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Abstract. Manufacturing has recently experienced increased adoption of optimised and fast solutions for checking product quality during fabrication, allowing for manufacturing times and costs to be significantly reduced. Due to the integration of machine learning algorithms, advanced sensors and faster processing systems, smart instruments can autonomously plan measurement pipelines, perform decisional tasks and trigger correctional actions as required. In this paper, we summarise the state of the art in smart optical metrology, covering the latest advances in integrated intelligent solutions in optical coordinate and surface metrology, respectively for the measurement of part geometry and surface texture. Within this field, we include the use of a priori knowledge and implementation of machine learning algorithms for measurement planning optimisation. We also cover the development of multi-sensor and multi-view instrument configurations to speed up the measurement process, as well as the design of novel feedback tools for measurement quality evaluation.

Keywords. Industry 4.0; optical metrology; smart measurement system; flexibility and automation; measurement quality

1. Introduction

During recent decades, measurement processes have become more flexible, due to the integration of knowledge-driven algorithms in combination with multiple sensors and/or measurement technologies [1,2]. Exploiting the advantages offered by different measurement solutions, the design of advanced configurations contributes to the definition of what is now called a “smart system” [3,4]. By monitoring in-process measurements, smart solutions can adaptively control the production line, stopping a process when errors are detected or even adjusting parameters to retain consistency. Automation of inspection processes is increasingly used to aid in the measurement and control of manufacturing processes, reducing dependence on manual inspection, speeding up processes and minimising the possibility of human error [5].

We begin this review with a definition of smart systems and an overview of the concepts of flexibility and automation. Then, we illustrate the latest advances in the field of optical metrology, particularly covering the key technologies in optical coordinate and surface metrology, respectively for the measurement of part geometry and surface texture, and discuss the current state of the art in the two respective areas. We conclude the review with a discussion of the latest developments in smart measurement solutions and their application in industrial production lines. Particularly, we report examples of information-rich metrology (IRM) and the use of a priori knowledge about measurements; the combination of multiple sensors and/or measuring technologies within the same measuring setup (i.e. multi-sensor data fusion); optical multi-view systems for in-line, on-machine and post-process measurement applications; machine learning for measurement optimisation; and incorporation of real-time and/or post-measurement feedback in the form of performance indicators.

1.1 Smart systems: a definition

To address the current challenges and limitations relating to the integration of measurement technologies within the factories of the future, faster and more sophisticated software and hardware are being developed to drive the deployment of "smart" measurement solutions. In this work, an instrument is defined as smart when it can incorporate functions of automatic operability and consequent correction mechanisms, making decisions based on the available data in a predictive or adaptive way; quickly targeting issues and responding to specific situations [3,6]. For example, the last five to ten years have seen a decrease in the sources of error coming from human operators, leading to a significant reduction in measurement cycle times. We have also seen increased accuracy, reliability and continuity as a consequence of the introduction of adaptive technologies and programmed robotic-based sensors to factory floors [7]. The increased integration of such advanced instruments in production highlights the need to measure manufactured workpieces along the production line more effectively, flexibly and autonomously, while maintaining high levels of accuracy [8,9].

1.2 The concepts of flexibility and automation

To address complex applications, measuring instruments have become more flexible, automated and intelligent, as a result of the development and incorporation of smart algorithmic solutions (including machine learning) and automated technologies. The concept of flexibility, defined in the "Manufacturing Metrology 2020" roadmap (VDI/VDE-GMA [10,11]) as the "adaptation to changes in measurement tasks", indicates the capability of an instrument to respond smartly to changes in the measurement conditions and requirements [9]. Primarily linked to the concept of automation (i.e. "the use or introduction of automatic equipment in manufacturing with a minimal direct human operation" [10,11]), flexibility has become one of the pillars of productivity enhancement in industrial manufacturing lines.

To handle complex tasks, flexible and automated solutions require not only robust planning of actions but must also the ability to self-adapt to runtime changes. Despite the underlying measurement principles staying the same, flexible devices feature the ability to automatically inspect new components and adapt to different measuring tasks. Flexible devices must also operate with the same precision and accuracy on surfaces with different optical characteristics (for example, translucent, highly reflective), materials (for example, glass, polymer, metal), colouring (including black/white), and size and complexity of part shapes (for example, freeform geometries) [12]. Adaptability can be achieved using knowledge-driven algorithmic solutions, which represent the key to guide instruments towards fast measurement executions. Such solutions can involve running intuitive functions and feedback mechanisms for performing automated corrective actions, changes in the measuring parameters or adjustments of tolerance limits before initiating production [3,6]. Particularly, available pre-existing information (for example, a priori knowledge of the manufacturing process, knowledge about the measured object, knowledge of the measurement technology principles) can help guide instruments in the inspection and verification of parts and be used to monitor the manufacturing process [13–15]. The IRM paradigm is discussed in depth in section 3.1, along with other examples of current advanced software and hardware measurement solutions.

2. Measurement technologies for part geometry and surface texture

In recent years there have been significant advances in optical measurement in both optical coordinate and surface metrology [16,17]. In-depth discussions of the many advances in these fields are somewhat beyond the scope of this review, but we will cover some of the key technologies in brief and discuss the current state of the art in both part geometry and surface texture measurement.

2.1 Optical coordinate measurement technologies

Coordinate metrology is the science and application that refers to the measurement of the physical geometry of an object [18], either via contact or non-contact measuring machines. More specifically, an optical non-contact three-dimensional coordinate measuring system (3D CMS) performs the measurement of the spatial coordinates exclusively by using optical sensors (as defined in ISO/DIS 10360-13 [19]). Many definitions can be found in literature to indicate this type of measurement. Often it is called “part geometry”, “shape” or “form” measurement. Throughout the review, we have opted for the term “part geometry measurement” to differentiate from the specific measurement of deviation from some nominal shape (i.e. form measurement) and as a more specific term than simple coordinate/shape measurement. In addition, the terms calibration and characterisation used in this work in the context of optical coordinate metrology are here clarified. Calibration is defined in the International Vocabulary of Metrology (VIM) as the “operation that, under specified conditions, in a first step establishes a relation between the quantity values with measurement uncertainties provided by measurement standards and corresponding indications with associated measurement uncertainties and, in a second step, uses this information to establish a relation for obtaining a measurement result from an indication” [20]. Calibration is in simple terms a comparison between two measurements, one of which is a reference or a standard value, and the other which is being tested [18]. On the other hand, the term characterisation is used in this work to specifically indicate the determination of the parameters necessary for the calibration of a measuring system. In the specific case of optical measuring technologies such as fringe projection and photogrammetry, we refer to the intrinsic and extrinsic camera parameters. Further definitions relating to optical coordinate metrology in general can be found in [18].

Optical measurement of part geometry is generally performed using one or more technologies that are the focus of a large array of current research studies. In a recent book, Leach [16] covers the state of the art in optical part geometry measurement in more depth than we will do here but, in brief, the key technologies are the following. Because of the diversity of technologies encompassed with optical coordinate measurement, it is not possible to convey a single working principle of all optical co-ordinate measurement technologies through discussion of a working principle, measurement pipeline or other technical specifications (for example measurement range), but we have outlined below the working principles of various key optical coordinate measurement technologies.

- Laser-based measurement systems (triangulation and time-of-flight [TPF]): Laser-based measurement systems have been common in measurement for some years, with two technologies, based on the principles of triangulation [21,22] and TOF [23], respectively, being most common. TOF-based systems are particularly common in large-scale applications (for example, civil engineering) where long range capability is required, while triangulation-based systems are more common in industrial manufacture, where the relative increases in precision are of significant benefit. Within the context of technologies covered by this review, triangulation systems are significantly more common, and recent research developments in this area have been focussed on the development of novel sensing technologies, understanding the effect of surface properties on measurement systems and evaluating uncertainty for triangulation-based systems. A significant amount of research is currently also being devoted to new applications of triangulation-based systems. A thorough review of recent advances in laser triangulation-based measurement technologies is available elsewhere [21].
- Photogrammetry: Photogrammetry has recently become a key optical measurement technology and involves the reconstruction of a three-dimensional (3D) point cloud from two-dimensional

(2D) images of the measured object. Common for some time in the film, video games and remote sensing industries [24–26], recent advancements have seen close-range photogrammetry more heavily applied to industrial manufacture, particularly through the development of methods of characterisation and calibration of photogrammetry systems, as well as improvements to speed and accuracy through process optimisation [27,28]. Thorough reviews of recent advances in close-range photogrammetry technologies are available elsewhere [29,30].

- Fringe projection: Fringe projection technologies involve the optical measurement of surfaces by measuring the distortion of a projected fringe pattern as a result of the object onto which that pattern is projected [31]. Non-fringe-based patterns are occasionally used in other "structured light" technologies, though fringes are by far the most common pattern type used. Recent research in the area has focussed on generation of advanced fringe patterns [32], as well as in developing novel methods of fringe analysis and phase unwrapping [33,34]. Further research has recently been published in the use of high dynamic range fringe projection [35], as well as calibration and performance verification methods for fringe projection technologies [36,37]. There has also been a significant amount of recent research in increasing measurement speed [38], automating fringe projection systems [39,40] and integrating them into in-line manufacturing scenarios [41,42]. A thorough review of recent advances in fringe projection technologies is available elsewhere [31].

The above hardware technologies are supported by ongoing research into software and analysis techniques. Such research is particularly focussed on the development of novel machine learning methods for data analysis; new ways of interrogating point cloud data to provide information about a measured part; methods of measuring freeform geometries; and the development of performance verification methods for optical part geometry measurement. These technologies and techniques are summarised as follows.

