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CRITICAL REVIEW

Optical metrology for digital manufacturing: a review

Sofia Catalucci[1] · Adam Thompson[1] · Samanta Piano[1] · David T. Branson III[1] · Richard Leach[1]

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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 enabler for adoption of novel Industry 4.0 methodologies in manufacturing.

✉ Sofia Catalucci
Sofia.Catalucci2@nottingham.ac.uk

[1] Manufacturing Metrology Team, Faculty of Engineering, University of Nottingham, Nottingham, UK

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 multi-sensor 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]).

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

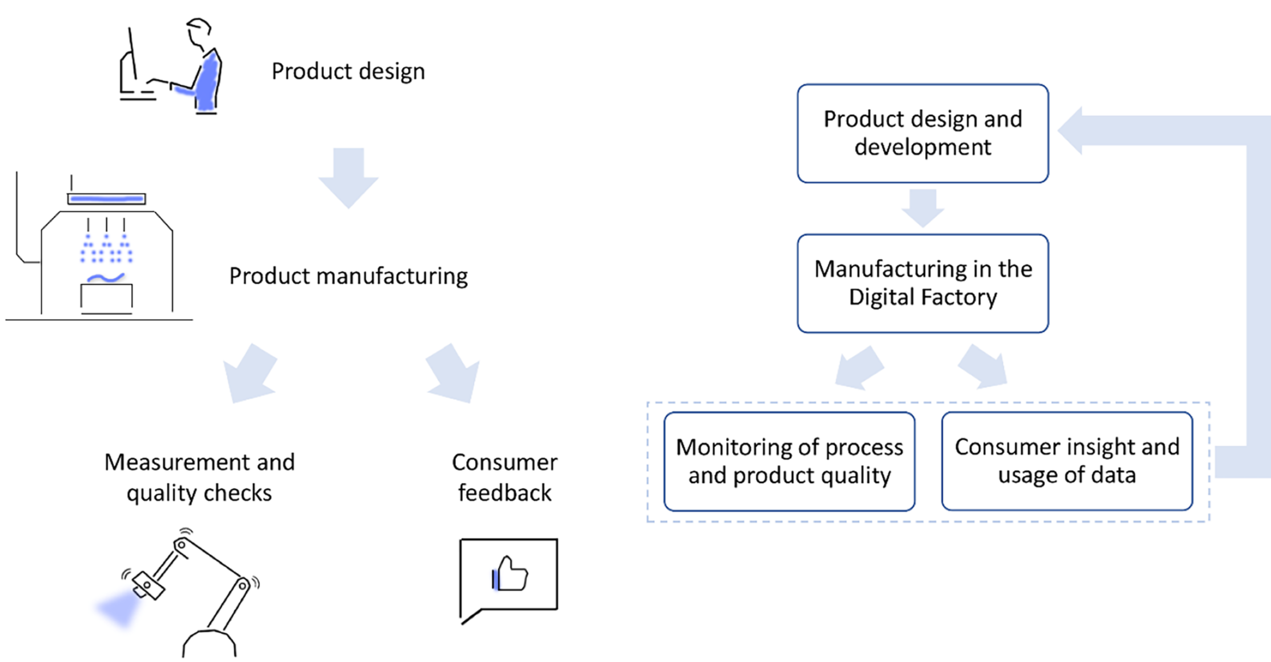


Fig. 1 The production workflow starts from the design and manufacturing of products employing digital technologies, followed by measuring operations and inspection. The data collected from the consumer feedback is then linked back to product development departments, allowing rapid enhancement of the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

context-driven recommendations [17]. The collected data can then be employed to redesign and improve systems, as well as to aid production planning and management of operations [18–20].

