-based portable device and a fringe projection system, for the inspection of aircraft skin surfaces and the gap of a car door, respectively. Kosmopoulos et al. [37], proposed a stereo camera-based system for automated dimensional inspection in automotive production. Their measurement setup consisted of two calibrated stereo cameras and two infrared LED lamps, used for highlighting the edges of gaps and recessed features via specular reflection. The proposed method has significant advantages, in being fully automated and independent to colour variation.

Despite the latest developments, in most assembly lines and quality control stations, some of the inspection tasks (for example, the inspection of critical features in an automotive body shell, gap/flush measurements and aircraft skin surface defects detection) are still performed manually. Manual measurement often involves employing handheld devices or is carried out as a separate activity, moving the parts away from the production line to an independent department [38]. Generally, handheld devices show obvious limitations in the rapid and continuous collection and storage of data. Additionally, because of their portable configuration, they generally require the intervention of highly qualified operators. Furthermore, moving a manufactured workpiece in and out of the production line increases time delays and interrupts the continuous monitoring of processes/part quality. Therefore, the rapid detection and correction of part quality issues and assembly defects are increasingly desired in real-time.

2.2.2 Surface defect detection

The presence of defects on the surfaces of fabricated workpieces (for example, on the paint finish of an automotive panel, such as scratches, orange peel, colour mismatches [39], or in the internal structures of a manufactured part, such as porosity, internal cracks and thermal/internal stress [40, 41]) is one of the key factors directly affecting efficiency and profitability in industrial manufacturing. Along with geometrical and dimensional issues, surface defects can significantly alter the quality, aesthetic, mechanical properties and safety of fabricated parts. With the rapid development of machine vision, image processing and pattern recognition methods, manual approaches for defect detection are being overturned by advanced optical solutions combined with machine learning technologies. In other words, current instruments are designed, trained and integrated to predict surface texture defects of fabricated parts autonomously, minimising the intervention of operators [42]. Further, in closed-loop manufacturing scenarios, developed on-machine measurement solutions for in-process monitoring of fabricated parts are becoming increasingly appealing, particularly in the case of AM [43-46]. A schematic example of fringe projection technology applied to in-process surface metrology in metal AM is shown in Fig. 4.

![Fig. 3 Measurement of gap/flush in assembly of automotive vehicles: setup developed by Tran and Ha [34]. a Camera-laser module (high-resolution camera and a multi-line laser-based sensor), b view of the entire setup, c three camera-laser modules attached to a robotic-arm for real application (i.e. vehicle assembly)](image-url)
2.2.2.1 In-process monitoring

In-process monitoring is commonly aimed at detecting defects of the AM powder bed while the component is being built (i.e. direct inspection layer by layer), to find issues that might jeopardise the quality of the manufactured parts. As such, real-time monitoring can lead to either corrective actions (for example, the re-deposition of the powder bed, the substitution of a worn recoating system) or to the immediate stoppage of the printing process [47]. On-machine measurement solutions offer the potential opportunity to either salvage or discard defective parts at an early stage of their production, avoiding wastage of time and resources encountered, particularly in the case of high value-added parts in low production volumes.

Optical instruments have become an appealing solution for the direct imaging of the powder bed [48], and instruments are now preferably designed by implementing machine learning algorithms for the automated assessment of the quality of 3D printed parts [49–52]. Along with coaxial [53], off-axis [46] melt pool monitoring systems and thermal imaging [54], several authors have proposed in situ monitoring methods employing optical measurement technologies (for instance, the analysis of the powder bed via the use of a line scanner mounted on the recoater blade [55, 56] or digital fringe projection [57–65]), specifically for the acquisition of the surface height information. In particular, multi-view fringe projection configurations (Fig. 5) have been proposed by Kalms et al. [64] and Dickins et al. [65], achieving improved results compared to single-view projection configurations. Additionally, image segmentation approaches have been employed for high-resolution imaging of each printed layer to detect powder recoating errors, as well as surface texture and geometrical defects [48, 66, 67]. These solutions allow for the capture of topographical information of surface features more easily than melt pool monitoring or traditional imaging methods. General aspects about optical in-process surface topography measurements and in situ process monitoring for AM parts have been extensively reviewed elsewhere [47, 68–71].

---

**Fig. 4** Schematic example of in-process fringe projection setup in laser powder bed fusion (LPBF) (from Gao et al. [27])

**Fig. 5** Example setups of multi-view configurations for the acquisition of topographical information of surface texture: a two-camera fringe projection system installed inside a laser beam melting (LBM) building chamber (from Kalms et al. [64]); b four-camera fringe projection system installed inside a mock-up of powder bed fusion (PBF) chamber (from Dickins et al. [65])
On-machine measurement solutions allow for the monitoring of each fabricated layer, inspection of the powder bed, and the capture of melt pool dynamics [72, 73]. Nevertheless, direct integration of measurement solutions must consider the effects on the measurement results given by the high temperatures and random disturbances due to volatilities [74]. It is also important to ensure that the manufacturing process itself is not disturbed by the measurement. Additionally, the integration of measurement solutions within the factory line may positively affect the speed of production, significantly reducing the time rates needed for the fabrication and inspection of workpieces. However, numerous challenges remain. Speed bottlenecks, along with other advantages and limitations of integrated measurement solutions are further discussed in Sect. 3.

3 The challenges of integrated metrology

Various challenges exist in integrated metrology, which can be separated broadly into a series of research areas. For the purposes of this review, the challenges discussed are separated into those relating to speed and data bottlenecks, including the physical limits of both hardware and software especially for in-line measurements; those related to shape complexity, size and surface texture; those related to user-dependent constraints, which are still present in many inspection tasks; and those related to measurement in harsh environments.

3.1 Measurement speed and data bottlenecks

For in-process measurement (where high speeds are often a requirement), one of the most significant barriers is bottlenecks in the physical measurement process and data processing pipeline [69, 75]. The presence of bottlenecks in data handling pipelines often dominate manufacturing process cycle times and can significantly impact the frequency at which measurements can take place. Such bottlenecks are often caused by software limitations, such as maximum data transfer or data processing speeds, or by hardware limitations, such as camera framerates. As discussed in Sect. 2, the application of advanced optical coordinate and surface texture measurement technologies in an industrial scenario is still characterised by numerous challenges [20], due to the high speeds of production on the shop floor, the large variety of product designs, and sudden changes of part surface textures which magnify the difficulties encountered while performing routine inspection tasks [68]. For instance, Syam et al. [69] split the challenges of in-line measurements into (a) dynamic spatial range issues (i.e. the property of the sensors to achieve sufficient resolution and range), and (b) temporal range issues (i.e. the speed of the sensors).

Conventional co-ordinate measurement commonly takes minutes to hours to acquire a relatively small number of data points [76], and, as such, it is generally assumed that contact measurement is unviable as an integrated metrology solution. Optical technologies, however, are more easily applicable in integrated scenarios, as their inherent speed advantages make fast measurement possible. Significant challenges remain, however, and hardware limits, such as those discussed in the following paragraph, often make true real-time measurement difficult or impossible. Particularly, while fast measurement of static objects is possible in a few seconds, fringe projection techniques cannot realistically be applied for the measurement of dynamic objects, such as those moving along the production line, as these systems generally require at least a few seconds to acquire measurement data and require calibration to provide useful data [77].

Fringe projection and other camera-based optical systems are hardware-limited by the camera framerate. As such, they generally require measured objects to remain static for the time taken to acquire a few camera exposures. Changes to the measurement environment (such as temperature fluctuations) also significantly alter the conditions of the system, which often prevents or voids any meaningful calibration. To reach high-speed 3D shape measurement, the structured fringe patterns must be switched rapidly, and captured in a short period of time. Zhang [78] states that the low level of automation in advanced 3D shape measurement is one of the major challenges. Particularly, the determination of the desired optimal camera exposure rapidly without human intervention is a significant issue. To address this issue, Zhang developed a rapid auto-exposure technique for 3D shape measurement using fringe projection, proving that the proposed method is appropriate for real-time applications.