- Machine learning: machine learning methods have been increasingly applied to the field of smart optical measurement in recent years. Such methods are the subject of a significant part of this review (see section 3.4) so we will not detail them here, but a further review of machine learning approaches in optical measurement of part geometry is given elsewhere [43].
- Point clouds: A 3D cloud of points, where each point comprises a set of *x*, *y*, *z* Cartesian co-ordinates and the cloud represents the measured 3D object [44]. Recent developments in point cloud analysis involve the development of new algorithms for aligning and filtering point clouds [45], as well as to provide new methods of faster and easier searching of information within a point cloud. Pre-processing of point clouds is also a research focus, with a wealth of research aimed at improving aspects of the point cloud, such as part coverage and point sampling, as well as developing and optimising methods of point feature determination, surface model fitting and point cloud registration [46]. Determination of measurement uncertainty for point clouds also remains a significant challenge (see [47] for an example method for doing so). Thorough reviews of recent advances in point cloud technologies are available elsewhere [44–46].
- Performance verification: Efforts to develop standardised methods of verifying the performance of optical measurement systems have been underway for a number of years. VDI/VDE 2634 parts 2 and 3 [48,49] are published guides to verifying optical co-ordinate measurement instrument performance which have been available since 2012 and 2008, respectively, while ISO 10360-13 [19] (the international standard method for verifying instrument performance) is now at international draft standard stage. A summary of guidance to performance verification for optical co-ordinate measurement is available elsewhere [37].

2.2 Optical surface measurement technologies

Optical measurement of surfaces is a core part of many modern manufacturing processes, with the measurement of functional surfaces becoming increasingly critical in high-value manufacturing applications across industry [50]. Surface texture measurement involves the measurement and characterisation of the fine-scale topography of surfaces, and there is a current wealth of ongoing research in developing new technologies for that purpose, often focussed around improving measurement speeds and an instrument's ability to be robust to environmental changes; decreasing instrument sizes; and developing calibration pipelines. In a recent book, Leach [17] covers the state of the art in optical surface texture measurement in significantly more depth than we will do here but, in brief, the key technologies are as follows (also see [51] for a summary of the terminology used in surface metrology). As in the coordinate case, because of the diversity of technologies encompassed with optical surface measurement, it is not possible to convey a single working principle of all optical surface measurement technologies through discussion of a working principle, measurement pipeline or other technical specifications (for example resolution), but we have outlined below the working principles of various key optical surface measurement technologies.

- Coherence scanning interferometry (CSI): CSI is a common method for optical measurement of areal surface topography, which uses a type of reflection-mode interference microscopy that builds up a 3D height map of a surface by stacking 2D images along the optical axis of the instrument [52]. Ongoing research in the area focusses on expanding the applications of CSI systems to complex surfaces (for example, those containing high slopes, step-like transitions or thin films [53–56]), as well as developing new surface reconstruction methods and improving theoretical modelling of CSI systems [57,58]. Development of system calibration and error correction pipelines is also an area of active research [59,60], that ties directly into efforts to improve theoretical models. A thorough review of recent advances in CSI technologies is available elsewhere [52].
- Focus variation microscopy (FVM): FVM is another well-established surface measurement technology that uses local contrast in narrow-depth-of-field 2D images to build up a 3D height map of a surface [61]. Current research in FVM technologies includes development of algorithms to improve measurement of, for example, smooth surfaces and vertical walls [62,63], as well as in measurement speed increases and measurement system size decreases to allow for in-process measurements [2]. A thorough review of recent advances in FVM technologies is available elsewhere [61].
- Imaging confocal microscopy (CM): CM involves the use of confocal pinhole to create optically-sectioned 2D images that are then stacked into a 3D height map of a surface [64]. Research into CM is currently focussed on development of methods for calibration and adjustment of CM systems [65], as well as in integrating confocal technologies with other surface measurement technologies, such as FVM, by developing methods for performing simultaneous FVM and CM in a single scan [66]. Other technologies exist that are similar to CM, such as active illumination focus variation [62] and structured illumination microscopy [67], though these are less well established in industrial surface measurement. Non-scanning chromatic confocal technologies can also be used for surface measurement [68], though their applications are more abundant in the biomedical sector than in manufacturing due to the generally poorer precision exhibited by chromatic systems compared to imaging systems [68,69]. A thorough review of recent advances in CM technologies is available elsewhere [64].
- Non-scanning technologies: While CSI, FVM and CM represent the cutting edge in areal surface topography measurement, these technologies are inherently limited in terms of their measurement speed by the fact that they require a scanning operation in at least one axis [17]. For real-time applications, non-scanning areal surface texture measurement technologies, such as wavelength-scanning interferometry [70,71], dispersed reference interferometry [72], chromatic confocal microscopy [68] and micro-scale fringe projection are required [73]. These technologies are commonly capable of significant decreases in measurement time, generally at the cost of

decreased precision and/or accuracy. A thorough review of recent advances in non-scanning technologies is available elsewhere [73].

- Scattering approaches: Another non-scanning technology, scattering approaches offer a fast route to surface measurement. Unlike the technologies listed in the previous paragraph, scattering approaches do not measure areal surface topography on a pixel-by-pixel basis, instead using the light scattered from a surface to holistically reconstruct the surface [74]. Recent advances in these technologies involve the extension of this technology (which is established in smooth surface measurement) to rougher surfaces [75], expanding its range of applications and developing advanced algorithms for ever-faster computational surface reconstruction [76,77]. A thorough review of recent advances in scattering approaches is available elsewhere [74].

3. State of the art in smart optical measurement solutions

Research into smart optical measurement technologies generally aims to build on the current state of the art in the technologies discussed in section 2. In many cases, this research aims to incorporate additional aspects into the measurement pipeline, such as a priori information about the measured objects and the measurement process itself. In this section, we discuss the state of the art in solutions for smart optical measurement, which have been widely applied across industry. Throughout this review, we have reported examples of smart solutions within the context of traditional manufacturing and additive manufacturing, including applications in the automotive and aerospace industries. Applications in the medical sectors, as well as in small scale metrology (particularly manufacturing of electronics and semiconductors), are considered to be outside of the scope of this review, as these areas are broad enough to constitute additional review works in their own right. The role of optical metrology specifically in the context of digital manufacturing is discussed elsewhere [78], in which the authors have reported numerous examples of optical measurement solutions applied into different manufacturing environments.

Exploiting the advantages offered by existing optical measuring technologies, there are a large range of intelligent solutions, with increased capability for self-adaptation and flexibility [7,11,79]. These solutions not only allow for the measurement process to be optimised, but also for performing autonomous operations and corrections to deliver results often in real-time [80]. These advances are possible because of the use and integration of intelligent algorithms and optimised configurations in the instrument designs [7].

Advanced solutions allow for new integrated smart manufacturing methods that exhibit high levels of adaptability and rapid design changes, digital information technology, and more flexible technical workforce training [81]. Examples of such smart advanced solutions are described in the following sections, including:

- incorporation of a priori knowledge into the measurement pipeline (information-rich metrology paradigm) and data-driven approaches;
- combination of multiple sensors and/or measuring technologies within the same measuring setup (i.e. multi-sensor data fusion);
- optical multi-view systems for in-line and on-machine measurement applications, and post-process maximisation of measurement coverage;
- machine learning-integrated algorithms for optimisation of measurement procedures;
- incorporation of real-time and/or post-measurement feedback in the form of performance indicators for corrective actions and adjustment mechanisms.

3.1 Information-rich and data-driven metrology approaches

Leach at al. [15] introduced the term "information-rich metrology" (IRM) to indicate the enhancement of any measurement process through the use of pre-existing (i.e. a priori) information. The IRM paradigm workflow is shown in schematic form in figure 1. In the IRM approach, information comes from knowledge of an object/surface being measured, knowledge of the measuring instruments employed and knowledge of the physical interactions/principles underlying the measurement technology itself, with respect to the object being measured [13–15]. The use of additional sources of information contributes to the enhancement of the performance of a measurement system, and thus increases the final quality of its measurement output. For a digital manufacturing scenario, IRM tools can be applied in the production lines and in digital future factories. Learning from prior measurements would signify an improvement of future measurement processes and results.

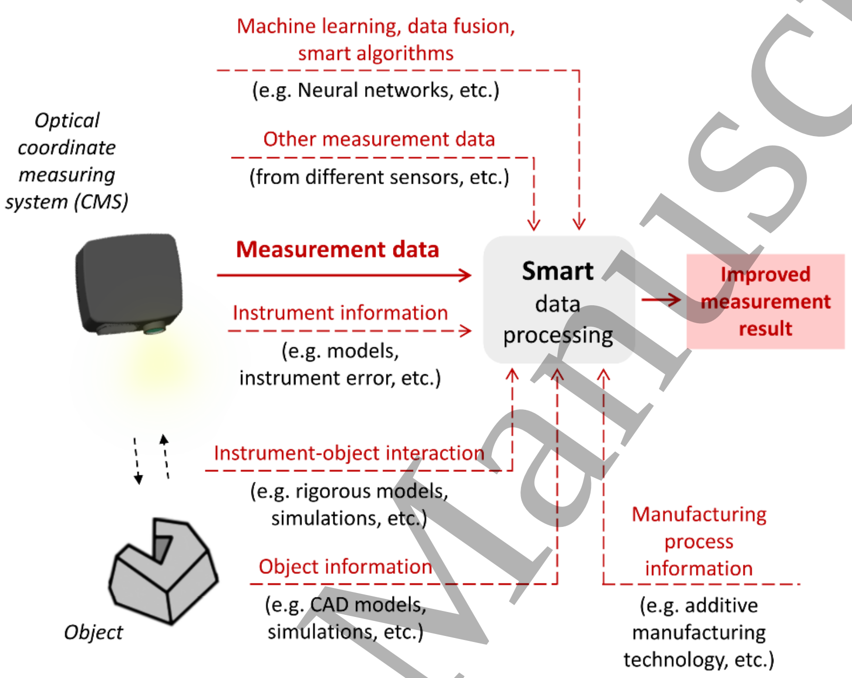

Figure 1. The information-rich metrology (IRM) paradigm (adapted from [13]). The raw measured data (i.e. the direct result from the measuring instrument) and the final result (i.e. improved optimised measurement result) are indicated with solid red arrows and they are the primary input and the final output of the process; the additional a priori information (for example knowledge of an object/surface being measured, knowledge of the measuring instruments employed and knowledge of the physical interactions/principles underlying the measurement technology itself, with respect to the object being measured, etc) are indicated with dashed red arrows.