The standardisation of metrology data and integration of metrology data with other parts of manufacturing processes is an important matter that ISO Committee has been trying to address. The development of new data model standards based on ISO 10303 Standard for Exchange of Product Model (STEP) data [21] and ISO 14649 STEP-Numerical Controllers (STEP-NC) [22] provide product information from all steps of the manufacturing chain. Kubota et al. [23] presented a framework in which a STEP-NC model data combined with machine tool digital twin (MTDT) is employed to deliver rich structured information about the machining process. This combination allows both the application of the digital twin concept on machine tools and knowledge for the optimisation of the machining process. Zhao and Xu [24] developed a cognitive process planning system based on ISO STEP/STEP-NC standardisation that integrates machining, inspection, and feedback in a manufacturing system. In a later publication [25], the same authors proposed an integrated process planning system architecture for combined machining and inspection, able to carry out on-machine inspections in between machining operations and provide feedback in real-time. Rodriguez and Alvares [26] described an approach for the implementation of the STEP-NC standard in additive manufacturing. The geometric information of the built layers was converted as input data to generate the STEP-NC data model. A verification process was carried out through toolpath simulation within the STEP-NC Machine software environment, including the configuration of the machine's kinematic 3D model and the tool shape geometry.

Further information about the implementation of ISO data models STEP/STEP-NC for process planning, machining and inspection are comprehensively reviewed elsewhere [24].

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), whist 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,

Table 1 Current software and hardware solutions for in-line (and off-line) measurements and relative applications

Category	Technology/type	Application
Software suite	• Module • Library • Virtual measuring room (VMR)	➢ Visual product quality inspection and connection in a cloud of all production systems ➢ Digital twin environment ➢ Robotic control, improving absolute positioning and performance
Robot-mounted sensors (collaborative robot, inside an enclosed measuring cell or next to the conveyor)	• Fringe projection • Laser-based • X-ray (parts positioning via an automated door, robots loading/unloading from conveyors) • Coherence scanning interferometry	➢ In-line (and off-line) automated inspections (e.g. inspection of shape and surface texture, critical dimensions, defects, scratches, flatness, deformations, etc.)
Mobile measuring stations	• Fringe projection • Laser-based	➢ In-line (and off-line) automated inspections (e.g. inspection of shape and surface texture, critical dimensions)
On-machine devices	• Fringe projection • Electron imaging • High speed infra-red cameras • Deflectometry	➢ On-machine inspections for real-time measurement ➢ In-process monitoring (for full traceability and layer-by-layer quality assurance)
Multi-sensor devices	• Multiple measurement technologies (combination of coordinate and surface texture measurement)	➢ Direct integration into machine tools or combination with tactile coordinate measuring machines
Hand-held devices	• Fringe projection • Laser-based	➢ Dimensional inspections (e.g. gap/flush, critical features) ➢ Surface defect detection