Due to high measurement speed, Fourier transform profilometry (FTP) methods have been demonstrated successful for fast motion capture applications, such as measuring vibrations or capturing flapping wing robots [79]. Su and Zhang [80] and Wang [81] reviewed the state of the art in real-time 3D shape measurement techniques capable of reconstructing dynamic objects. In particular, these authors noted that some preliminary attempts at dynamic measurement have been performed by keeping the projected pattern fixed (for example, by using a dot pattern instead of varying fringes) and/or using a multi-view approach [82, 83]. The multi-view approach is still in its infancy for in-line measurement applications, where robot-mounted sensors are generally preferred.

Photogrammetry has been employed for the measurement of dynamic objects in combination with an additional light source (i.e. flash illumination), which is used to decrease the exposure time needed for the measurements and to speed up data acquisition [84]. An example use of photogrammetry for automatic in-line inspections is shown in Fig. 6, where the
use of an additional source of homogenous light can potentially decrease the generation of occlusions and shadowing in correspondence to hidden and difficult to access geometric features [77]. Another example is given by Sjödahl et al. [85] who developed an industrial demonstrator designed for in-line inspection of metal sheet components based on close-range photogrammetry. For this case, in addition to the redesign of the required illumination system, the measurement device used information derived from the computer-aided design model of the part to detect features in the images and perform reconstruction. The authors demonstrated that the system was able to measure in real-time on a conveyor belt that moves at about 1 m/s at a frequency of approximately 0.5 Hz without fixturing.

Data transfer and data processing are also significant barriers to the implementation of in-process measurement. Particularly, the adoption of integrated metrology is often prohibited by the vast amount of data that can be produced with high-resolution fast sensing technologies, and the associated challenges of handling big data. Optical technologies may be able to acquire data in a matter of seconds, but if processing that data requires hours of computation per measurement and creates large volumes of data that must be stored for extended periods of time, an initially enticing measurement solution can quickly become unviable. While these challenges clearly exist, big data can also represent an opportunity, provided advanced data handling, analysis and learning methods are employed to deal with the challenges they present [86]. Big data problems are ideal for machine learning, which is increasingly being applied to measurement cases to improve the capabilities of measurement instruments [87]. Examples include the employment of machine learning methods to understand surface orientations [88], automatically segment 3D point clouds [89], infer surface information from missing data using a priori information [90] and automatically segment objects, especially for machine vision applications [91].

### 3.2 Geometric complexity, part size and surface texture variation

In digital manufacturing, there are various challenges for optical measurement that relate to part complexity, size and geometry: different considerations are required for small parts, large parts, complex parts and parts with varying surface textures. The impacts of these issues must be included as part of a measurement plan, particularly regarding how data coverage (i.e. the proportion of non-measured points) and measurement time are affected.

When measuring small parts, the key concerns are generally instrument resolution and depth of field, as well as the trade-off between these two considerations [92]. For example, when performing photogrammetry, to prevent diffraction effects limiting the measurement system a low f-number (the ratio of the camera’s focal length to the diameter of the entrance pupil—a property of all optical systems) lens can be used, though doing so will limit the depth of field of the camera. However, a large depth of field is desirable as the working range of the instrument is dictated by the depth of field. This problem can be overcome by using, for example, image stacking [93] or by altering the optical setup entirely using plenoptic setups [94], but doing so comes at the cost of increasing measurement time or decreasing resolution, respectively. Similarly, a resolution limit always exists when performing any kind of optical measurement. In all optical setups, there exists a maximum theoretical physical limit for any system (the diffraction limit) [95] that limits the resolution of the system in the absence of any other limiting factor. However, in optical coordinate measurement, systems are more commonly limited by some other issue, such as imperfections in the construction of the system (for example, errors in measurement scales). In fringe projection, for example, system resolution can be limited by the spatial resolution of the projector used to generate the pattern of fringes [96]. Achievable resolutions are generally on the order of a few tens of micrometres in the best case scenarios [97]. While the depth of field and resolution issues exist for parts of all sizes, their effects become increasingly significant the smaller the parts being measured become, and consideration of their effects becomes increasingly important when performing measurement of smaller parts (or, indeed, small part features).

While the biggest issues in optical measurement of small parts are most commonly depth of field and resolution, large
parts elicit a different set of considerations. The main consideration that must be accounted for when measuring large parts is the total measurement volume (or field of view) of the instrument, and any associated stitching that may be required to combine multiple measurements together [98, 99]. Many optical systems do not have physical limitations on their total measurement volume, in that they are often free roaming and not attached to stationary hardware (such as a co-ordinate measurement machine base). When increasing volume size and larger numbers of stitched fields of view, measurement errors stack and the quality of measurement data can quickly become poor. Larger scale measurement systems now commonly employ some form of robotic manipulation of a measurement sensor as well as in-measurement tracking of the measurement head [100, 101], designed to minimise the errors created by stitching together many single-view measurements over a large area. Such systems then commonly incorporate information from an additional secondary tracking system into the main measurement setup to improve the quality of the measurement. Different methods of incorporating that information exist, and the optimum solution for doing so will vary in different measurement scenarios. As such, tracking of measurement sensors remains an open research question and is commonly the topic of many publications. Another consideration of large parts is the effect of environmental changes, which are exaggerated as parts increase in size. For example, thermal fluctuations can result in large changes to dimension, and warping due to gravity and fixturing errors becomes a significant problem [99].

With the increasing adoption of modern manufacturing technologies (and of AM in particular), recent years have seen a drastic increase in the number of products coming to market that have shape complexity that has not previously been achievable [102]. While other technologies also provide parts with complex shape, this issue is most prominent within AM, so this subsection is focussed primarily on parts produced using that technology. Such complex parts bring new opportunities for lightweighting, mass customisation, etc., but with the removal of tool access requirements that AM technologies provide, comes the side effect of measurement probe access no longer being possible. Modern parts commonly exhibit complex freeform geometries, hollow shapes, internal and inaccessible features, as well as a mix of random and deterministic surface features [103].

As an example, a frequent issue is represented by the inherent limitation requiring optical solutions to operate successfully within the line-of-sight, making the acquisition of large and/or complex structures from a single measurement position impossible [88, 104] (see Fig. 7). This complication is usually minimised by placing the part on a rotary table and performing multiple measurements at incremented angles [105]. However, maximising the acquisition of the part surface using such expensive and time-consuming manual methods is often undesirable, particularly in large production volume environments. A common solution, in the current industrial market, to overcome such limitation is the use of optical robot-mounted automated sensors, programmed and movable around the part [100, 106, 107].

In their recent review, Leach et al. [108] go into significant depth discussing the challenges of AM part measurement, noting great difficulty in measuring complex parts where probe access is not possible. It should be noted that “probe access” does not solely refer to whether a physical probe can contact a part, but also whether there is an unobstructed optical path between the part and the measurement sensor.

In the measurement of surface texture, significant challenges exist because of features present on measured parts that make optical measurement of modern manufactured parts difficult. In metal AM, for example, surface features such as a large range of scales of interest, step-like transitions, overhangs, highly reflective and opaque surface regions cause significant difficulty for a variety of measurement instruments [103, 109, 110]. Polymer AM surfaces exhibit similar difficulties in measurement [111], with the added complexity of material translucency. While AM surfaces arguably exhibit the widest plethora of difficult-to-measure surface features simultaneously, many modern manufacturing processes come with their own challenges. Composite materials are another commonly problematic surface, as the dark colours and material translucency often present can similarly make optical measurement difficult, and there is a lack of research published that directly focusses on the measurement of composite surfaces. In 2016, Dubouste et al. [112] and Geier and Pereszlai [113] performed measurements of composite materials using focus variation and contact stylus instruments, noting the
difficulties involved comparisons of profile and areal surface texture parameters, as well as qualitative examinations of the features present on these surfaces. To the authors knowledge, no inter-technology comparison of composite surfaces has yet been performed using other optical surface measurement technologies.