Several authors have presented examples of the integration of a priori information into the measurement pipeline/instruments to improve the quality of a measurement. Syam et al. [82] developed a methodology for the design of in-line surface measuring instruments based on the IRM framework. The developed pipeline is divided into three phases: phase 1 is knowledge and a priori data gathering, phase 2 is instrument and control software development, and phase 3 is the use of the developed in-process measuring instruments for in-line control. In particular, phase 1 consists of gathering both knowledge (information) and data related to instrument requirements, measured surfaces, measurement models and manufacturing processes [83]. Another attempt to incorporate pre-existing knowledge to the measurement pipeline and, more specifically to the characterisation of surface topographical measurements, is illustrated elsewhere [13]. The advantages and challenges of introducing heterogeneous sources of information in the surface characterisation pipeline were discussed, providing examples about the incorporation of knowledge of part nominal geometry, the manufacturing process and the measurement instrument selected.

A fundamental part of the IRM paradigm involves the development of smart algorithms and machine learning solutions. Peuzin-Jubert et al. [84] recently reviewed state-of-the-art methods for optimisation of the measurement view planning of mechanical parts on machine tools, controlled in real time without human intervention, thereby allowing for automated adjustment of machine parameters and tool paths during the fabrication process. Their classification considered a priori knowledge methods (i.e. optimisation of the scanning path based on information from CAD, mesh model, etc.), and search-based methods (i.e. without the need of any input model, iterative adjustment of the scanning path in real-time for reverse engineering applications). In their classification, they introduce numerous quality criteria, including coverage and part accessibility (see section 3.5). Prior to this work, Catalucci et al. [85,86] developed a set of algorithmic solutions for the assessment of the quality of complex measured shapes, based on knowledge of a reference model in the form of a triangle mesh and the intrinsic properties of measured point clouds. Zhang et al. [87] proposed a technique to optimise the number of cameras and their respective positions for the measurement of the geometry of a given object. Using visible point analysis, their approach was based on the exploitation of the information given by the reference CAD underlying the measured part. Kinnell et al. [88] presented an algorithm for determining optimal positions for a robot-mounted 3D vision system used in a wide range of manufacturing tasks, such as locating tools and parts, inspecting part geometry and checking of alignment in assemblies, for applications that are subject to large inherent variation. For example, these vision systems are commonly employed in challenging pick and place operations that require components, presented in a random orientation, to be located and manipulated by a robot. In their work, a priori information from a CAD model was used to identify visible key points on the surface of the model per camera viewpoint and, thus, determine optimal positions. A priori information of the CAD part model to perform a guided inspection planning strategy was presented by Sadaoui et al. [89]. Through recognition and extraction of geometric features on the measured part CAD model, a laser line sensor and a touch probe were combined for automatic generation of inspection scanning sequences (i.e. a computer-aided inspection planning approach). A fuzzy logic model was used to define the best positions and orientations for the measurements. Other example applications of the IRM paradigm are presented elsewhere [14].

As the IRM is used to improve the final result based on gathered pre-existing information (including measured data), a similar process is the so-called “data-driven” approach; a pillar of the latest manufacturing revolution [90]. Data-driven methods are based on the availability of a large amount of data collected by smart systems equipped with advanced sensors from which observations and evaluations can be drawn to further improve a process. If scarce, data results in poor information, whereas an abundance of data can be used to keep track of the manufacturing process and, consequently, make better evaluations and predictions [91]. More specifically, data-driven methods that stem from statistics to machine learning can potentially enable intelligent, cost-effective measurement and thus allow manufacturers to use data for better decision-making results [92]. The data-driven framework is reviewed elsewhere [91]. The workflow consists of four layers and is outlined in Figure 2.

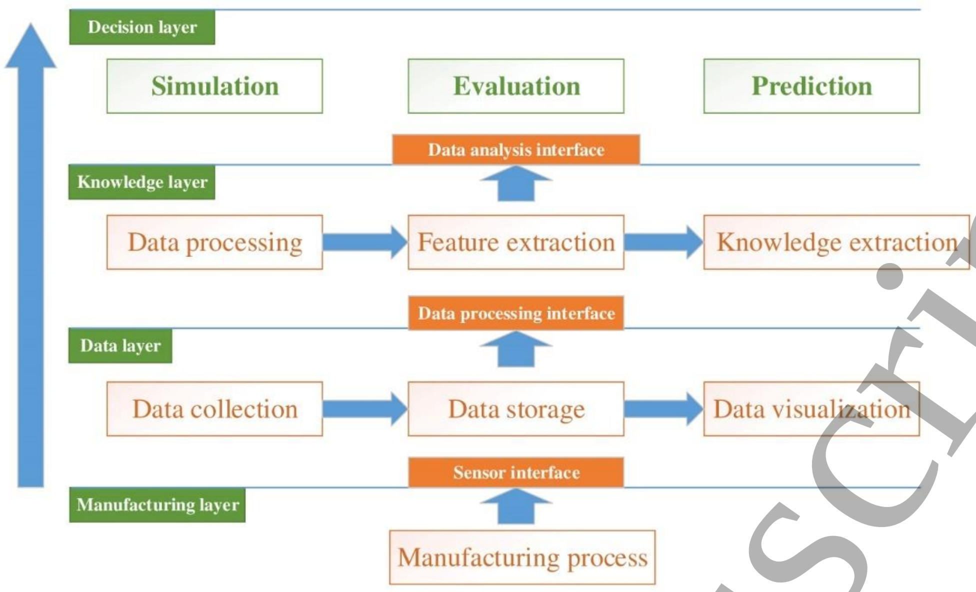

Figure 2. The data-driven framework from Xu et al. [91], comprised of four layers: manufacturing, data, knowledge and decision.

The first layer of this framework is known as the 'manufacturing layer', which comprises different types of manufacturing process, through which a product is designed, manufactured, assembled and checked. The second layer is the 'data layer' where data is collected, stored and visualised for the preparation of data processing. Via data processing, raw data is transformed into useful knowledge in the 'knowledge layer'. Finally, in the 'decision layer', knowledge is used to make decisions that help to create accurate simulations, evaluations and predictions to facilitate smart manufacturing.

Several authors have presented example applications of data-driven metrology in manufacturing (for example, additive manufacturing [93–95], manufacturing of semiconductors [96] and aerospace manufacturing [97]). Particularly, Susto et al. [96] proposed dynamic sampling approaches for data-driven metrology plan optimisation and cost reduction in the semiconductor manufacturing industry. Brunton et al. [97] reviewed the opportunities and challenges of integrating data-driven science and engineering into the aerospace industry using machine learning techniques for safety-critical applications (i.e. aerospace design, manufacturing, verification, validation, and services). Guo et al. [98] proposed an automated data-driven measurement pipeline for rapid 3D shape reconstruction including characterisation of the selected optical measuring instrument, multiple measurement acquisitions and automated full registration. Their optimised algorithm could find corresponding homologous point pairs in range data from different view angles, using knowledge extracted from the rectified images. Yang et al. [99] reviewed the state of the art in data-driven spatial/spatiotemporal interpolation and sampling methods for geometry measurement with a focus on manufacturing applications. The methods reviewed are based on knowledge coming from data extracted from highly dense measured areas to draw inferences about unmeasured regions of the part geometry.

3.2 Multi-sensor data fusion

Multi-sensor data fusion is a broad topic, that involves research across disciplines and fields. Here, however, we will focus on aspects of multi-sensor data fusion relating specifically to smart optical metrology. In their 2013 review, Khaleghi et al. [100] summarised the general state of the art in the broad field of data fusion at the time, noting that research in data fusion was steadily becoming more commonplace and highlighting some key research challenges. These challenges were related particularly to scale (i.e. the need for large-scale data fusion from a large number of sources) as well as the abundance of non-conventional data (such as written reports and web pages). Khaleghi et al. concluded their paper with a prediction that the future of data fusion research lay in the development and adoption of evaluation protocols that are independent of the given application domain and that there would be extensive ongoing research into the performance of data fusion system security and reliability in the coming years. Similarly, in their 2015 paper, Wang et al. [101] reviewed data fusion within the context of surface metrology, noting that holistic workpiece measurement is increasingly becoming necessary in modern engineering, with new fusion technologies required to characterise complex surface geometries featuring high-dynamic range structures and re-entrant features, such as friction-resistant feature arrays, broad spectrum absorption surfaces and self-cleaning surfaces, engineered with repetitive structures on the micro-/nano-scale. Wang et al. also commented that there are common threads in spatial data fusion solutions, particularly that they follow similar process frameworks, comprising four steps: pre-processes, registration, fusion and post-processes. Within these four processes, registration had been widely investigated, while fusion had a more limited set of available algorithms, with significant further investigation required. Post-processing efforts were also limited, with the development of specialised spatial database management systems required.

