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Optical sensor-based process monitoring in additive manufacturing

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Abstract

A significant barrier to the broad adoption of Additive Manufacturing is the lack of quality and repeatability on the manufactured part. A promising approach to overcome this limitation is process monitoring and real-time process control. This paper provides an overview of current works related to the in-situ monitoring of the properties related to material (e.g. geometry, surface, or thermal property) in AM processes using optical sensors. The research contents of these works, such as the parameter under monitoring and the types of sensors, are categorized and summarized. Based on the review, an outlook of future works is presented.

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Keywords: Additive Manufacturing; in-situ process monitoring; optical sensors; material performance; quality check

1. Introduction

Additive Manufacturing (AM) allows producing complex geometries with nearly complete design freedom in a rapid design-to-manufacture cycle and is a breakthrough in the manufacturing field [1,2]. Nevertheless, a barrier to the broad adoption of AM is the lack of quality and repeatability of the manufactured part [3]. This issue is particularly critical for high-tech sectors such as the aerospace and automotive industries, where such quality issues can lead to increased costs and delays. To achieve quality checks and improvements during the in-processing stage of AM, in-process monitoring and process control using sensors are promising approaches [3].

The in-process monitoring and process control of AM can be realized based on closed-loop information feedback systems that collect and process the information features of the printing process, such as acoustic emission, vibration, and temperature [3,4]. Online quality prediction and control can be achieved using physical or data-driven models mapping the relationships between the process features and final quality indicators.

This paper provides an overview of representative works related to the in-situ monitoring of the material-related features (e.g. geometry, surface, or thermal property) in AM processes using optical sensors. Based on the review, an outlook of future research directions is presented. Before review results are introduced, the scope of the review is defined as follows:

- The review only considers the online monitoring related to optical sensors, e.g. CCD (charge-coupled device) and CMOS (complementary metal oxide semiconductor) cameras, pyrometers, and infrared (IR) cameras. The other sensors such as acoustic or vibration sensors are excluded. Moreover, the review only focuses on material-related

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properties, which means that other signals, such as sounds, vibration, or energy demand of machines, are excluded.

- The approaches are reviewed according to the AM process categories. The criteria to categorize the literature include the monitoring parameter, type of sensor, and technological features of AM processes. For example, in powder bed fusion, the monitoring can be done before, during, or after the material scanning. This means that pre-/during/post-scan can be used to categorize the literature. However, in directed energy deposition, the material processing and feeding are performed at the same time, and hence, it is not necessary to use pre-/during/post-scan to categorize the approaches.
- The review only considers journal and conference articles with original research in English. Review papers, reports, or literature in other languages are excluded.

2. Process monitoring in PBF

Powder Bed Fusion (PBF) uses high-energy beams (e.g. laser) to scan selective areas of a powder bed to generate 3D parts. As shown in Table 1, the related works can be classified into three major categories: (i) melt pool, (ii) powder deposition, and (iii) defects on layers.

Table 1. Overview of the works for the in-process monitoring of PBF.

Parameter	Methods/Technique	Pre/during/ post scan	References
Melt pool	CCD/CMOS cameras	During	[5–10]
	IR camera	During	[11–14]
	2-Channel pyrometer	During	[15,16]
	Multi-spectral sensor	During	[17]
Powder deposition	CCD/CMOS cameras	Pre	[18–21]
	Fringe projection	Pre	[22,23]
	IR camera	Pre	[24]
Defects on layers	CCD/CMOS camera	Post	[13,19,20,25–27]
	Line scanner	Post	[28]
	Fringe projection	Post	[22,23]
	Optical coherence tomography	Post	[29]