The effects of surfaces are not limited to surface texture measurement, as coordinate measurements are also commonly affected by modern manufactured surfaces. For example, smooth finished surfaces with highly reflective properties cause ineffective inspections, forcing the inconvenient employment of markers, coating sprays and retroreflectors combined with the selected optical solutions [114] that limit fully automated measurement. Conversely, rough surfaces have been shown to cause significant deviations between coordinate measurements made using contact systems, optical systems and X-ray computed tomography systems, making measurement comparability and measurement traceability difficult to establish [108].

Difficulties related to shape complexity, size and surface texture variation can often be overcome by optimising measurements using advanced measurement functions (for example, lighting conditions and software corrections [115, 116]). However, such exercises often result in longer measurement times as many advanced measurement functions come with some process time increase. The difference made by these additional functions is often to fill in many of the non-measured points that occur in their absence (essentially making the measurement result viable), with a time penalty on the order of a few seconds to a few minutes. While these novel functions can allow measurement where it was not previously possible; in an integrated metrology scenario these time increases can be the difference between an appropriate solution and an intolerable speed decrease. Ongoing research and development are required to further optimise the amount of time required to take appropriate data, but as discussed in Sect. 3.1, measurement speeds can be a significant bottleneck.

3.3 User-dependent constraints

It has long been established that measurement system users themselves represent a significant challenge in the digital manufacturing ecosystem [117]. Operator expertise and experience always has some effect on any manufacturing process, and within measurement and characterisation that effect is evident in the setup of a measurement and characterisation pipeline. Particularly, the setup of any one measurement will differ between users and a measurement result will ultimately vary by some amount as a result of any operator input. The development of good practice guidance (for example, see [76]) is performed to mitigate these effects through the sharing of appropriate methods to optimise measurement and characterisation procedures. However, good practice will always be limited by the skill of the measurement instrument operator. Indeed, there will always be some inherent discrepancy between one skilled operator and another, and while international standardisation (for example, verification procedures, such as those described in the ISO 10360 series of standards [118]) aims to eliminate such variation, complete removal of operator discrepancy is difficult. As such, the high level of user-dependency in most of the inspection tasks [87], including the iterative review and re-processing of the measuring plan until a satisfying set of measurements is taken, presents a complex challenge. To address this issue, there exists a requirement for autonomous actions for measurement and data processing, capable of implementing appropriate measurement and characterisation optimisation without the need for a skilled operator.

In recent years, machine learning algorithms have been developed to optimise the measuring procedure, not only by improving the acquisition and processing of the data, but also by giving the opportunity to automate non-contact instruments, allowing sensors to be repositioned without the need for recalibration of the extrinsic parameters [119]. An example is shown in Fig. 8. After a measurement is carried out, a large amount of data is generated and collected implying excess/redundant surface sampling information, which severely augments the data processing computational time and jeopardises the correct assessment of whether a part conforms to dimensional and geometric specification requirements [120]. Thus, algorithms for the optimisation of data acquisition and simplification that can preserve unaltered the properties and the main features of a measurement are required.

3.4 Measurement in harsh environments

Improvement in the speed, accuracy and information density of sensor technologies is a clear requirement in the advancement of integrated metrology. The ability to obtain higher quality data at a faster rate is a common goal for many sectors of industry. More specific to integrated metrology is the ability to use sensors in harsh environments where it has not been previously possible to make measurements. Harsh environments, such as those with high temperatures, are common in manufacturing, particularly close to the tool/part interaction, and obtaining measurements at these locations can be difficult. In their recent review, French et al. [121] addressed measurement in harsh environments, noting that measurement systems must often be constructed using alternate design strategies, for example using materials that are suitable for the intended harsh environment, or housing measurement devices within protective casings or
coatings. To function, such systems must be adjusted in the harsh environment, which provides an additional challenge.

For example, the implementation of compact distance sensors in the machining environment is difficult due to the hostile operating conditions. However, low coherence interferometry has shown promise for operating in challenging environments, with a small footprint due to integration into fibre optic systems [122]. Similarly, in their recent work, Remani et al. [74] designed a fringe projection sensor for integration directly into a metal AM machine, shielding it from the surrounding environment by housing the measurement sensors inside a protective casing. Future developments of sensors are expected to address the current limitations of these harsh environments, enabling sensors to be used in-situ [20].

4 The implication of measurement uncertainty

Uncertainty in optical measurement of both coordinate and surface texture remains a complex, open research question. As highlighted throughout this paper and in others (for example, see [108]), establishing traceability for optical measurement systems in a digital manufacturing setup is often complicated by both the measurement technology and the objects being measured. However, there is research ongoing that is aimed at addressing uncertainty evaluation, and various groups are working towards traceability. In their recent paper, Ferucci and Ametova [123] discuss the move towards traceability in X-ray computed tomography measurement, proposing a framework for model-based uncertainty assessment via Monte Carlo simulation and instrument scale calibration. Similarly, Gayton et al. [124] have recently proposed a virtual-instrument calibration method for fringe projection systems based on Monte Carlo simulation. This approach mirrors methods of uncertainty evaluation developed for contact measurement that are now relatively well established in contact co-ordinate metrology [125]. Current developments in measurement uncertainty are also discussed, divided approximately by their association to coordinate measurement (particularly in relation to point clouds) and surface texture measurement, respectively.

In the next 10 years, there is an expectation that methods of traceability and calibration will be incorporated into in-line and on-machine measurement processes [27]. Common solutions will include the use of calibration artefacts to achieve reliability [6] and self-calibration methods within manufacturing [27, 126], to better accommodate the specific setup and environment in which the equipment is operating. Additionally, standardised procedures and methods are expected to be developed for integrated, metrology-specific data processing applications, such as sampling strategy [127, 128], defect identification and handling [129–131], and data acquisition and analysis.

A thorough review of uncertainty evaluation within the context of co-ordinate measurement is a rich and deep topic in and of itself, and to complete this review is significantly beyond the scope of this paper. Such a review would represent an interesting topic for a future review paper.

4.1 Uncertainty associated with point clouds

3D point clouds are the outcome of a chain of events and physical phenomena that define a measurement process. In particular, optical technologies for the inspection and verification of shapes are centred around the acquisition
and manipulation of this kind of data, and evaluating its uncertainty is far from trivial.

Generally, each digital point is associated with an uncertainty in its position in 3D space (i.e. defined as positional uncertainty—the uncertainty in where the point should actually be located in the absence of measurement error [132]). Measurement error propagates through typical data processing pipelines (for example, simplification, filtering, partitioning, datum fitting and registration), ultimately affecting the results of the characterisation process [133]. Essentially, any dimensional or geometric assessment extracted from a point cloud is associated with an uncertainty in the variation of the points’ positions in 3D space. Additional error sources can also be introduced by the processing methods and algorithms selected [133]. As an example, concerning the uncertainty evaluation in form error characterisation, Forbes and Minh [134–136] investigated the relationship between measurement uncertainty and fitting. Pauly et al. [137] discussed the error associated with surface reconstruction from a point cloud and included an adaptive re-sampling method, an algorithm for reconstructing surfaces in the presence of noise and a technique for robustly registering a set of scans into a single point-based representation. Pauly et al. assumed the point cloud to be a finite set of noisy samples that provide incomplete information about the underlying reconstructed surface. To capture uncertainty, they introduced a statistical representation that quantifies the likelihood that a surface fitting the data passes through that point for each point in space. Uncertainty in registration and fusion of point clouds has been widely explored in literature [138, 139]. Particularly, the uncertainty of global matching algorithms for pairwise correspondences has been evaluated via statistical means [140–143]. Another example of implication of uncertainty in the data processing pipeline is given using different filtering methods for point clouds. Han et al. [144] evaluated to what extent the choice of the filtering algorithm affects the measured data contributing to uncertainty, additionally including in their experimental evaluation the robustness and computational efficiency of the chosen methods.