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

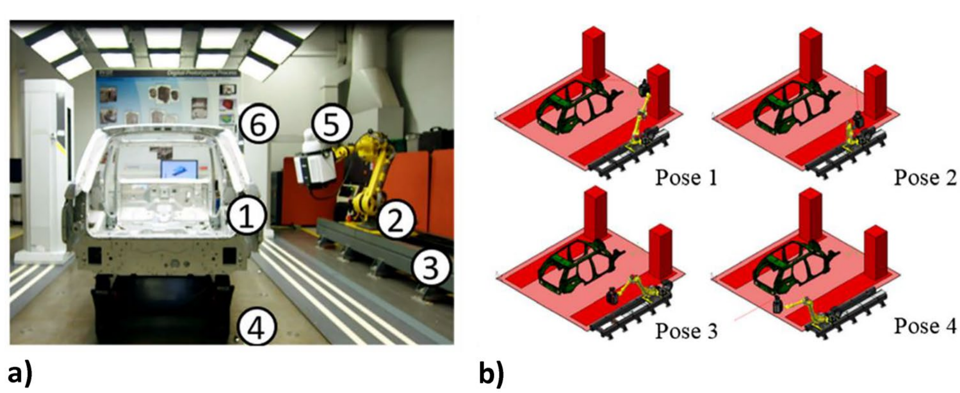


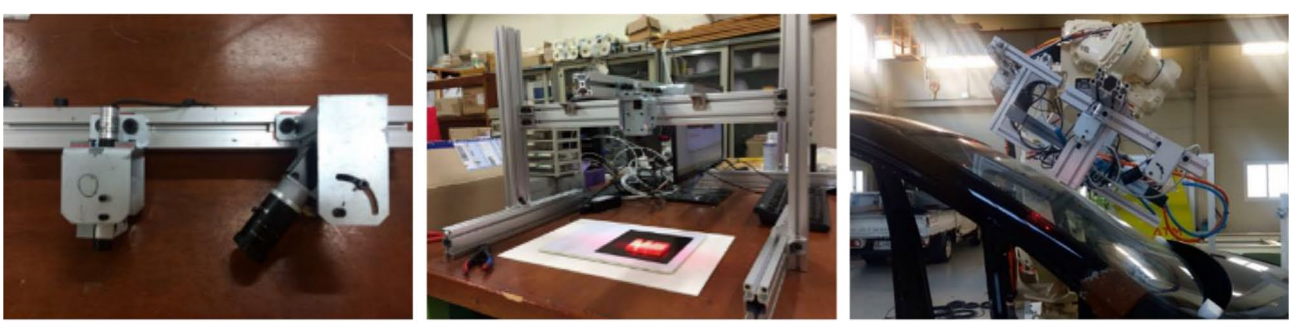
Fig. 2 In-line dimensional inspections using laser radar: industrial demonstrator developed by Kiraci et al. [32]: **a** experimental setup (1, workpiece; 2, robot; 3, trail; 4, tooling balls; 5, laser radar sensor; 6, tactile coordinate measuring system); **b** the four positions of the robot moving along the trail

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.



a) b) c)

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)

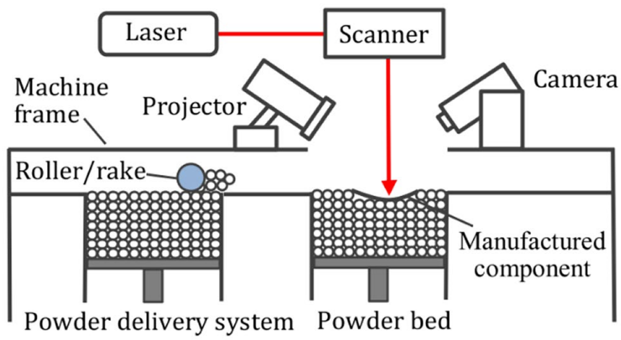


Fig. 4 Schematic example of in-process fringe projection setup in laser powder bed fusion (LPBF) (from Gao et al. [27])

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 co-axial [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].