In state-of-the-art measurement systems, data fusion can be used to synthesise information from multiple individual sensors (i.e. featuring different measurement technologies), with the common goal of providing results greater in quality that the sum of their parts. In other words, multi-sensor data fusion refers in this work specifically to the fusion of heterogeneous data captured using measurement technologies of different nature. In their 2009 review, Weckenmann et al. [102] discussed the use of data fusion in dimensional metrology, noting ongoing challenges in merging and processing multiple data models, multiscale technology, uncertainty of multi-sensor measurements and automation. While this review is now somewhat older than the state of the art, these challenges remain broadly applicable today. In 2020, Meng et al. [103] provided a review on machine learning in data fusion as a general field, noting four key open issues. The first of these relates to the current relative simplicity of machine learning implementations, with Meng et al. noting the opportunity for deep learning to be implemented for data fusion. The second open question relates to the efficiency of fusion algorithms (or lack thereof), with Meng at al. noting that little effort has been put into improving the computational efficiency of current implementations. The third open issue relates to a lack of robust methods for data fusion, with many current methods lacking suitability for practical applications due to failures in algorithm implementations as a result of, for example, noisy data. Meng et al.'s final observation relates to data privacy and security, with the authors noting the sensitivity of machine learning methods to data leakage [103].

Further to the publication of these review works, there have been many studies conducted on development of machine learning methods for data fusion in optical metrology, used for applications ranging from micro-scale surface texture measurement to mapping (for example, [104–107]). One trend in research in the field of multi-sensor data fusion is improvement of the functionality of traditional algorithms with machine learning or other artificial intelligence (AI) techniques. For example, Gong et al. [105] proposed an machine learning algorithm based on Gaussian process regression, using a four-view stereo vision system to gather data. Gong et al. tested their new method using a high-order curved surface and experiments with a freeform surface, with results indicating that this Gaussian process-based machine learning method performed better than traditional Gaussian process-based algorithms, in terms of the accuracy and efficiency of the reconstruction. Another example of the combination of traditional algorithms with machine learning is a neural network method named "DeepFit", developed by Ben-Shabat et al. [106]. This method involves the application of neural network algorithms to learn point-level weights for weighted least-squares polynomial surface fitting. The method is also able to extract normal vectors and other geometrical properties from the surface data. The experimental results presented by Ben-Shabat et al. show the algorithm's robustness to noise and the application on noise removal. Abdelazeem et al. [107]

proposed a data fusion method for high-coverage 3D mapping of building constructions. This method involved fusing high-density but low-coverage point cloud data obtained using a terrestrial camera with a high-coverage but low-density data point cloud obtained using an unmanned aerial system (UAS). Using data obtained from a terrestrial laser scanner (TLS) as a reference, the results showed an improvement in registration error when registering the fused camera/UAS-based point clouds to TLS data compared the registration results for the unfused datasets.

In-process optical measurement is another common thread in multi-sensor data fusion, with, for example Moretti et al. [108], developing methods for in-process measurement of additive manufacturing processes. It is clear from the available literature that multi-sensor data fusion is a topic of current research, much of which is intertwined with research into machine learning methods. A thorough review of the intersections between multi-sensor measurement and data fusion was recently published by Kong et al. [109], who noted the emergent nature of multi-sensor data fusion research and the rapid increase in publications in this general area. Kong et al. suggest that demand for data fusion algorithms is likely to increase over time, and that fusion technologies are likely to be at the core of the next generation of industrial measurement systems. Current issues that Kong et al. noted, however, relate to the lack of a consistent narrative surrounding a generalised model for data fusion and the preliminary nature of much of the recent research into data fusion algorithms. They conclude by suggesting that a unified approach and generalised model represent the next steps, with solutions to problems with data registration, data pre-processing, database construction, database management, human-machine interface and general software package development being required. Kong et al. also noted their expectation that artificial intelligence is likely to feature heavily in data fusion in the future and that further algorithm testing pipelines need to be established and standardised.

3.3 Multi-view measurement systems

In ISO/DIS 10360-13 [19] a multi-view measurement is defined as the “measurement of spatial coordinates through registration and fusion of multiple single-view measurements in different locations and orientations of the optical sensor relative to the workpiece”. Based on this definition, multi-view instruments have shown themselves as appealing solutions, especially for post-process measurement applications, becoming an emerging research area in both 3D geometry and surface texture metrology over the last two decades [110]. Weinmann et al. [111] presented a measuring framework for a fringe projection system based on a multi-camera-projector configuration. Their experimental setup consisted of multiple cameras mounted on a hemispherical gantry (approximately 150 cameras) and they simulated a multi-projector framework by placing one projector, mounted on a tripod, at different locations. At least five different projector positions were used to cover the whole surface of the selected test cases (as test cases, two common objects featuring freeform shapes with surface of challenging reflectance behaviour were used). Weinmann et al.’s approach paved the way for the removal of time-consuming registration/stitching methods for multiple measurements whilst maximising object coverage. Following this work, Groh et al. [112] developed a multi-view fringe projection system composed of two cameras (moving along an arc-shaped gantry) and three projectors. Once again, the degree of coverage of the measured objects was maximised and the time for the acquisitions was largely reduced. The objects chosen to test the setup were a white ball target, a wooden figurine painted in different colours and a rubber and plastic mug.

In a production-line scenario, the employment of multi-view configurations for the inspection of fabricated workpieces could be beneficial to shop floor productivity, ultimately speeding up quality checks by maximising measurement coverage and improving measurement results by minimising the effects of occlusions. Particularly, the inspection of large objects (for example, the complete assembled body of an automotive vehicle) or freeform geometries (such as those produced via additive manufacturing) may appear as challenging due to the limited field-of-view of conventional single-view instruments [113]. To overcome this limitation, the simultaneous measurement of an object from multiple viewpoints could significantly reduce the inspection time, meaning both the time required to either rotate the object placed on a rotary stage or move the robot-mounted sensor around it, and the time required to merge multiple acquisitions into a single scanning output. Mineo et al. [114] developed a multi-robot flexible inspection cell, equipped with cameras for photogrammetric measurements, to assess the position of large composite aerospace components placed within the robots working environment. Essentially, multi-view measurements could offer advantages to in-line inspection scenarios; however, their exploitation in factories is still largely avoided due to the instrument complexity and lack of flexibility in the characterisation process.

3.3.1 Characterisation approaches

The most significant complexity of multi-view instruments is the structural relationship between the components (multi-camera, multi-camera-projector, etc.) and their individual characterisation [115]. In the last decade, several authors have proposed methods to solve the issues surrounding multi-view characterisation. The most common approach is an extension of the method developed by Zhang [116] and Zhang and Huang [117] for a single camera-projector configuration. Using this method, each camera is characterised with an accurately manufactured planar pattern (for example, a checkerboard or circle board) and the relationship between different views is obtained by global optimisation of the extrinsic parameters of all the views. For example, Albers et al. [118] presented a flexible characterisation method for a multi-sensor fringe projection system by incorporating the Scheimpflug optics for the cameras and defining a common world coordinate system using a planar target. In the paper, Albers et al. also discussed the benefits of multi-camera systems with single projector over a multi-projector unit (for example, the improvement of measurement accuracy and the potential for performing measurement without calibrating the projection unit). Feng et al. [119] proposed a characterisation method based on the use of a transparent glass checkerboard, refractive projection model and ray tracing to reduce calibration errors. Several researchers have proposed flexible methods to solve the inherent complexity of multi-view system characterisation using 3D targets [120,121]. This method allows for the characterisation of all cameras with limited-overlapping or non-overlapping fields of view in a single operation, unifying the multi-camera coordinates in the same reference frame and avoiding extensive workloads and accuracy losses caused by repeated processes. A pyramid-shaped calibration object with triangle-coloured patterns on its faces was used by Abedi et al. [122] for circular multi-camera system characterisation. All cameras were processed simultaneously, and the error accumulation issue was solved. To verify the robustness of the method, further tests were performed in dynamic scenarios and 3D modelling applications. Other authors have proposed different characterisation methods that do not require the use of any calibration target or other auxiliary calibration devices. Gai et al. [123] proposed a user-friendly characterisation method for multi-view fringe projection, where digital fringe projection and phase maps are used to acquire global characterisation information. Similarly, Shaheen et al. [115] proposed a characterisation approach for a multi-view fringe projection system based on correspondences between rectified unwrapped stereo phase maps, where the matched phase values between the stereo phase images are triangulated to acquire 3D point clouds. The developed setup comprised of two stereo pairs (four DSLR cameras and two projectors) is shown in figure 3. Other authors [124,125] developed global characterisation methods for multiple camera-projection systems avoiding the pair camera cross-talks by employing particular light bandwidths (i.e. RGB optical colour filters).