Concerning the evaluation of uncertainty associated with point clouds, conventional approaches (such as [145, 146]) are not suitable, due to the multitude of possible error sources and the complexities of their interactions. These issues can lead to significant difficulties in the mathematical modelling of the aggregated errors failing to produce a comprehensive analytical representation of uncertainty.

Approaches devoted to the understanding and modelling of the uncertainty associated with the individual points of the point cloud are still in their infancy and the current state of the art in this respect is addressed elsewhere [120]. The two most diffuse approaches are expressed in probabilistic terms and illustrated in Fig. 9, as reported in [120]. The first configuration (in Fig. 9a) shows a random variable as only associated with a displacement in the direction defined by the local surface normal; in Fig. 9b, a full 3D probability ellipsoid (tri-variate random variable) is associated with each digital point. Univariate random variables associated with local surface normals have been explored, for example by Thompson et al. [147], specifically as a means of addressing measurement uncertainty. Random variables may be defined as independent between points or spatial dependency can be captured by modelling co-variance [148]. Senin et al. [133] developed a statistical model based on fitting Gaussian random fields to high-density point clouds produced by measurement repeats to capture the variability of points along the direction defined by the local normal.

4.2 Uncertainty in surface texture measurement

The current state of the art in uncertainty for surface texture measurement is elsewhere [149]. In this work, the authors review the metrological characteristics approach to evaluation of uncertainty in surface texture measurement [150] (see Fig. 10), discussing the quantification of the different characteristics required to make an uncertainty evaluation. In particular: amplification coefficients and linearity deviations in the $x$, $y$ and $z$ axes, flatness deviation, measurement noise, topographic spatial resolution, $x$–$y$ mapping deviations and topography fidelity. Leach et al. noted that the metrological characteristics approach is generally employed when
quantification of individual uncertainty influence factors (i.e. the GUM method [151]) is deemed to be too great a task. Often, in surface texture measurement instruments, the influence factors are too complex to be easily quantified in a majority of measurement setups. The metrological characteristics approach simplifies the GUM method and inherently double counts some influence factors but is used as a trade-off between double-counting influence factors and the difficulty in performing the evaluation.

Leach et al. also noted that quotation of uncertainty alongside surface topography measurements remains rare in the literature, attributed in [149] to the complexity of doing so. However, the base science and general groundwork now exists, and there are an increasing number of worked examples and good practice guides, such as [152], that provide end users with appropriate methods of working through a surface texture uncertainty evaluation. Leach et al. also noted that there is still research to do in the creation of virtual instruments for uncertainty modelling, though some work has recently been published to that end [153]. Unsolved problems remain with the metrological characteristics approach to uncertainty evaluation. The most notable of these problems is the incorporation of topographic resolution and topography fidelity into uncertainty budgets, the evaluation of which remains a challenge in many applications.

5 Conclusions and future work

In this review, the various challenges associated with performing optical measurement within a digital manufacturing context have been discussed. Through assessment of the state of the art, a number of common threads can be pulled through to form these conclusions, which are summarised here, alongside appropriate related avenues for future research. To summarise, the questions from Sect. 1.1 are readdressed here:

1. Has the role of metrology (more specifically optical coordinate and surface texture metrology) changed significantly inside the manufacturing flow over the last few years?

   The pressing need for optimisation of the manufacturing process is starting to gain a new importance and quality control is becoming a vital part of the process. To reach this point, there has been a significant revolution in the manufacturing shop floor that has changed the role of metrology. A range of current software and hardware solutions exist for in-line and off-line measurement, with existing solutions being increasingly applied to in-line scenarios. Many of these solutions remain proprietary, however, and the lack of transparency in their algorithms provides a significant barrier that can prevent many of these solutions from being fully integrated into digital manufacturing processes. Future work in this area will include iterative efforts to better integrate existing solutions into the digital manufacturing research ecosystem, as well as more disruptive approaches to developing new solutions for problems that the current solutions cannot solve. Thanks to innovations such as smart multi-sensor systems, virtual metrology and metrology-driven operations, the role of metrology on the manufacturing shop floor has significantly changed. Previously, measurement operations for inspection were run as post-process activities during the final step of a product’s conformity verifications. Now, as reported by Gao et al. [27], the integration of manufacturing operations and measurement activities is possible during the production process: metrology integrated into the manufacturing flow provides significant benefits over conventional, off-line methods, including...
sped up the inspection rates, allowing for continuous monitoring of process quality and promoting fully automated manufacturing cells.

Zero-defect manufacturing strategies have been made possible in recent years because of the application of in-line measurement and in-process monitoring. Measurement instruments have seen significant improvement, both in their intrinsic performance and in terms of design and planning of measurement procedures. Through review of the existing literature, it is clear that most currently available inspection devices for co-ordinate measurement in industrial applications use optical technologies. The most common of these technologies are laser-based instruments; examples are reported in [32–37]. Despite the latest developments, some of inspection tasks are still performed as separate activities using hand-held devices. Aiming at minimising the direct intervention of human operators, on-machine measurement solutions for in-process monitoring of fabricated parts are becoming increasingly appealing, particularly in the case of AM [48–52, 55–67]. Open challenges still remain: on-machine inspection allows for the monitoring of each fabricated layer, but direct integration of measurement solutions must consider the effects on the results from high processing temperatures and random process variations.

To summarise, this area of research is far from complete and many avenues of future research exist that will further facilitate zero-defect manufacturing including development of intelligent and adaptive integrated inspection devices (tailor-made measuring cells able to address multiple tasks autonomously with minimum human intervention); enhancement of decision-making processes (machine learning algorithms for prediction of errors and correction of operations); promotion of knowledge-driven solutions (use of a priori information of parts, instruments and procedures for enhanced real-time process control). Notably, there is a lack of research focussed on correlating in-process phenomena with part function, as a means to identifying which defects can be ignored and which require some process intervention to correct. To further establish zero-defect manufacturing approaches, these correlations should be established.

2. What are the major challenges given by the integration of metrology in digital manufacturing?

A number of key challenges exist in performing integrated measurements and, in this review, the challenges discussed are separated into those relating to speed and data bottlenecks, including the physical limits of both hardware and software; those related to shape complexity, size and surface texture; those related to user-dependent constraints; and those related to measurement in harsh environments.

Limitations resulting from measurement and data processing speed, particularly in the case of in-process measurement, are often caused by software limitations, such as maximum data transfer or data processing speeds, or by hardware limitations, such as camera framerates. Commonly, contact measurement is recognised as unviable as an integrated metrology solution. Conversely, optical non-contact technologies are more easily applicable in integrated scenarios. Still, hardware limitations often make true real-time measurement difficult to achieve, despite recent attempts made to overcome such barrier [79–85].

Different issues may be found when measuring small parts, large parts, complex parts and parts with variable surface texture. Currently, a wealth of active research is being devoted to addressing these limitations [93, 94, 100, 101, 106, 107, 115, 116]. When measuring small parts, the key concerns are generally instrument resolution and depth of field, while for the measurement of large parts, the main issues are identified by limitations relating to the instrument field of view and any associated measurement stitching procedure. To minimise the latter problem, larger scale measurement systems employ robotic manipulation as well as in-measurement tracking solutions. Parts with complex shape, mostly produced with AM, exhibit freeform geometries, hollow shapes, internal and inaccessible features that strongly affect access of the measurement probe, both contact and non-contact. The commonly adopted solution is to place the part on a rotary table and perform multiple measurements at incremented angles, whereas the most modern solutions use robot-mounted automated optical sensors, programmed and movable around the part. In surface texture measurement, significant challenges exist because of features present on measured parts, material translucency, dark colours, smooth finished surfaces with highly reflective properties that make optical measurement difficult. For example, there is a lack of research published that directly focusses on the measurement of composite surfaces. In general, due to the high production speeds on the shop floor, the large variety of product designs and sudden changes of manufactured workpieces magnify the difficulties encountered while performing routine inspection tasks.