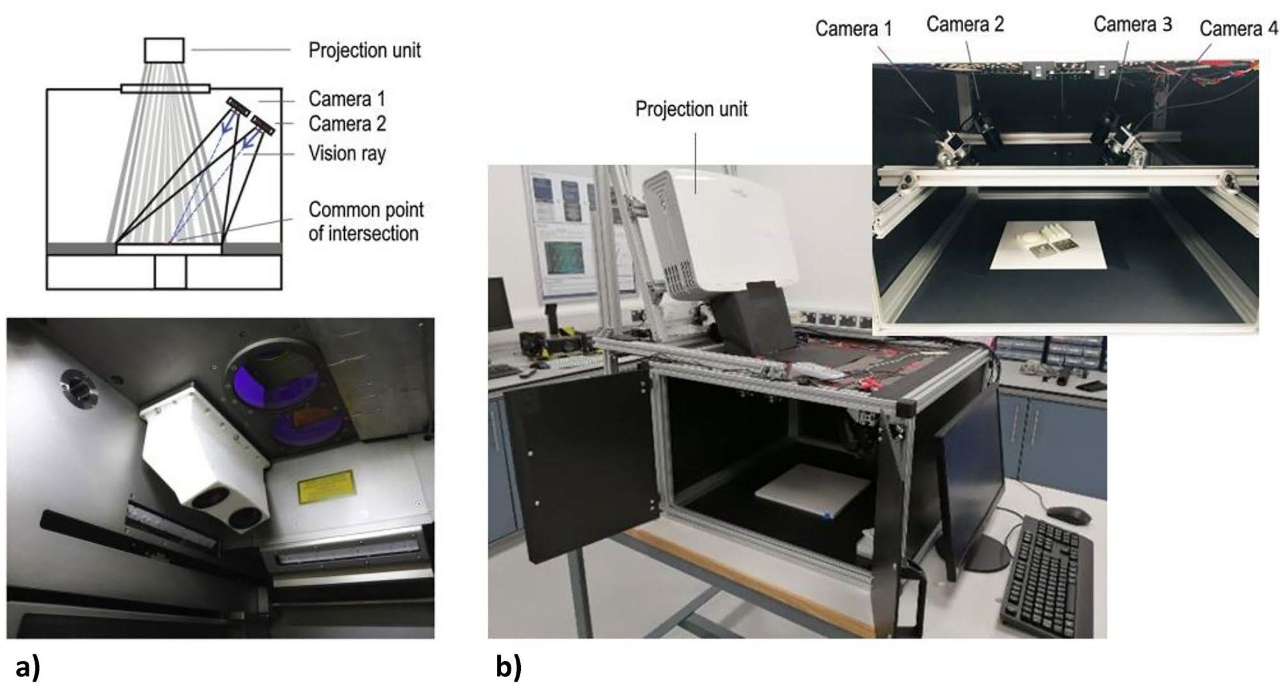


Fig. 5 Example setups of multi-view configurations for the acquisition of topographical information of surface texture: **a** two-camera fringe projection system installed inside a laser beam melting (LBM) building chamber (from Kalms et al. [64]); **b** four-camera fringe projection system installed 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

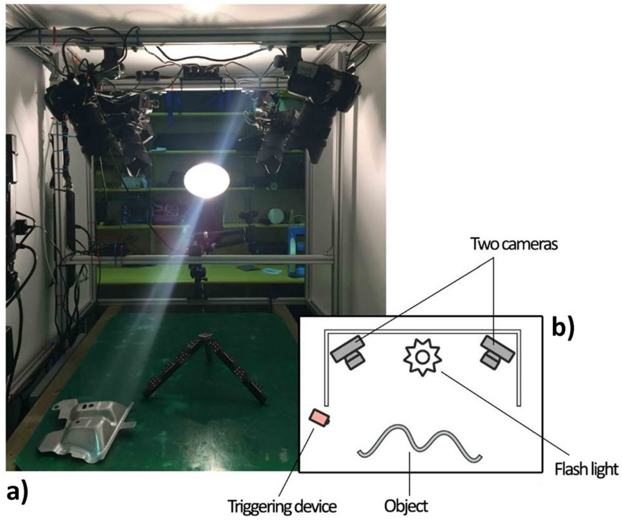


Fig. 6 Photogrammetry for in-line inspection. The setup proposed by Bergstrom et al. [84] consists of two cameras, a flash light, and a triggering device. The sensor is placed on one end of the conveyor belt: **a** picture of the setup; **b** schematic of the design

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

Fig. 7 Example complex AM part containing features that are problematic for optical measurement systems, because of a lack of line-of-sight resulting from occlusion

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, Duboust et al. [112] and Geier and Pereszlai [113] performed measurements of composite materials using focus variation and contact stylus instruments, noting the difficulties related to measuring composite surfaces. These studies 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 is 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