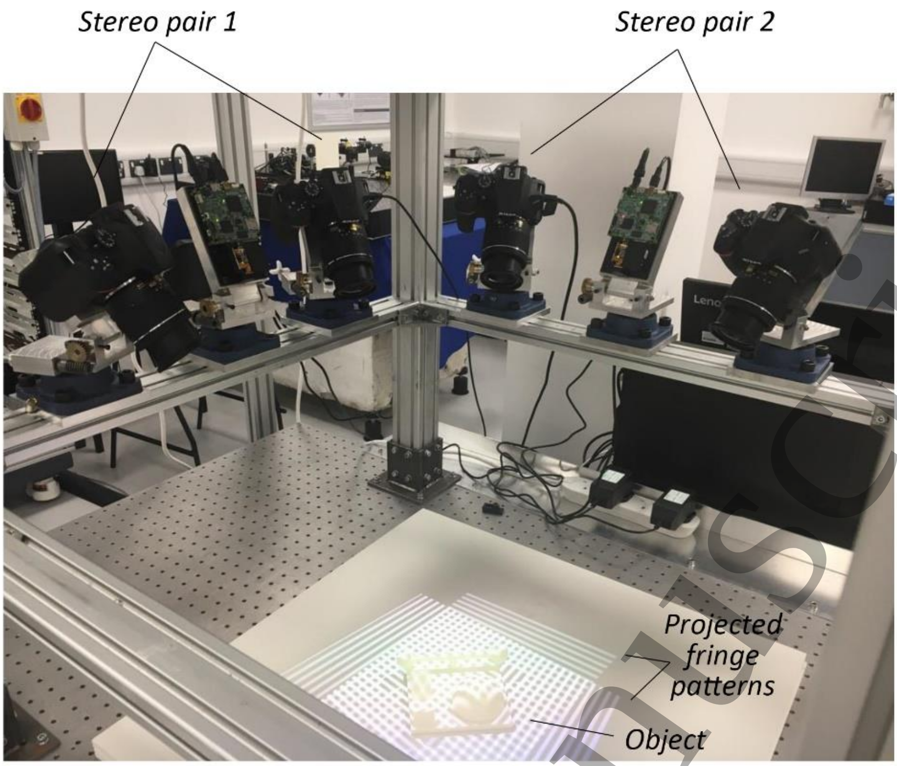

Figure 3. Multi-view systems: fringe projection setup comprised of four DSLR cameras and two projectors for post-processing applications (adapted from [115]).

3.3.2 Examples of in-line applications

Not many examples of multi-view configurations with direct applications in in-line measurements have been published, either as research prototypes or commercial solutions. However, Perez-Cortes et al. [126] developed a multi-camera system able to reconstruct the complete shape of a measured object using image processing methods. This setup composed sixteen synchronised cameras, uniformly distributed within the measurement cell (a cell in the shape of a polyhedron with sixteen faces, unparallel with each other to avoid overlapping of the cameras field of view). The setup demonstrated a high level of measurement coverage without suffering from occlusions and shadowing. Adequate diffuse illumination was created by employing high-power LEDs attached to the camera supports or to the inner faces of the measuring cell. The setup was tested on simulated objects of simple primitive geometries (for example a sphere, a cube, and a spring), which showed its applicability to a production line, augmenting workpiece measurement coverage while minimising the acquisition time. Similarly, Deetjen et al. [125] tested their global characterisation method using four camera-projector pairs setup as shown in Figure 4 that successfully captured flying birds, demonstrating its applicability in an industrial quality control environment for the dynamic measurement and reconstruction of rapidly moving, complex objects. Birdal et al. [127] developed a multi-view, close range optical metrology system, composed of multiple static, locally overlapping cameras, to inspect automotive parts with various geometries.

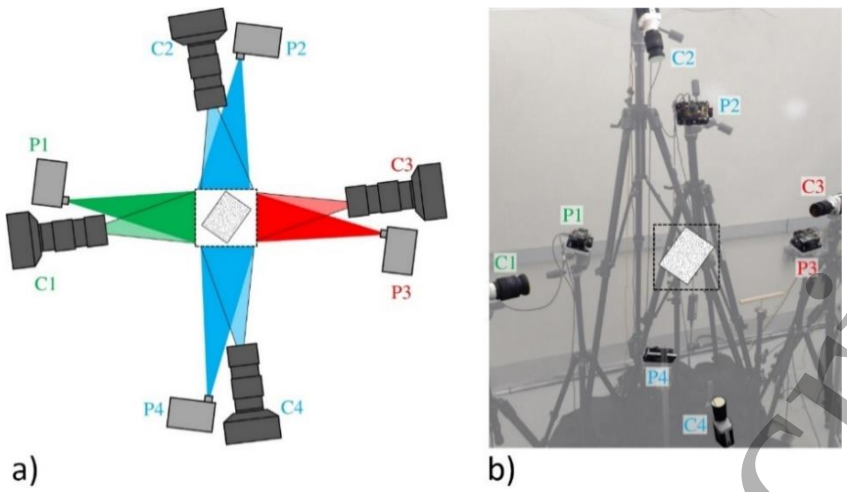

Figure 4. The multi-view structured light system designed by Deetjen et al. [125]. a) Schema showing the configuration of four camera and projector pairs. To reduce cross-talk between the four projected patterns, three different colours matched by camera colour filters for pairs 1 to 3 were used (green, blue and red respectively). The colour of the 4th pair (blue) is duplicated from the 2nd pair; b) an image of the actual setup.

Preliminary research on the integration of multi-view solutions for in-process monitoring applications has been recently carried out. Kalms et al. [128] developed a new approach to evaluate 3D laser printed parts in powder bed fusion-based additive manufacturing in-line within an enclosed space. Dickins et al. [129] developed a prototype on-machine multi-view fringe projection system for the acquisition of high-resolution surface topography information of a metal powder bed, implementing the system into a mock-up powder bed fusion (PBF) chamber. The setup, composed of four cameras and one projector (shown in Figure 5a), allowed for a high degree of surface coverage, maintaining a high resolving power over the entire powder bed area. Areas not measured by a single camera are accessed from other views, reducing data drop out. A similar configuration was proposed by Remani et al. [130] (shown in Figure 5b). In their paper, they presented a multi-sensor approach to evaluate the layer-by-layer development of printed parts. The metal laser PBF build is monitored in-process using a multi-view fringe projection system, a high-speed thermal camera and other sensors, to capture defects as they form during the process. Remani et al. note that this system will soon be integrated into a commercial metal PBF system.

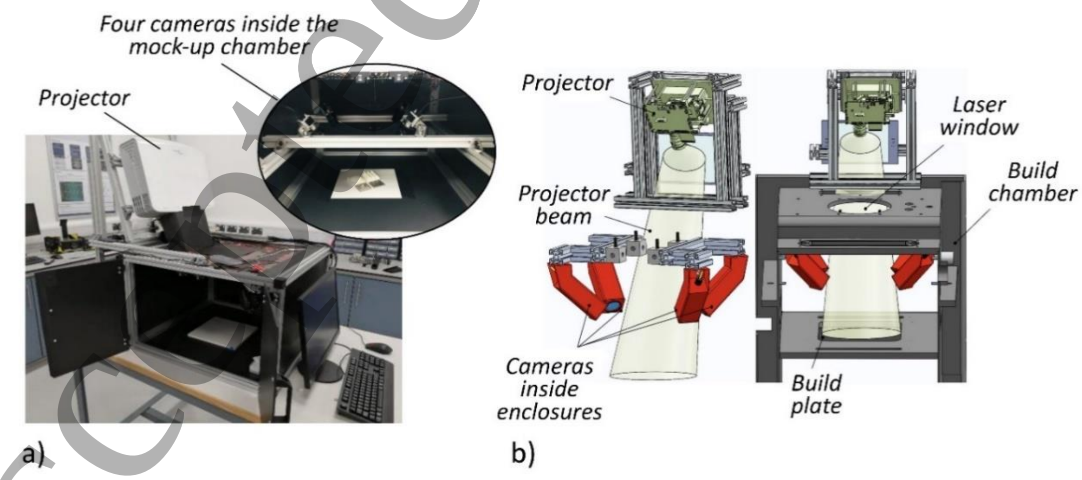

Figure 5. Examples of in-process fringe projection setups: a) mock-up of a four cameras-one projector system, designed to be integrated in a powder bed fusion (PBF) chamber for the measurement of surface topography (adapted from [129]); and b) CAD design of a multi-sensor measurement system for in-situ defect identification in metal additive manufacturing (adapted from [130]), which includes a multi-view fringe projection configuration and a high-speed thermal camera.

3.4 Machine learning integrated algorithms for measurement optimisation

Machine learning techniques differ from classical programmatic methods, in that they do not require the programmer to explicitly state how a problem should be solved. Instead, a statistical model is built that learns how best to represent an approximation through training on a dataset. This training can be either supervised (with ground truth labels) or unsupervised (without labels, also referred to as pattern recognition). These statistical approaches were previously an approach constrained to research laboratories, but the recent increase in highly parallelised processing and Big Data has allowed these approaches to be deployed industrially [43]. Machine learning methods have already found applications in small scale metrology, particularly in the process monitoring of semiconductors [131–133], but these scales are outside the scope of this review.

Machine learning approaches can be applied effectively to the entire measurement pipeline; indeed, machine learning can be used as a part of a traditional pipeline or can replace it entirely in a so-called 'end-to-end' learned system [134,135]. The following sections describe the current state of the art in machine learning for metrology across the various measurement stages, followed by a consideration of the ramifications of using these methods on measurement uncertainty.

3.4.1 Measurement planning

Learning techniques can be used in the measurement planning stage before data is collected. For example, Zhang et al. [87] presented an automated view planning and part detection pipeline for close-range photogrammetry. The proposed pipeline was based on a priori information exploited from the CAD model of the measured part. First, a local optimisation procedure located a seed camera, from which the largest number of surface points could be seen. A global objective function was built to consider a combination of surface coverage, convergence angle between camera pairs, normal angle of views to part faces, and baseline distance between camera pairs. A genetic algorithm performed the global optimisation to maximise the objective function, producing a list of camera coordinates relative to the CAD data.

An alternative approach is to leverage machine learning to produce the measurement plan during the measurement. This approach is performed through a next best view (NBV) method, which iteratively finds the next camera position based on previously collected data. An approach presented by Arce et al. [136] employed structure from motion to create an initial point cloud, from which the next position was iteratively generated using an unsupervised model. This approach was specifically designed for situations where the CAD model is unavailable, an unlikely scenario in production engineering. If the CAD model of the object is known, the NBV positions can be precomputed. Mendoza et al. [137] took a supervised approach to NBV by using a traditional view-planning method based on ray tracing; the latter was used to calculate labels and generate a dataset of 15,000 training point clouds. A 3D convolutional neural network (CNN) was then used to predict the NBV position directly. Comparing their machine learning based approach to traditional methods, Mendoza et al. showed that machine learning methods appeared to be consistently faster, often by many orders of magnitude. Furthermore, they showed that machine learning approaches were particularly effective at finding early camera locations but performed worse when calculating later positions; consequently, they suggested a fused approach employing machine learning to initially find a small number of camera positions and then using a traditional algorithm to compute the following positions.