Future work is likely to include iterative improvement of software and hardware limitations, aimed at decreasing measurement and data processing times. While many processes can capture data in near-real time, data processing in particular remains a complex problem that will ease over time as processing technologies improve with regard to speed. Current solutions are given by the implementation of machine learning approaches applied effectively to the entire measurement pipeline.
and real-time 3D shape measurement techniques. Preliminary attempts at dynamic measurements have been performed by enhancing the existing measuring technologies using for instance advanced configurations (i.e. multi-view approaches), as reported in [79–83]. However, their implementation into the pipeline is still in its infancy. Good practice guides and machine learning algorithms have been developed to optimise measuring procedure and overcome the constraints relating to the user-dependence of many measurement and characterisation protocols [76, 119, 120]. Further developments are expected to address the current limitations given by measurements held into harsh environments. The solution is to enable instruments to be used in situ, for example shielding sensors from the surrounding environment by housing protective casings, as presented, for example, in [74].

3. What are the latest trends for uncertainty and traceability, especially in the context of a digital manufacturing setup?

Uncertainty remains a difficult active area of research that continues to present a series of complex challenges [6, 27, 123–131]. In the future, methods of traceability and calibration are expected to be incorporated into in-line and on-machine measurement processes. Common solutions will include the use of calibration artefacts to achieve reliability and self-calibration methods within manufacturing. Additionally, standardised procedures and methods are expected to be developed for integrated, metrology-specific data processing applications.

Ongoing research in evaluating uncertainty in point clouds represents an interesting new method of uncertainty evaluation [120, 132–148], particularly within the scope of optical in-line measurement. Future work will investigate how error in 3D point clouds may propagate through the algorithmic procedures commonly applied at the industrial level, to verify whether workpieces conform to geometric and dimensional specifications. Solutions for the accurate estimation of uncertainty associated to the verification process will be investigated, thus providing a fundamental contribution towards the development of the manufacturing solutions of the future.

Similarly, the metrological characteristics approach to uncertainty evaluation that has recently been standardised within the surface texture measurement framework provides a useful solution for evaluation of uncertainty not just for surface texture but potentially also in the coordinate measurement world [149, 150, 152, 153]. However, significant challenges remain relating an understanding of fidelity and resolution into the model and further research is required to apply this framework to the measurement of shapes.

While it is clear that there have been numerous significant developments in the field of optical measurement within digital manufacturing, it is equally clear that significant further work is required to take full advantage of the available technologies, particularly in the areas outlined above.

Author contribution Resources: Sofia Catalucci and Adam Thompson. Supervision: Samanta Piano, David T Branson III, Richard K Leach. Writing—original draft: Sofia Catalucci and Adam Thompson. Writing—review and editing: Sofia Catalucci, Adam Thompson, Samanta Piano, David T Branson III, Richard K Leach.

Funding The authors would like to thank the UKRI Research England Development (RED) Fund for funding this work via the Midlands Centre for Data-Drive Metrology.

Availability of data and material Not applicable.

Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Conflict of interest The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article’s Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