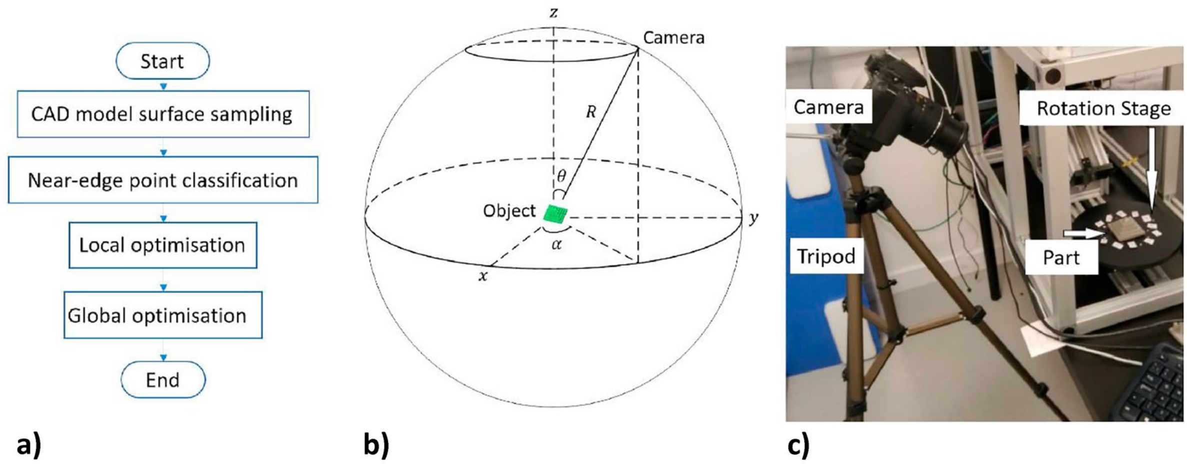


Fig. 8 Automation of measuring instruments with machine learning: sensor repositioning without the need for recalibration of the extrinsic parameters (from Zhang et al. [119]). **a** Outline of the method, **b** camera pose parameterisation, and **c** experimental setup

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

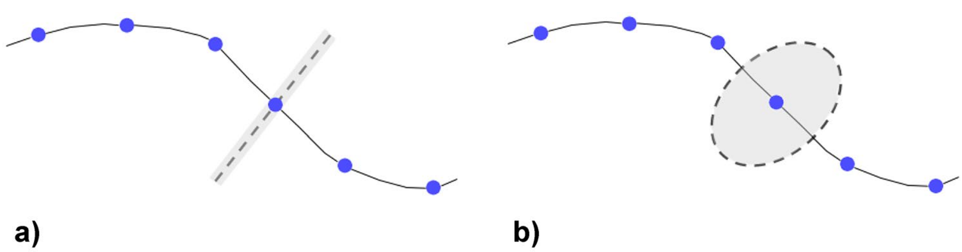


Fig. 9 Models of point positional uncertainty: **a** random variable associated to a displacement in the direction defined by the local surface normal, **b** full three-dimensional probability ellipsoid (tri-variate random variable) associated to each point (from Catalucci and Senin [120])

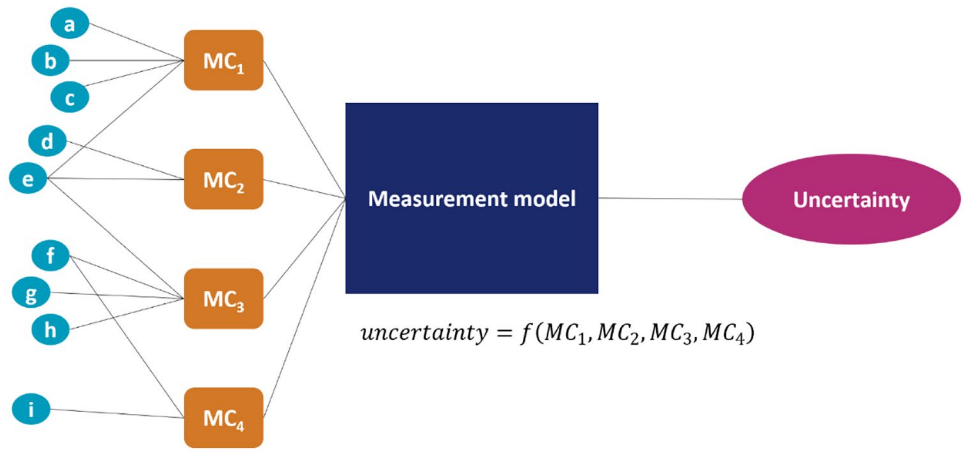


Fig. 10 Illustration of the metrological characteristics framework to estimate measurement uncertainty. (a) to (i) are influence quantities and MC1 to MC4 are metrological characteristics (from Leach et al. [149])

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 speeding 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.

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