The list of positions generated are generally given relative to the measured object, and this approach can cause an issue as the coordinate system of the CAD data is unlikely to be aligned with the measurement system's coordinate frame. Eastwood et al. [138] presented a solution to this problem by directly regressing the CAD offset from the camera coordinate system using a residual neural network (RESNET-50). The RESNET-50 was trained on photorealistic renders of the measurement volume using a realistic extracted material texture, which could be applied to the CAD data, and the ground truth offset of these images was known explicitly. Once the offset was determined, the camera coordinates could be transformed to allow for fully automated data acquisition.

3.4.2 Learned depth

Optical measurement requires raw optical sensor data to be decoded into height data, this process often requires complex and computationally expensive algorithms. Here, we cover attempts to augment, or in some cases replace, these traditional approaches with machine learning models.

3.4.2.1 Machine learning for phase unwrapping

Both fringe projection profilometry and various forms of interferometry produce data with wrapped phase [139]. Unwrapping this phase can be slow and ambiguous, especially when the surface is not smooth within the range of the fringe wavelength. Machine learning has much to offer here: first, it can provide fast phase unwrapping, allowing for depth maps to be produced at high refresh rates, enabling in-situ monitoring applications. Secondly, it can provide informed predictions for the removal of ambiguities. Early work in this field was conducted by Feng et al. [33], a dataset was created using a traditional phase shifting method. This dataset trained a pair of CNNs to extract intermediate values required for phase retrieval. This idea was extended by Liang et al. who used a new phase unwrapping segmentation network for fringe projection to unwrap the phase in a single step (see figure 6) [140].

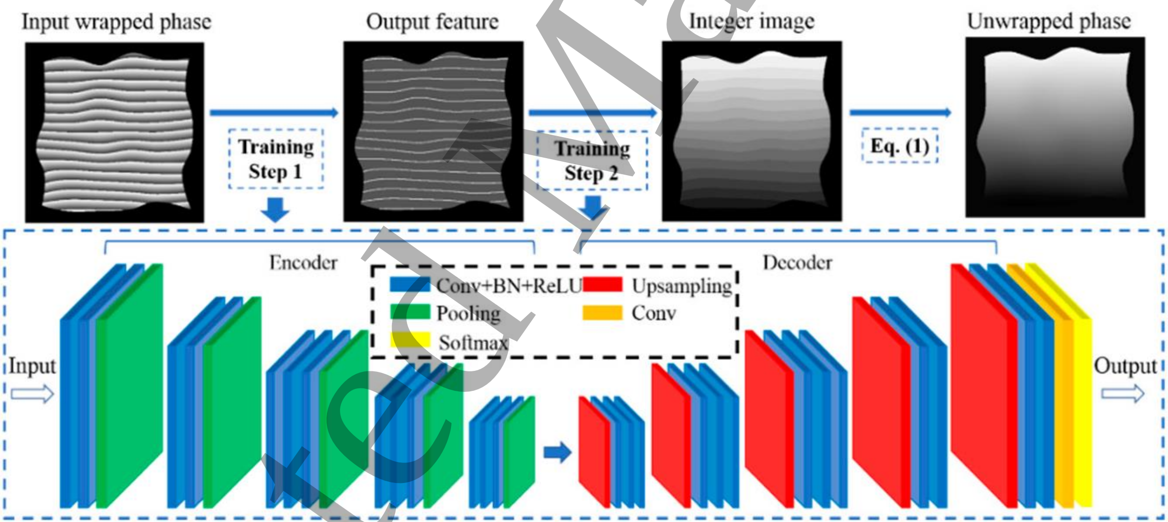

Figure 6. The workflow of the method proposed by Liang et al. [140] showing the network architecture for phase unwrapping (from [140]).

Similarly, Wang et al. [141] used a U-NET (similar to one shown in figure 6) to unwrap phase in a single step. The training dataset was created in reverse by generating synthetic surfaces from a combination of random and Gaussian distributions, that constituted the ground-truth labels. These surfaces were then wrapped to create the training features [141]. The training process used in this method is shown in figure 7.

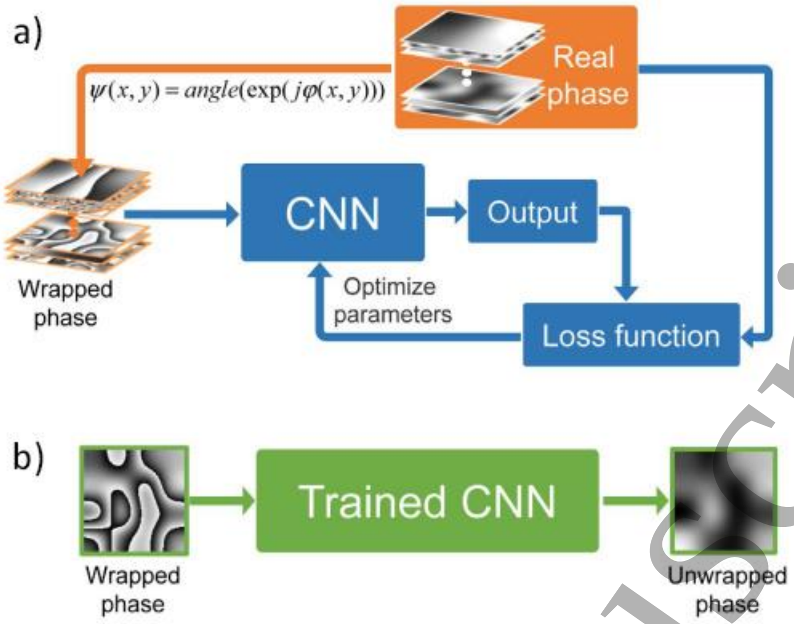

Figure 7. Training and testing the learned phase unwrapping: a) the unwrapped phase is wrapped to produce training features with which to train and optimise the CNN; b) the deployed CNN predicts the unwrapped phase on unseen samples (from [141]).

Wang et al.'s method was tested against unseen simulated data with added noise and aliasing, and real measurement data. The CNN was shown to be robust to both noise and aliasing and performed favourably when compared to traditional unwrapping approaches. Further models have been developed to improve performance on noisy data [142,143]; Zhang et al. [143] used a similar U-NET-based CNN to perform phase unwrapping. However, in this case, the input was passed through an additional modified U-NET that performed a denoising operation. A labelled training set was generated by synthetically adding Poisson and salt-and-pepper noise to interferograms at a signal to noise ratio of 4 dB. When compared to traditional approaches for unwrapping phase (i.e. Goldstein's method [144] and the quality-guided path following method [145]), the learned method was shown to outperform the traditional methods. Experiments performed by Yin et al. [146] showed machine learning methods can be used in temporal phase unwrapping to reconstruct absolute phase maps from a pair of relative phase maps robustly. They also show that their model can reduce the number of fringe patterns required enabling real-time applications such as process monitoring. A book chapter by Chen, Xu and Zhang [31] concludes that experiments have shown machine learning models can perform fringe analysis more accurately than traditional phase retrieval methods but that the huge datasets and uncertainty surrounding the generalisation of learned models remain large barriers to widespread adoption.

3.4.2.2 Stereo matching

Due to its applications in machine vision (especially within self-driving cars), learned stereo matching is a highly researched area that saw an initial breakthrough in 2015 with the work carried out by Zbontar et al. [147], who computed stereo matching cost using a CNN. Since then, there have been many developments (see [148] for a thorough review). One of the most popular approaches is called Geometry and Context (GC-Net) [134]. GC-net takes a pair of rectified stereo images as input and employs a twin 2D CNN to generate a cost-volume; a 3D-CNN auto-encoder architecture processes the cost volume before it is de-convolved and passed to a soft argmax function that outputs the depth in the form of a disparity map. A recent approach (ResDepth) is to use deep learning for matching refinement in a two-step process [149]. First, the dense reconstruction is generated through any chosen method, which can be learning-based or not, as the case may be. To fully leverage the performance of a CNN, the reconstruction should be represented in a regular grid such as a depth map. Re-projecting the depth map is performed to find the residual depth. Then, a U-Net based CNN takes both the initial reconstruction and the residual depth as input to produce a final refined reconstruction. In this work, Stucker and Schindler presented a robust characterisation and calibration pipeline for measurements, and, in their conclusions, they highlighted the benefits of using deep learning and pattern recognition to measure and classify surface defects.

Calculating the cost volume of the scene is highly computationally expensive and limits the resolution of stereo images on which it is feasible to deploy learned stereo machines. Yao et al. [150] proposed a recurrent multi-view stereo network (R-MVSNet) to sequentially regularise 2D cost maps along the depth direction rather than calculating the entire volume in one go. R-MVSNet dramatically lowers memory usage compared to using a 3D CNN, allowing for high resolution learning-based reconstructions. PatchmatchNet [151] is an end-to-end learned stereo machine which performs multi-scale feature extraction, correspondence and refinement. PatchmatchNet eschews the need to calculate a cost volume by implementing a learned version of Patchmatch (a randomised correspondence algorithm [152]) leading to naturally low memory requirements and high processing times. Finally, as was noted in section 3.4.2.1, generalisation is a concern for the widespread deployment of learned depth methods. Zhang et al. [153] address this problem in the context of stereo matching and propose two new loss functions which can be embedded into existing stereo networks. These loss functions are designed to promote consistency on learned features between stereo views across unseen domains. It is shown experimentally that generalisation is improved across a range of models on a range of datasets when these loss functions are used.