1. Simeone A, Caggiano A, Boun L, Deng B (2019) Intelligent cloud manufacturing platform for efficient resource sharing in smart manufacturing networks. Procedia CIRP 79:233–238
2. Imkamp D, Berthold J, Heizmann M, Kniel K, Manske E, Peterek M, Schmitt R, Seidler J, Sommer KD (2016) Challenges and trends in manufacturing measurement technology – the “Industrie 4.0” concept. J Sens Sens Syst 5:325–335
3. Tao F, Qi Q, Liu A, Kusiak A (2018) Data-driven smart manufacturing. J Manuf Syst 48:157–169
4. Lee J, Bagheri B, Kao HA (2015) A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manuf Lett 3:18–23
5. BIPM, IEC, IFCC, ILAC, ISO, IUPAC, IUPAP, OIML (2012) International Vocabulary of Metrology—Basic and General Concepts and Associated Terms (Bureau International des Poids et Mesures) JCGM 200
6. Carminati S, De Chiffre L, Bosse H, Leach RK, Balsamo A, Estler WT (2020) Dimensional artefacts to achieve metrological traceability in advanced manufacturing. Ann CIRP 69:693–716
7. Zhong Y, Xu X, Klotz E, Newman ST (2017) Intelligent manufacturing in the context of Industry 4.0: a review. Engineering 3:616–630
8. Alcácer V, Cruz-Machado V (2019) Scanning the Industry 4.0: a literature review on technologies for manufacturing systems. Eng Sci Technol Int J 22:899–919
9. Zheng P, Wang H, Sang Z, Zhong RY, Liu Y, Liu C, Mubarak K, Yu S, Xu X (2018) Smart manufacturing systems for Industry 4.0: conceptual framework, scenarios, and future perspectives. Front Mech Eng 13:137–150
10. Oztемel E, Gurses S (2020) Literature review of Industry 4.0 and related technologies. J Intell Manuf 31:127–182
11. Dotoli M, Fay A, Miśkowicz M, Seatzu C (2019) An overview of current technologies and emerging trends in factory automation. Int J Prod Res 57:5047–5067
12. Tseng M, Lim M, Wong WP (2015) Sustainable supply chain management: a closed-loop network hierarchical approach. Ind Manag Data Syst 115:436–461
13. Winkler H (2011) Closed-loop production systems—a sustainable supply chain approach. CIRP J Manuf Sci Technol 4:243–246
14. Berthold J, Imkamp D (2013) Looking at the future of manufacturing metrology: roadmap document of the German VDI/VDE Society for Measurement and Automatic Control. J Sens Sens Syst 2:1–7
15. Mourtzis D, Vlachou E (2018) A cloud-based cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance. J Manuf Syst 47:179–198
16. Wu D, Rosen DW, Wang L, Schaefer D (2015) Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation. CAD Comput Aided Des 59:1–14
17. Alexopoulos K, Makris S, Xanthakis V, Sipsas K, Chryssolouris G (2016) A concept for context-aware computing in manufacturing: the white goods case. Int J Comput Integr Manuf 29:839–849
18. Caggiano A, Segreto T, Teti R (2016) Cloud manufacturing framework for smart monitoring of machining. Procedia CIRP 55:248–253
19. Caggiano A, Segreto T, Teti R (2018) Cloud Manufacturing on-demand services for holistic quality assurance of manufactured components. Procedia CIRP 67:144–149
20. Caggiano A (2018) Cloud-based manufacturing process monitoring for smart diagnosis services. Int J Comput Integr Manuf 31:612–623
21. ISO 10303 series (2021) Industrial automation systems and integration — product data representation and exchange (International Organization for Standardization)
22. ISO 14649 series (2003) Industrial automation systems and integration — physical device control — Data model for computerized numerical controllers (International Organization for Standardization)
23. Kubota T, Hamzeh R, Xu X (2020) STEP-NC enabled machine tool digital twin. Procedia CIRP 93:1460–1465
24. Zhao YF, Xu X (2010) Enabling cognitive manufacturing through automated on-machine measurement planning and feedback. Adv Eng Informatics 24:269–284
25. Zhao YF, Xu XW (2012) Integration of machining and inspection. Int J Comput Aided Eng Technol 4:1–31
26. Rodríguez E, Alvaress A (2019) A STEP-NC implementation approach for additive manufacturing. Procedia Manufacturing 38:9–16
27. Gao W, Hattijema H, Fang FZ, Leach RK, Cheung CF, Savio E, Linares JM (2019) On-machine and in-process surface metrology for precision manufacturing. Ann CIRP 68:843–866
28. Leach RK (2020) Integrated Metrology 10-Year Roadmap for Advanced Manufacturing (HVM Catapult)
29. Takaya Y (2013) In-process and on-machine measurement of machining accuracy for process and product quality management: a review. Int J Autom Technol 8:4–19
30. Goch G, Schmitt R, Patzelt S, Stürwald S, Tausendfreund A (2013) In-situ and in-process metrology for optical surfaces. In: Brinksmeyer E, Riemer O, Gläbe R Fabrication of Complex Optical Components (Springer: Berlin, Heidelberg), 161–178
31. Zhou K, Liu T, Zhou L (2016) Industry 4.0: Towards future industrial opportunities and challenges. Proc. 12th FSKD, Zhangjiajie, China, Aug. 2147–2152
32. Kiraci E, Franciosa P, Turley GA, Olifent A, Attridge A, Williams MA (2017) Moving towards in-line metrology: evaluation of a Laser Radar system for in-line dimensional inspection for automotive assembly systems. Int J Adv Manuf Technol 91:69–78
33. Kiraci E, Palit A, Donnelly M, Attridge A, Williams MA (2020) Comparison of in-line and off-line measurement systems using a calibrated industry representative artefact for automotive dimensional inspection. Measurement 163, 108027
34. Tran TT, Ha CK (2018) Non-contact gap and flush measurement using monocular structured multi-line light vision for vehicle assembly. Int J Control Autom Syst 16:2432–2445
35. Zhou S, Xu J, Tao L, An L, Yu Y (2018) Automated inspection of gaps on the free-form shape parts by laser scanning technologies. Proc SPIE 10621:1062116
36. Long K, Xie Q, Lu D, Wu Q, Liu Y, Wang J (2021) Aircraft skin gap and flush measurement based on seam region extraction from 3D point cloud. Measurement 176:109169
37. Kosmopoulos D, Varvarigou T (2001) Automated inspection of gaps on the automotive production line through stereo vision and specular reflection. Comput Ind 46:49–63
38. Goh YM, Micheler S, Sanchez-Salas A, Case K, Bumblauskas D, Monfared R (2020) A variability taxonomy to support automation decision-making for manufacturing processes. Prod Plan Control 31:383–399
39. Peres RS, Barata J, Leitao P, Garcia G (2019) Multistage quality control using machine learning in the automotive industry. IEEE Access 7:79908–79916
40. Echeta I, Feng X, Dutton B, Leach R, Piano S (2020) Review of defects in lattice structures manufactured by powder bed fusion. Int J Adv Manuf Technol 106:2649–2668
41. Chen Y, Peng X, Kong L, Dong G, Remani A, Leach R (2021) Defect inspection technologies for additive manufacturing. Int J Extrem Manuf 3:022002
42. Qi S, Yang J, Zhong Z (2020) A review on industrial surface defect detection based on deep learning technology. Proc. ICPS, MLMI ’20, Hangzhou China, Sept. 24–30
43. Lane B, Mekhontsev S, Grantham S, Vlasea M, Whiting J, Yeung H, Fox J, Zarobila C, Neira J, McGlaunlin M, Hanssen L (2016) Design, developments, and results from the NIST additive manufacturing metrology testbed (AMMT). Proc. SFF, Austin, USA, Aug. 1145–1160
44. Bidare P, Maier RRJ, Beck RJ, Shephard JD, Moore AJ (2017) An open-architecture metal powder bed fusion system for in-situ process measurements. Addit Manuf 16:177–185
45. Zhao C, Fezzaa K, Cunningham RW, Wen H, De Carlo F, Chen L, Rollett AD, Sun T (2017) Real-time monitoring of laser powder bed fusion process using high-speed X-ray imaging and defraction. Sci Rep 7:3602
46. Leung CLA, Marussi S, Atwood RC, Trowie M, Withers PJ, Lee PD (2018) In situ X-ray imaging of defect and molten pool dynamics in laser additive manufacturing. Nat Commun 9:1335
47. Grasso M, Colosimo BM (2017) Process defects and in situ monitoring methods in metal powder bed fusion: a review. Meas Sci Technol 28:044005
48. Caltanisetta F, Grasso M, Petrò S, Colosimo BM (2018) Characterization of in-situ measurements based on layerwise imaging in laser powder bed fusion. Addit Manuf 24:183–199
49. Delli U, Chang S (2018) Automated process monitoring in 3D printing using supervised machine learning. Proc Manuf 26:865–870
50. Scime L, Beuth J (2018) A multi-scale convolutional neural network for autonomous anomaly detection and classification in a laser powder bed fusion additive manufacturing process. Addit Manuf 24:273–286
51. Gobert C, Reutzel EW, Petrich J, Nassar AR, Phoha S (2018) Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. Addit Manuf 21:517–528
52. Liu M, Fai Cheung C, Senin N, Wang S, Su R, Leach R (2020) On-machine surface defect detection using light scattering and deep learning. J Opt Soc Am A 37:B53–B59
53. Zhang B, Liu S, Shin YC (2019) In-Process monitoring of porosity during laser additive manufacturing process. Addit Manuf 28:497–505
54. Boone N, Zhu C, Smith C, Todd I, Willmott JR (2018) Thermal near infrared monitoring system for electron beam melting with emissivity tracking. Addit Manuf 22:601–605
55. Barrett C, MacDonald E, Conner B, Persi F (2018) Micron-level layer-wise surface profilometry to detect porosity defects in powder bed fusion of Inconel 718. JOM 70:1844–1852
56. Tan Phuc L, Setia M (2019) A high-resolution and large field-of-view scanner for in-line characterization of powder bed defects during additive manufacturing. Mater Des 164:107562
57. Zhang B, Land W S, Ziegert J, Davies A (2015) In situ monitoring of laser powder bed fusion additive manufacturing using digital fringe projection technique. Proc ASPE 2015 Spring Topical Meeting
58. Zhang B, Ziegert J, Farahi F, Davies A (2016) In situ surface topography of laser powder bed fusion using fringe projection. Addit Manuf 12:100–107
59. Land WS, Zhang B, Ziegert J, Davies A (2015) In-situ metrology system for laser powder bed fusion additive process. Procedia Manuf 1:393–403
60. Li Z, Liu X, Wen S, He P, Zhong K, Wei Q, Shi Y, Liu S (2018) In situ 3D monitoring of geometric signatures in the powder-bed-fusion additive manufacturing process via vision sensing methods. Sensors 18:1180
61. Liu Y, Blunt LA, Gao F, Jiang X, Zhang Z, Saunby G, Dawes J, Blackham B, Rahman HA, Smith C (2018) In-situ areal inspection of powder bed for electron beam fusion am system based on fringe projection. Proc ASPE/euspen Advancing Precis in Addit Manuf Berkeley, USA, July 62. Liu Y, Blunt L, Zhang Z, Rahman HA, Gao F, Jiang X (2020) In-situ areal inspection of powder bed for electron beam fusion system based on fringe projection profilometry. Addit Manuf 31:100940
63. Sounth N, Stavroulakis P, Goodridge R, Leach R (2018) In-process measurement and monitoring of a polymer laser sintering powder bed with fringe projection. Mater Des 157:227–234
64. Kalms M, Narita R, Thomy C, Vollertsen F, Bergmann RB (2019) New approach to evaluate 3D laser printed parts in powder bed fusion-based additive manufacturing in-line within closed space. Addit Manuf 26:161–165
65. Dickins A, Widjanarko T, Sims-Waterhouse D, Thompson A, Lawes S, Senin N, Leach R (2020) Multi-view fringe projection system for surface topography measurement during metal powder bed fusion. J Opt Soc Am A 37:B93–B105
66. Foster BK, Reutzel EW, Nassar AR, Hall BT, Brown SW, Dickman CJ (2020) Optical, layerwise monitoring of powder bed fusion. Proc 26th Annual Int Solid Freeform Fabr Symp, Austin, USA, August
67. Imani F, Gaikwad A, Montazeri M, Rao P, Yang H, Reutzel E (2018) Process mapping and in-process monitoring of porosity in laser powder bed fusion using layerwise optical imaging. J Manuf Sci Eng Trans ASME 140:101009
68. Everton SK, Hirsch M, Stavroulakis P, Leach RK, Clare AT (2016) Review of in-situ process monitoring and in-situ metrology for metal additive manufacturing. Mater Des 95:431–445
69. Syam WP (2020) In-process surface topography measurements. In: Leach R K Advances in Optical Surface Texture Metrology (IOP Publishing), Chap. 7
70. Mani M, Lane BM, Donnez MA, Feng SC, Moylan SP (2017) A review on measurement science needs for real-time control of additive manufacturing metal powder bed fusion processes. Int J Prod Res 55:1400–1418
71. Grasso MLG, Remani A, Dickins A, Colosimo BM, Leach RK (2021) In-situ measurement and monitoring methods for metal powder bed fusion – an updated review. Meas Sci Technol 32:112001
72. Mazzoleni L, Demir AG, Caprio L, Pacher M, Previtali B (2020) Real-time observation of melt pool in selective laser melting: spatial, temporal, and wavelength resolution criteria. IEEE Trans Instrum Meas 69:1179–1190
73. Yadav P, Rigo O, Arvieu C, Le Guen E, Lacoste E (2020) In situ monitoring systems of the SLM process: On the need to develop machine learning models for data processing. Curr Comput-Aided Drug Des 10:524
74. Remani A, Williams R, Thompson A, Dardis J, Jones N, Hooper P, Leach R (2021) Design of a multi-sensor measurement system for in-situ defect identification in metal additive manufacturing. Proc ASPE/euspen Advancing Precis in Addit Manuf
75. Wollschläger M, Sauer T, Jasperneite J (2017) The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. IEEE Ind Electron Mag 11:17–27
76. Plack DR (2001) Good Practice Guide No. 41 CMM measurement strategies (National Physical Laboratory)
77. Chen R, Xu J, Zhang S (2020) Digital fringe projection profilometry. In: Leach RK Advances in Optical Form and Coordinate Metrology (IOP Publishing), Chap. 5
78. Zhang S (2020) Rapid and automatic optimal exposure control for digital fringe projection technique. Opt Lasers Eng 128:106029
79. Zhang S (2018) High-speed 3D shape measurement with structured light methods: A review. Opt Lasers Eng 106:119–131
80. Xu X, Zhang Q (2010) Dynamic 3-D shape measurement system: a review. Opt Lasers Eng 48:191–204
81. Wang Z (2020) Review of real-time three-dimensional shape measurement techniques. Measurement 156:107624
82. Wang Y, Laughner JI, Efimov IR, Zhang S (2013) 3D absolute shape measurement of live rabbit hearts with a superfast two-frequency phase-shifting technique. Opt Express 21:5822–5832
83. Deetjen ME, Lentink D (2018) Automated calibration of multi-camera-projector structured light systems for volumetric high-speed 3D surface reconstructions. Opt Express 26:33278–33304
84. Bergström P, Fergusson M, Folkesson P, Runnemalm A, Ottosson M, Andersson A, Sjödahl M (2016) Automatic in-line inspection of shape based on photogrammetry. 7th Swedish Prod Symp 1–9