2.1. Melt pool

Most early studies concentrate on observing and analyzing melt pool geometry, temperature, and spatter using CCD/CMOS monochrome or color cameras such as high frame rate visible light and infrared (IR) cameras. In these studies, the placement of the cameras is either coaxial or off-axis. For the works using CCD/CMOS cameras, additional pyrometers or the near-infrared (NIR) wavelength filters are combined with CCD/CMOS cameras to capture the thermal radiation [5,6]. Moreover, high-speed cameras are also applied to capture the spatter ejection and powder dynamics in the melt pool [7,8]. For monitoring the temperature within the melt pool or the heat-affected zones caused by the melt pool, IR cameras, as well as pyrometers, are more common means [11–15]. Moreover, pyrometer and multi-spectral sensor can be applied during the scanning process to estimate the final product quality levels or material porosities [16,17]. Finally, X-ray systems based on high-speed CMOS cameras can be used to evaluate the melt pool, even though they are only for academic research and not used in industrial cases yet [9,10], and optical sensors are not only used to capture optical signals, but also other types of signals, e.g. acoustic measurement using membrane fee optical microphone [30].

2.2. Powder deposition

Pre-scan imaging can be used to monitor the condition of the deposited powder prior to the beam scanning. Any anomalies in the deposited powder can be embedded in the AM part leading to damage or failure. Using image processing to analyze images collected by CCD/CMOS cameras, the issues related to the powder deposition can be monitored, e.g. issues after powder deposition caused by a worn or damaged coater or by the distortion of the part raising above the powder (super elevation) [18] or by anomalies in the recoating and powder spreading process [21]. Moreover, fringe projection systems are employed to monitor the complete powder bed and the consolidated surface before and after the scanning [22,23]. IR cameras are used to calculate the powder layer thickness and estimate local powder layer thermal properties [24]. Other promising optical sensors, such as an integrating sphere setup, are used to measure the absorption and reflection properties of the material, even though only ex-situ measurements have been performed so far [31].

2.3. Defect on layers

Post-scan imaging of the part prior to depositing the next layer of the powder can be used to assess the quality of the AM layer as the part is being built. Given the thickness of each layer, the images captured by CCD/CMOS monochrome or color cameras can be stacked to generate a 3D model of the part as it is being built, e.g. [13,27]. Moreover, other optical sensors such as line scanners, fringe projection, and optical coherence tomography are used to evaluate the part defects (e.g. distortion and porosity) during the post-scan stage [22,23,28,29]. For the signal analysis, image processing with or without machine learning are applied. In approaches related to machine learning, supervised learning for predicting defects and unsupervised learning for anomaly detections are considered. In assessing these approaches, most works only focus on the prediction of defects during the process, whereas process control is not considered.

3. Process monitoring in DED

Directed Energy Deposition (DED) is a metal AM process in which wires or powders are melted by thermal energy while being deposited. DED has the potential to manufacture both functionally graded and single metal components, as well as it allows cladding of worn pieces that could not be mended otherwise. Table 2 summarizes the current works that can be categorized into two groups: (i) in-process melt pool temperature and (ii) layer height and geometry. It is also noted that the instrument displacement in DED has more options because the part is not immersed in a powder bed like it is in PBF. Therefore, it is also specified in the category.

Table 2. Overview of the works for the in-process monitoring of DED.

Parameter	Method/ technique	Instrument placement	References
Melt pool	CCD/CMOS camera	Coaxial	[32–36]
	NIR camera	Lateral and Coaxial	[37–39]
	MWIR camera	Lateral and Coaxial	[33,39–42]
	Pyrometer	Lateral	[43–46]
Layer height and geometry	CCD/CMOS camera	Lateral and coaxial	[33,34,49,50,35,38–41,46–48]
	Laser point/line scanner	Lateral and coaxial	[35,51–56]
	Structured light scanner	Lateral	[57–60]

3.1. Melt pool

Recording the temperature of the melt pool and the fusion zone is essential during DED processes. Temperature provides valuable information which informs the choice of process parameters and ensures part quality [1]. In addition to CCD/CMOS monochrome or color cameras [32–36], most studies dealing with temperature monitoring exploit the principles of pyrometry to measure temperature. Photodiodes and digital cameras are the main of pyrometer types used in related works. Pyrometry is used to capture temperature details during powder-DED in such a way that this data can be used for closed-loop control. IR cameras can be distinguished according to the detected wavelength, such as NIR [37–39] and mid-wave infrared (MWIR) cameras [33,39–42]. Most cameras are placed either coaxially or laterally to capture images from the melt pool to adjust laser power and ensure uniform temperature distribution. One challenge of melt pool monitoring is extracting and exploiting useful information from the raw data. Even though the dedicated custom software can process thermal images, many efforts are devoted to developing tailored algorithms for image processing aimed at specific objectives.