3.4.3 Machine learning enabled in-situ monitoring

As machine learning approaches become increasingly popular smart manufacturing, there has been an increasing need for solutions for quality assurance of measured data, including defect classification, recognition and detection in surface texture [154–157]. Data-driven methods, using machine learning to extract characteristic features of aluminium die castings industrial surfaces have been investigated by Schmitt et al. [158]. In their work, the authors proposed a generative deep learning framework using style-based autoencoding to extract surface deviations. Similarly, Ren et al. [159] developed a generic deep-learning-based approach for automated inspection of surfaces based on image classification and defect segmentation.

The current major challenge in industry is the need for large datasets to accurately train the machine learning models, as collecting training datasets is usually costly and related methods are highly dependent on the datasets available. Eastwood et al. [160] recently presented an approach to numerical surface texture generation applicable to any encoded surface, based on a progressively growing generative adversarial network. By encoding height data into grayscale values within an image, the authors demonstrated that the network could create realistic synthetic surface data, both qualitatively and quantitatively. Their model was trained on two example surfaces obtained using different manufacturing processes and measured with different techniques; the results showed good agreement between the synthetic and real data in the distributions of areal surface texture parameters. Moriz et al. [161] investigated the employment of cycle-consistent generative adversarial networks (CycleGANs) to augment the available image datasets and detect defects on surfaces.

As discussed in section 3.3.2, machine learning is a powerful tool for in-situ monitoring and process control. In much of the recent literature, particular attention is given to additive manufacturing applications, due to the complex and numerous surface defects that can occur on a layer-by-layer basis. Recent reviews have comprehensively covered machine learning for additive manufacturing [162–164].

Work by Liu et al. [165] showed how a fringe projection system can be set up for in-situ monitoring of an electron beam powder bed fusion process. Liu et al. concluded that deep learning and pattern recognition are required for timely measurement and detection of defects. To achieve high speeds, several authors have presented methods that rely on 2D imaging (i.e. containing no explicit depth information), due to the increased speed of data acquisition, compared to fringe projection or photogrammetry [166]. An approach presented by Caggiano et al. [167] employed a deep CNN trained on images of the powder bed for in-line defect detection during PBD. The model was a bi-stream (i.e. two inputs) CNN, with each stream using an image taken after laser scanning and one after powder recoating. Both inputs were passed through parallel convolutional layers before being combined through a fully-connected (dense) layer from which the final classification was drawn. Here, the classification indicated the presence of a variety of defects. A similar approach was used to monitor the porosity in a laser additive manufacturing process [168]. Scime and Beuth [169] used images as the data source in a laser powder bed fusion process, focusing on the morphology of the melt pool. A number of steps were taken to transform the high-dimensionality nature of an image of (1024×1024) pixels to a lower-dimensional vector representation. In their approach, Scime and Beuth proposed splitting the melt pool image into nine sub-images and using the scale invariant feature transform (SIFT) algorithm to detect local gradients. A bag-of-words algorithm was used to assign a 50-element vector to each image, based on the distribution of detected local gradients before finally concatenating the three vectors into a single 450-element "fingerprint" vector. A support vector machine was trained to predict the presence of five kinds of defects from the fingerprint. Scime and Beuth showed that this approach could accurately detect defects based on the melt pool fingerprint even though its data size was only 0.04 % of the original image size. In their review, Yu and Jiang [170] discussed how machine learning approaches can be adapted for defect detection in 3D bio-printing. In tandem with optical sensing, other sensors can be used to provide additional data and context to the machine learning model, such as data from thermographic [171] and acoustic sensors [172,173]. As an example, photodiode sensors can be placed to detect the backscattered laser light from the melt pool in a laser powder bed fusion process [174].

Post-processing techniques, such as X-ray computed tomography, can be used to build the ground truth datasets required to train a model, as demonstrated by Gaikwad et al. [175]. In this example, X-ray computed tomography data was used to evaluate statistical build quantifiers that parametrise the build quality of a thin-walled additively manufactured part. A CNN was then trained on this data to predict, from in-situ optical images, the thin-wall quality.

Machine learning techniques are not only limited to additive manufacturing processes. For instance, the civil engineering sector employs machine learning for in-process monitoring applications. Tuan et al. [176] employed a machine learning model monitoring a rectified stereo camera pair for in-situ monitoring of a concrete slump test. A particularly novel application of this technology is in construction monitoring [177], where photogrammetry is used to capture point clouds while a building is constructed. By re-projecting the CAD data from the known camera positions, a CNN was used to automatically label different sections of the construction even if the view was partially occluded. Additionally, a structure-from-motion photogrammetry method was developed to detect defects within masonry walls [178]. The measured point cloud of the wall was segmented into smaller units using a 2D continuous wavelet transform from which a CNN predicted the presence of multiple defect categories. Hachem et al. [179] proposed a method based on deep learning to automate visual quality inspection of automotive components. The method showed its potential in detecting object movement and was able to readjust the camera's angle with respect to the new object position to optimise the inspection process. Malaca et al. [180] developed a real-time vision inspection system for classifying car door interior fabric textures, based on machine learning techniques. The authors addressed the challenges given by poor, uncontrolled lighting conditions in the automotive industry by developing a robust pre-processing technique and selection of fabric characteristics using two machine learning classifiers.

3.4.4 Calibration and characterisation

As manufacturing environments become more inter-connected and autonomous, a metrological framework for the complete life cycle of measured data is required: from calibration capabilities for individual sensors to uncertainty quantification associated with machine learning in sensor networks. The "Factory of the Future" project [181] has developed the concept of "smart traceability" which combines digital pre-processing of sensor data with traceable calibration of micro-electromechanical system (MEMS) sensors. In their US patent for the calibration of small angle X-ray scatterometry, Hench et al. [182] use machine learning to solve the inverse problem when modelling the interaction between the X-ray beam and occlusion elements in the calibration device.

The largest body of work relating to calibration of optical measurement relates to camera calibration and characterisation [183–185], likely due to the relevance to machine vision problems. It has been shown that CNNs can be more effective than standard algorithms at detecting calibration checkerboards in photographic images [183]. Due to the requirement for multiple images acquired at different angles, traditional calibration methods can be significantly affected by low-accuracy components such as rotation stages. There is potential to use deep neural networks (DNNs) to characterise a camera's intrinsic parameters and a parameterised form of the radial distortion in a single step from a single image [184], rather than the many images required for conventional approaches. Li and Liu [185] used a MEMS micro-mirror device and a laser to stimulate single camera pixels. A DNN was then trained on this single pixel illumination data to calibrate the camera. It was shown that this approach was highly accurate and required fewer computations than traditional calibration algorithms. It is likely that much of the work on applying machine learning to camera calibration can be generalised or extended to other optical sensors and measurement techniques.

3.4.5 Implications for uncertainty in machine learning

For machine learning to be integrated into traceable measurement pipelines, particularly when machine learning is included in virtual instruments, the uncertainty in predictions produced by machine learning models must be quantifiable [186]. As discussed by Sediva et al. [187], when models become complex it becomes more difficult to apply the methodologies outlined in the *Guide to the Expression of Uncertainty in Measurement* (GUM) [188] and stochastic approaches such as Monte Carlo simulations must be employed (as outlined in Supplement 1 to the GUM [189]). Early work showed how uncertainty could be propagated from input through to the model output for simple linear regression models [190]. This uncertainty analysis has been expanded to apply to more general machine learning regression models.

Cheung and Braun [191] proposed that the following uncertainty components should be considered:

- model output: the uncertainty relating to the difference between the model prediction and the ground truth value;
- calibration data: the uncertainty in the data which make up the model training dataset;
- input measurement: the uncertainty in the input data to a model; and
- output measurement: the output uncertainties outside the calibration data set.

Cheung and Braun showed that increasing the size of the training dataset reduced uncertainty in the calibration data but did not affect the other uncertainty contributions. They also conclude that the uncertainty will be larger if the model is used to estimate outputs which are outside the bounds of the training data.

Given the prevalence of machine learning models in indirect measurement and virtual instruments, there is little literature on their uncertainties, and this area is ripe for further research. Recently, machine learning itself has been used to attempt to provide uncertainty evaluations during stereo matching [192]. In this work, similar to some of the work discussed in section 3.4.2.2, a DNN approach was employed for stereo matching. The difference here, when compared to the work discussed in section 3.4.2.2, is that the model used was a probabilistic network. This network, rather than learning the network parameters directly, learned a distribution from which the parameters were sampled at every prediction. Therefore, the variation between predictions given on the same input approximated the model uncertainty.

3.5 Performance indicators

In the manufacturing sector, performance monitoring leads to the improvement of production and the optimisation of fabrication processes and indicators of performance are indispensable for improving the quality of the manufacturing shop floor. Quality indicators are performance measures designed to monitor one or more processes during a defined time and are useful means for service demands, production, personnel, inventory control and process stability evaluations. In this work we specifically focus on those criteria strictly related to 3D point clouds processing and their intrinsic properties (for example level of noise, coverage, density, etc), designed as metrics for the evaluation of the quality of a measured output rather than focusing on any other aspect of the measurement pipeline. We primarily intend to highlight how quality in measurement can be interpreted from the final result and how information can be translated into smart automated feedback tools for correction and optimisation of the entire measurement process.