85. Sjödahl M, Bergström P, Fergusson M, Soderholm K, Andersson A (2021) In-line quality control utilizing close-range photogrammetry and a CAD-model. Eng Res Express In Press

86. Razvi SS, Feng S, Narayanan A, Lee YTT, Witherell P (2019) A review of machine learning applications in additive manufacturing. Int Des Eng Tech Conf Comput Inf in Eng Conf 59/179:V001T02A040

87. Eastwood J, Sims-Waterhouse D, Piano S (2020) Machine learning approaches. In: Leach R K Advances in Optical Form and Coordinate Metrology (IOP Publishing). Chap. 6

88. Stavroulakis PI, Leach RK (2016) Review of post-process optical form metrology for industrial-grade metal additive manufactured parts. Rev Sci Instrum 87:041101

89. Monti F, Boscaini D, Masci J, Rodoi E, Svoboda J, Bronstein MM (2017) Geometric deep learning on graphs and manifolds using mixture model CNNs. Proc IEEE Conf on Comput Vis Pattern Recognit, Honolulu, USA, July. 5115–5124

90. Senin N, Leach R (2018) Information-rich surface metrology. Procedia CIRP 75:19–26

91. Lecun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521:436–444

92. Sims-Waterhouse D, Leach R, Piano S (2020) Close range photogrammetry. In: Leach R K Advances in Optical Form and Coordinate Metrology (IOP Publishing), Chap. 4

93. Gallo A, Muzzupappa M, Bruno F (2014) 3D reconstruction of small sized objects from a sequence of multi-focused images. J Cult Herit 15:173–182

94. Zeller N, Quint F, Stilla U (2014) Calibration and accuracy analysis of a focused plenoptic camera 2:205

95. Born M, Wolf E (2013) Elements of the theory of diffraction. In: Born M, Wolf E Principles of Optics (Cambridge University Press), Chap. 8

96. Lei S, Zhang S (2009) Flexible 3-D shape measurement using projector defocusing. Opt Lett 34:3080

97. Hu Y, Chen Q, Feng S, Zuo C (2020) Microscopic fringe projection profilometry: a review. Opt Lasers Eng 135:106192

98. Cuypers W, Van Gestel N, Voet A, Kruth JP, Mingeneau J, Bleys P (2009) Optical measurement techniques for mobile and large-scale dimensional metrology. Opt Lasers Eng 47:292–300

99. Harding KG (2020) Large part metrology challenges and lessons learned. Proc SPIE 11397:113970I

100. Du H, Chen X, Xi J, Yu C, Zhao B (2017) Development and verification of a novel robot-integrated fringe projection 3D scanning system for large-scale metrology. Sensors 17:2886

101. Summan R, Pierce SG, Macleod CN, Dobie G, Gears T, Lester W, Pritchett P, Smyth P (2015) Spatial calibration of large volume photogrammetry based metrology systems. Measurement 68:189–200

102. Gibson I, Rosen D, Stucker B (2015) Design for additive manufacturing. In: Gibson I, Rosen D, Stucker B Additive Manufacturing Technologies (Springer), Chap. 17

103. Senin N, Thompson A, Leach RK (2017) Characterisation of the topography of metal additive surface features with different measurement technologies. Meas Sci Technol 28:095003

104. Shalheen A, Sims-Waterhouse D, Bointon P, Takushima S, Piano S, Leach RK (2020) Characterisation of a multi-view fringe projection system based on the stereo matching of rectified phase maps. Meas Sci Technol 32:045006

105. Song LM, Gao Y, Zhu XJ, Guo QH, Xi JT (2016) A 3D measurement method based on multi-view fringe projection by using a turntable. Optoelectron Lett 12:389–394

106. Kinnell P, Rymer T, Hodgson J, Justham L, Jackson M (2017) Autonomous metrology for robot mounted 3D vision systems. Ann CIRP 66:483–486

107. Rao MR, Radhakrishna D, Usha S (2018) Development of a robot-mounted 3D scanner and multi-view registration techniques for industrial applications. Proc Comput Sci 133:256–267

108. Leach RK, Bourell D, Carmignato S, Donnem A, Senin N, Dews D (2019) Geometrical metrology for metal additive manufacturing. Ann CIRP 68:677–700

109. Senin N, Thompson A, Leach R (2017) Feature-based characterisation of signature topography in laser powder bed fusion of metals. Meas Sci Technol 29:045009

110. Townsend A, Senin N, Blunt L, Leach RK, Taylor JS (2016) Surface texture metrology for metal additive manufacturing: a review. Precis Eng 46:34–47

111. de Pastre MA, Thompson A, Senin N, Quinast Y, Albahez García JA, Leach RK (2019) Polymer powder bed fusion surface texture measurement. Meas Sci Technol 31:055002