3.2. Layer height and geometry

There is an increasing interest in dimensionally controlling the DED part while it is being manufactured since some process characteristics, such as high heat input, induced residual stresses, and irregular deposition patterns, directly affect the part geometry [61]. The appropriate in-process measuring instrument choice depends on the aimed DED control strategy. Common CCD/CMOS monochrome or color cameras are low-cost solutions (e.g. USB cameras) [33,34,49,50,61,62,35,38–41,46–48], and they provide almost immediate information to the controller. Thus, they are the preferred option to enable closed-loop control. However, they are not ideal for accurate measurements in the melt pool area. Therefore, laser point/line scanners [35,51–56,63,64] and structured light projection scanners [57–60,64] are applied to the DED head with a coaxial or lateral placement to improve accuracy. Those systems allow the acquisition of the 3D representation of the object but require pausing the DED process for data acquisition.

Moreover, it is to mention that the quality check of DED parts is still performed outside the machine (off-line test). For these approaches, computered tomography has been widely used to check the internal/external geometry and the porosity, please refer to [65]. Considering this review only focuses on in-process approaches, offline approaches are not discussed here.

4. Process monitoring in ME

Material Extrusion (ME) is mainly used for polymers and composites. The related works are shown in Table 3 and can be categorized by three groups: (i) dimensional accuracy, (ii) defects on layers or parts, and (iii) thermal properties. Moreover, the monitoring dimension is important in ME, as most approaches focus either on entire parts/walls, or on layers, or on molten filaments. Accordingly, the dimension and the corresponding instrument placement are specified in Table 3.

Table 3. Overview of the works for the in-process monitoring of ME.

Parameter	Method/ technique	Dimensions (placement)	References
Dimensional accuracy	CCD/CMOS cameras	Entire part and outer wall (off-axis and lateral)	[66,67]
		Layer cross-section (coaxial)	[68,69]
		Molten filament from the nozzle (lateral)	[70]
	2D Laser scanner	Molten filament from the nozzle (off-axis)	[71]
		Layer cross-section (coaxial)	[72]
Defects on layers or parts	CCD/CMOS cameras	Entire part and outer wall (off-axis and lateral)	[73–77]
		Layer cross-section (coaxial and off-axis)	[78–83]
		Molten filament from the nozzle (off-axis)	[84]
Thermal properties	IR camera/ pyrometer	Entire part and outer wall (off-axis and lateral)	[85–87]
		Layer cross-section (coaxial)	[84,88]
		Molten filament from the nozzle (lateral)	[89–91]

4.1. Dimensional accuracy

The dimensional accuracy is a measure that describes the deviation between the true geometry of the printed product and the desired geometry. In some works, CCD/CMOS cameras are placed at different locations to acquire the contours of an entire part, layer, or single track printed by the nozzle [66–70]. Image processing is used to extract the contour of the real components. By comparing real contours with the desired contours of the CAD (Computer-aided design) model, the dimensional errors can be measured, and the geometrical accuracies can be calculated. Moreover, to generate the virtual model of the real printed part, 3D reconstruction approaches, as well as augmented/virtual reality (AR/VR) tools, are used [66,69,70].

In addition to the CCD/CMOS cameras, laser scanners are applied to examine the geometrical accuracy of the printed filament and the layers [71,72].