From a measurement standpoint, performance indicators or criteria were first introduced in relation to 3D point clouds by Hoppe et al. [193], designed as metrics for the evaluation of the quality in measurements. Implemented as built-in functions, performance indicators represent useful means for developing intelligent measuring instruments, able to autonomously plan a measurement process and assess measurement performance while the inspection task is in progress. This goal can be achieved by combining such indicators with available pre-existing knowledge of parts, instruments and technologies (section 3.1) and employing smart algorithms for the optimisation of measuring procedures (such as machine learning technologies, see section 3.4).

3.5.1 Indicators of point cloud quality

Hoppe et al. [193] suggested in their early work related to the reconstruction of surfaces from unorganised point clouds to qualify data according to indicators of noise and density. Both indicators appeared to be representative of the quality of each point, highlighting the performance of the point-to-surface reconstruction algorithm. Following this work, Lartigue et al. [194] proposed a set of four quality indicators for point clouds obtained with non-contact probes. These indicators were noise, density, completeness and accuracy of the point cloud data. The noise indicator can be found in Contri et al. [195], where the effects of the digitising noise are taken into account to evaluate the global positional uncertainty of a subset of points in a 3D point cloud measured with a laser triangulation system. Similar indicators can be found in Mehdi-Souzani et al. [196], where they are used to support measurement planning for freeform surfaces in reverse engineering. In both works, the methods presented relied on an initial scan of the object set as a reference, without the involvement of a CAD model. The point cloud was converted into a voxel space representation to evaluate the density indicator, considering the number of points that belong to each voxel (i.e. volumetric density). To compute the completeness and rate of coverage indicators, the point cloud was converted to a triangle mesh and the distances between neighbouring points in the mesh were evaluated.

Based on this early work, Catalucci et al. [85,86] proposed a set of indicators to assess the quality of 3D point clouds acquired using two optical measuring instruments. The indicators are locally mapped to the measured object's reference geometry (i.e. a triangle mesh), highlighting measurement behaviour in correspondence to diverse geometric features of the measured part. The designed criteria include measurement time, surface coverage, density of point-based sampling and point dispersion (see in figure 8). Performance indicators based on local mapping on the 3D mesh model surface have also been proposed by Phan [197] to evaluate scanning noise. The noise is calculated for each triangular facet in the mesh, and it is qualified based on comparison with a threshold value obtained from the sensor qualification protocol. Again, in their work Vlaeyen et al. [198] reported that the quality of 3D point clouds can be characterised based on the indicators of density, completeness, noise and accuracy, developed earlier by Hoppe et al. and Lartigue et al..

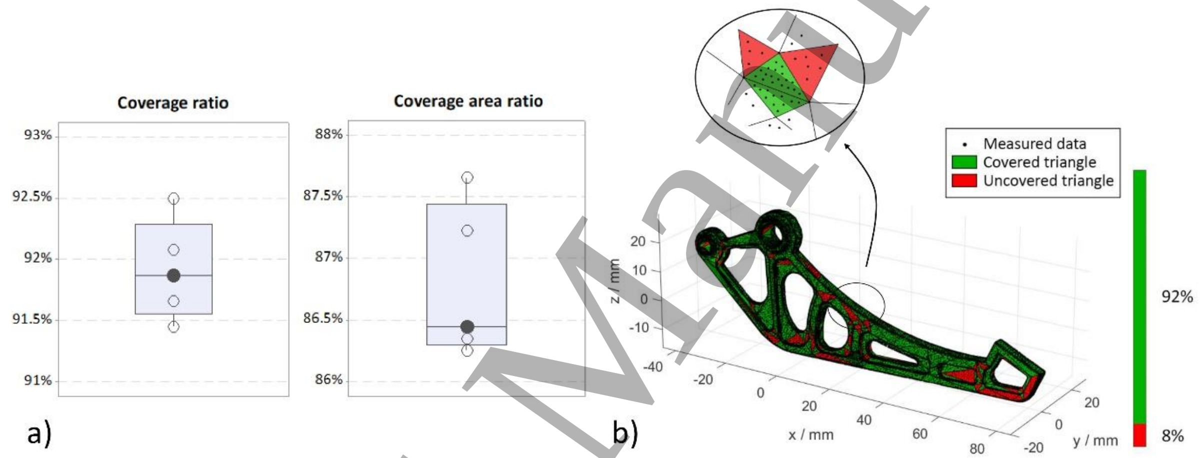

Figure 8. Performance indicators of part coverage from Catalucci et al. [86]: a) boxplots from five measurement repeats indicating coverage ratio, and coverage area ratio respectively (individual results for each of the five repeats, and median); and b) covered and uncovered triangles rendered using binary colouring projected onto the triangle mesh surface.

Evaluation indices have been used not only to determine the quality of a measurement but also to prove the performance of different algorithms and stages of the point cloud processing pipeline, such as registration. For example, Wang et al. [199] developed a novel registration method for partially overlapping featureless 3D point clouds in large-scale metrology applications. The authors compared the performance of their algorithm against a number of existing registration solutions using four pre-defined quantitative criteria (used by [200]), including rotation error, translation error, Root Mean Squared Error (RMSE), and success rate (i.e. the number of point correspondences that satisfy a defined threshold over the number of points belonging to the overlapping area, expressed in percentage). Applied to simulated and real test cases, their algorithm showed its high potential in handling outliers and featureless point clouds when compared to other existing methods. The RMSE, as well as the Mean Squared Error (MSE) and the Mean absolute error (MAE), is a common evaluation indicator in point cloud registration. Mei et al. [201] proposed a novel point cloud registration network based on deep learning. Based on a performance analysis using the aforementioned indicators, their proposed method showed higher registration accuracy and stronger robustness to noise compared with several mainstream algorithms.

3.5.2 Indicators as means for comparisons and process optimisation

Performance indicators can potentially serve as tools for quantitative comparison of test parts, measurement conditions and instruments in large measurement campaigns [202]. For example, Zuquete-Guarato et al. [203] presented a comparison between three optical measuring instruments based on noise, trueness, measured area and surface accessibility indicators. The trueness indicator was based on the measurement of a linear distance set as reference (i.e. the distance between two parallel planes fit to a calibrated step height). The accessibility indicator quantified a measurement system's ability to access critical areas, while the measured area indicator computed the regions where the data was missing.

By comparing collected data to available a priori information (for example, the underlying CAD model from a measured object), an intelligent system can analyse the dispersion of the measurements on a point by point basis, as well as return feedback in real-time regarding any extra required scan views, locating occlusions or areas needing more data to satisfy sampling density criteria [85]. In tandem with machine learning algorithms, quantitative indicators related to point clouds have also been used in the context of pose estimation: Karaszewski et al. [204] compared the results obtained for thirteen next best view planning algorithms based on four criteria: the number of directional measurements, digitisation time, total positioning distance and surface coverage, the latter specifically computed on the point cloud.

4. Summary and future work

In this review, we have covered the state of the art in smart optical metrology, as applied in the context of digital manufacturing. A large variety of smart measurement solutions developed over the past decades have been illustrated, including knowledge-driven algorithms built on a priori knowledge of technologies and processes, multi-sensor and multi-view measurement configurations, machine learning and quality feedback algorithms. Despite the latest advances in the fields of engineering, robotics and computer science, each of the topics discussed still present a significant number of challenges that we have summarised here.

Flexible and automated measurement solutions require versatility to deal with complex tasks and unexpected scenarios. For this reason, as good practice, robust action planning prior to the measurement process is required. Available a priori information aids in the successful performance of a measurement, as learning from prior knowledge improves the quality of the obtainable results. Following the IRM principle discussed in section 3.1, knowledge-driven algorithms based on a priori information represent useful tools for smart machines and allow for optimisation of both system performance and data processing methods. The development of feedback tools in the form of quality indicators presented in section 3.5 are often based on the use of a priori knowledge. More specifically, the availability of a CAD model of the part being measured or a nominally more accurate measurement that can be set as reference enable direct evaluation of the quality in measurements. CAD use allows for local mapping of measurement performance in correspondence to each surface of the measured part.

Advanced configurations, such as multi-sensor instruments for data fusion applications, produce more consistent, accurate and useful information than those provided by any individual data source, as discussed in section 3.3. Multi-view optical instruments combined with smart algorithms eliminate time-consuming methods for merging multiple and heterogeneous measurements, while maximising part coverage. As discussed in section 3.2, the integration of multi-view configurations for the inspection of fabricated workpieces (especially the inspection of large objects, complex freeform geometries and in-line measurement applications) benefits shop floor productivity. Ongoing challenges in multi-sensor data fusion include merging and processing of multiple data derived from multiscale technologies; automation in the fusion process, computational efficiency of current solutions, a lack of robust fusion methods when dealing with noisy data and a lack of data privacy and security tools that can cause data leakage. Multi-view configurations are still largely avoided in industrial quality control environments due to the complex structural relationship between the instrument components (multi-camera, multi-camera-projector, etc.), the challenging and time-consuming individual characterisation of such components, the difficulties in dynamic measurement applications and reconstruction of rapidly moving objects along the production line.

Machine learning methods allow for automated inspection planning and best-view part detection pipelines, as demonstrated by the examples reported in section 3.4.1. For example, supervised learning approaches combined with the knowledge of the part CAD model allow the determination of the best camera locations/best-view positions, based on the largest number of surface points seen. Machine learning methods can speed up time-consuming processes, such as phase unwrapping and stereo matching, allowing for more reliable and accurate optical measurement calibration and characterisation; and providing useful tools for classification of surface defects, especially in the context of in-line metrology applications. Examples have been discussed in sections 3.4.2 to 3.4.4. Remaining challenges to widespread industrial adoption include: the collection and processing of large training datasets, high computational expense during training time, unclear implications on uncertainty and developing general models which perform well on a large range of input data.

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Statements and Declarations

The authors have no competing interests to declare that are relevant to the content of this article.

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