112. Dubouste N, Ghadbeigi H, Pinna C, Ayvar-Soberanis S, Collis A, Scaife R, Kerrigan K (2017) An optical method for measuring surface roughness of machined carbon fibre-reinforced plastic composites. J Compos Mater 51:289–302

113. Geier N, Pereszlai C (2020) Analysis of characteristics of surface roughness of machined CFRP composites. Period Polyttech Mech Eng 64:67–80

114. Sims-Waterhouse D, Piano S, Leach R (2017) Verification of micro-scale photogrammetry for smooth three-dimensional object measurement. Meas Sci Technol 28:055010

115. Gomez C, Su R, Thompson A, DiSciaccia J, Lawes S, Leach R (2017) Optimisation of surface measurement for metal additive manufacturing using coherence scanning interferometry. Opt Eng 56:111714

116. Newton L, Senin N, Gomez C, Danzl R, Helmi F, Blunt L, Leach R (2018) Areal topography measurement of metal additive surfaces using focus variation microscopy. Addit Manuf 25:365–389

117. Kang CW, Ramzan MB, Sarkar B, Imran M (2018) Effect of inspection performance in smart manufacturing system based on human quality control system. Int J Adv Manuf Technol 94:4351–4364

118. ISO 10360 series (2000) Geometrical product specifications (GPS) -- Acceptance and reverification tests for coordinate measuring systems (CMS) (International Organization for Standardization)

119. Zhang H, Eastwood J, Isa M, Sims-Waterhouse D, Leach R, Piano S (2021) Optimisation of camera positions for optical coordinate measurement based on visible point analysis. Precis Eng 67:178–188

120. Catalucci S, Senin N (2020) State-of-the-art in point cloud analysis. In: Leach R K Advances in Optical Form and Coordinate Metrology (IOP Publishing), Chap. 2

121. French P, Krijnen G, Roozeboom F (2016) Precision in harsh environments. Microsystems Nanoeng 2:1–12

122. Hovell T, Matharu RS, Petzing JW, Justham L, Kinnell PK (2020) Lensless fiber-deployed low-coherence interferometer for in-situ measurements in nonideal environments. Opt Eng 59:014113

123. Ferrucci M, Ametova E (2021) Charting the course towards dimensional measurement traceability by X-ray computed tomography. Meas Sci Technol 32:092001

124. Gayton G, Su R, Leach RK (2019) Model-based uncertainty estimation of uncertainty for fringe projection. Proc. 10th Int Symp on Meas Technol and Intell Instrum, Niigata, Japan

125. Gaška A, Harmatsys W, Gaška P, Gruza M, Gromczak K, Ostrowska K (2017) Virtual CMM-based model for uncertainty estimation of coordinate measurements performed in industrial conditions. Meas J Int Meas Confed 98:361–371
126. Papanianas M, McLeay TE, Mahfouf M, Kadirkamanathan V (2019) A Bayesian framework to estimate part quality and associated uncertainties in multistage manufacturing. *Comput. Ind* 105:35–47

127. Larsen L, Kim J, Kupke M, Schuster A (2017) Automatic path planning of industrial robots comparing sampling-based and computational intelligence Methods. *Procedia Manuf* 11:241–248

128. Lu W, Pagani L, Zhou L, Liu X, Wang J, Leach R, Jiang X (2019) Uncertainty-guided intelligent sampling strategy for high-efficiency surface measurement via free-knot B-spline regression modelling. *Precis Eng* 56:38–52

129. Tolle I, Lee J, Salvador D, Saville B, Yong PB, Marcuccilli G (2019) Defect learning with predictive sampling for process improvement. *Pro SPIE* 10959:1095930

130. Psarromatiss F, May G, Dreyfus PA, Kirisits D (2020) Zero defect manufacturing: state-of-the-art review, shortcomings and future directions in research. *Int J Prod Res* 58:1–17

131. du Plessis A, Yadroitseva I, Yadroitsev I (2020) Effects of defects on mechanical properties in metal additive manufacturing: A review focusing on X-ray tomography insights. *Mater Des* 187:108385

132. Forbes A (2018) Uncertainties associated with position, size and shape for point cloud data. *J Phys: Conf Ser* 1065:142023

133. Senin N, Catalucci S, Moretti M, Leach RK (2020) Statistical point cloud model to investigate measurement uncertainty in coordinate metrology. *Precis Eng* 70:44–62

134. Forbes A (2006) Surface fitting taking into account uncertainty structure in coordinate data. *Mater Sci Technol* 17:553

135. Forbes AB (2006) Uncertainty evaluation associated with fitting geometric surfaces to coordinate data. *Metrologia* 43:S282

136. Forbes AB, Minh HD (2011) Form assessment in coordinate metrology. In: Georgoulis EH, Iske A, Levesley J. Approximation Algorithms for Complex Systems. (Springer), Chap. 4

137. Pauly M, Mitra NJ, Guibas L (2004) Uncertainty and variability in point cloud surface data. *Symp point-based Graph, June*, 77–84

138. Wang J, Leach R K, Jiang X (2015) Review of the mathematical foundations of data fusion techniques in surface metrology. *Surf Topogr Metrol Prop* 3:023001

139. Li L, Wang R, Zhang X (2021) A tutorial review on point cloud registrations: principle, classification, comparison, and technology challenges. *Math Probl Eng* 9953910

140. Pu C, Li N, Tylecek R, Fisher B (2018) DUGMA: Dynamic uncertainty-based Gaussian mixture alignment. *Proc 2018 Int Conf 3D Vis, September, Verona, Italy*

141. De Asis LF, Ordóñez C, Roca-Pardíñas J, García-Cortés S (2014) Point cloud comparison under uncertainty Application to beam bridge measurement with terrestrial laser scanning. *Measurement* 51:259–264

142. Brossard M, Bonnabel S, Barrau A (2020) A new approach to 3D ICP covariance estimation. *IEEE Robot Autom Lett* 5:744–751

143. Wiens A, Kleiber W, Nyckha D, Barnhart KR (2021) Nonrigid registration using gaussian processes and local likelihood estimation. *Math Geosci* 53:1319–1337

144. Han XF, Jin JS, Wang MJ, Jiang W, Gao L, Xiao L (2017) A review of algorithms for filtering the 3D point cloud. *Signal Process Image Commun* 57:103–112

145. Barchiesi D, Grosjes T (2017) Propagation of uncertainties and applications in numerical modeling: tutorial. *J Opt Soc Am A* 34:1602–1619

146. Haitjema H (2018) Measurement uncertainty. In: Leach RK, Smith ST. Basics of Precision Engineering (CRC Press), Chap. 9

147. Thompson A, Senin N, Giusca C, Leach R (2017) Topography of selectively laser melted surfaces: A comparison of different measurement methods. *Ann CIRP* 66:543–546

148. Zhang M, Anwer N, Mathieu L, Zhao HB (2011) A discrete geometry framework for geometrical product specifications. *Proc 21st CIRP Des Conf, Korea 2011: Interdiscip Des, Korea, November 20*

149. Leach RK, Haitjema H, Su R, Thompson A (2021) Metrological characteristics for the calibration of surface topography measuring instruments: a review. *Meas Sci Technol* 32:032001

150. ISO 25178 part 600 (2019) Geometrical product specifications (GPS) - surface texture: areal - part 600: metrological characteristics for the calibration of surface topography measuring methods (International Organization for Standardization)

151. JCGM 100 (2008) Evaluation of measurement data — guide to the expression of uncertainty in measurement (JCGM)

152. Giusca CL, Leach RK (2013) Good Practice Guide No. 129: Calibration of the metrological characteristics of areal contact stylus instruments (National Physical Laboratory)

153. Thomas M, Su R, Nikolaev N, Coupland J, Leach R (2020) Modeling of interference microscopy beyond the linear regime. *Opt Eng* 59:034110

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.