4.2. Defects on layers or parts

Part defects in ME include, for instance, cracks, warping, pores, and layers that do not adhere to each other. Common approaches for monitoring these defects are based on low-cost CCD/CMOS cameras or digital microscopes to collect images of the entire components or layers [73,74,83,84,75–82]. Data processing is based on the approaches without [76,77,81,82] and with machine learning [73–75,78,79]. In machine learning-related approaches, failure detection is based on supervised learning. Moreover, it is seen that most works focusing on the failure prediction/detection do not consider process control.

4.3. Thermal properties

Temperature gradients on parts are important thermal properties in ME. In some works [84–91], IR cameras or pyrometers are used to measure the temperature gradient, and image processing is used to evaluate the thermal images. The true temperature profiles can be compared with the theoretical temperature profiles by numerical methods to assess the quality of the process. If the deviation between true and theoretical temperature profiles exceeds a threshold value, it can be said that the quality of the process is insufficient.

5. Process monitoring in other AM processes

In addition to DED, PBF, and ME, optical sensors are also applied in other AM processes. For Vat Photopolymerization (VP) using light-curable resins, IR cameras and pyrometers are used to analyze the temperature on the resin surface or the resin liquid during the light-curing [92,93]. Moreover, CCD/ CMOS cameras are used to evaluate the printed part height and the geometrical accuracy by comparing the captured geometry with the desired geometry [94,95]. For Binder Jetting (BJ) using droplet adhesion liquid to glue powders, a CMOS camera is applied to detect the part distortion during the sintering stage of the BJ-printed components [96], whereas for Material Jetting (MJ) using liquid light-curable resins, a CCD camera is used to evaluate the droplet behavior to enable in-situ process control [97]. Optical coherence tomography is also employed in MJ to detect holes on the surface of the part [98]. Multiphoton polymerization uses the nonlinear absorption of photons to produce 3D parts of sub-micron resolution [99]. The refractive index of the material changes during polymerization, allowing a CCD camera in combination with a dichroic mirror to capture the geometry and for online monitoring to take place [100]. According to the review, the majority of works focus on the DED, PBF, and ME, while there are few for the VP, BJ, and MJ. This may suggest that in the future, BJ, VP, MJ, or other innovative AM processes should receive more attention from the research community.

6. Conclusions and future directions

Based on the review, it is observed that current monitoring approaches for AM have used a variety of optical sensors to capture material-related features such as temperature and part defects. Sensor types include mono or color CCD/CMOS cameras that are widely adopted to identify part defects or geometrical accuracy; IR cameras or pyrometers are mainly applied to measure the temperature; and laser scanners or fringe projectors are employed to analyze the geometry of layers.

In-process monitoring for AM is not only about data collection but also about data processing and exploitation. Therefore, from the point of view of data understanding and usage, the following future directions are suggested. First, future works should have increased focus on using the data obtained from monitoring to optimize the process, including enabling closed-loop control. Only a limited subset of existing studies considered process control, with most only focusing on monitoring, especially for the approaches focusing on defect detection in PBF and ME. Second, the potential of machine learning for process monitoring and control should be further explored. In current approaches, machine learning is mainly applied for image processing to make predictions or anomaly detections. Other potentials of machine learning that can be studied in future works include applying reinforcement learning for process control, physics-informed neural networks to rebuild the material's temperature gradient, and deep learning-based photogrammetry to reconstruct a component's 3D structure during the build process. Third, current monitoring approaches are standalone without collaboration with the pre-processing and post-processing systems. Future work could consider bringing these systems together to build a unified digital platform that allows activities such as slicing, monitoring, control, and diagnosis to be done on a single platform. Finally, the literature search has shown that there is little work on optical monitoring of advanced AM techniques such as the printing of shape-memory materials and multi-material printing. In general, AM is anticipated to improve product performance by increasing the complexity of products' geometry and material. Consequently, the printing of complex products requires both a more thorough process performance monitoring and more precise process control. Therefore, tailored development of sensing for these AM processes would be highly beneficial for process monitoring so that the product functions enabled by advanced AM processes can be created exactly as they have been designed.

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