



Real-Time Monitoring and Control Technologies in 3D Printing

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Abstract. With the swift advancement of Industry 4.0, 3D printing is increasingly being applied across various industries, and its status is continually rising. However, many 3D printing technologies have problems of insufficient printing success rate and unstable printing quality. Enhancing the degree of automation in monitoring and controlling 3D printing is a currently widely studied topic. This paper provides a comprehensive overview of various real-time monitoring and control technologies for 3D printing, detailing technologies based on machine vision, sensors, and new-type 3D printing monitoring methods. This paper also introduces the closed-loop control technology after monitoring. Although various methods have achieved remarkable results in defect identification, state perception, and adaptive control, they still face many challenges, such as long data processing delay, weak system generalization ability, insufficient monitoring accuracy, and poor model interpretability. In the last part, this paper discusses the future research trends of 3D printing real-time monitoring and control, including cross-modal fusion, low-cost and high-precision sensing, and AI-driven intelligent feedback mechanisms. This paper serves as a reference framework for developing a highly reliable and intelligent 3D printing system.

Keywords: 3D printing monitoring, Real-time control, Defect detection, Closed-loop system.

1 Introduction

3D printing is a cutting-edge additive manufacturing (AM) technology. From the type of printing process, it can be classified as Stereolithography Appearance (SLA), Fused Deposition Modeling (FDM), Powder Bed Fusion (PBF), Digital Light Processing (DLP), etc [1]. Moreover, the quantity and diversity of materials employed in 3D printing are progressively expanding, including PLA, metals, and ceramics, etc [1]. 3D printing technology does not require traditional molds. It can produce three-dimensional components with complex and irregular shapes using computer design models. 3D printing has unique advantages such as shortening the time to market for products, rapidly producing highly complex and high-performance products, and mass customization. 3D printing has been applied in many industries such as automobiles, aerospace, and medicine [2]. The manufacturing accuracy and quality requirements of 3D printing

are increasing rapidly to meet the more diverse requirements of printed components. However, the complexity of the 3D printing process is prone to causing product quality problems. For instance, when printing metals using FDM technology, defects such as internal pores, surface cracking, and structural deformation are caused by thermal expansion and contraction of the material[3]. During the 3D printing process of Carbon Fiber-reinforced Polymer (CFRPC), improper flow rate of the base material may lead to problems such as printing path deviation, fiber breakage, and matrix rupture[4]. These problems reduce the performance of the printed components. Therefore, 3D printing requires monitoring technology to improve the quality and efficiency of products. Traditional quality monitoring methods, such as manual inspection and ultrasonic monitoring of internal defects in products, are usually carried out after the printing process is completed. If problems exist, it will directly lead to the scrapping of the product, increasing unnecessary material and time costs. Therefore, it is imperative to implement defect detection and correction mechanisms during both the preliminary printing stages and the real-time printing process. Notably, monitoring and control technologies have emerged as a critical focus area in contemporary additive manufacturing (AM) research.

This paper aims to provide a comprehensive review of (a) predominant real-time monitoring technologies and (b) closed-loop control systems in 3D printing. It critically examines current research challenges and methodological limitations, culminating in forward-looking perspectives and strategic recommendations for advancing in-situ process regulation frameworks.

2 Classification of monitoring technologies

The core objective of 3D printing monitoring technology is to capture abnormal signals during the printing process in real time, such as geometric deviations, material defects, and temperature fluctuations. The collected data is then analyzed to provide a basis for quality control.

Existing monitoring technologies can be broadly categorized into three groups based on data acquisition modalities and operational principles: (a) In-situ computer vision-assisted anomaly identification, (b) sensor data-driven monitoring approaches, and (c) new type monitoring paradigms, including digital twin-enabled monitoring and self-sensing material-integrated systems [5, 6].

2.1 In-situ computer vision-assisted anomaly identification

In-situ computer vision-assisted anomaly identification has become the mainstream method in 3D printing monitoring due to its non-contact and high-resolution characteristics. The core methodology involves capturing visual data of the printing process through imaging devices (e.g., cameras, laser scanners), integrating image processing algorithms with deep learning models to achieve defect detection and localization[7].

The realization of high-quality image acquisition fundamentally relies on the critical hardware configuration of the imaging system. The system typically integrates camera

units (e.g., high-speed cameras and industrial-grade CCD/CMOS cameras), lens assemblies (including fixed-focal, variable-focal, and telecentric lenses), and specialized illumination systems. These illumination components encompass ring lights for surface defect inspection, infrared sources for applications such as molten pool monitoring in metal additive manufacturing, and thermal imaging, as well as laser projection systems dedicated to contour detection and volumetric analysis. Through the coordinated operation of these devices, the imaging system captures comprehensive visual data of printed components. Key operational parameters, including image resolution, frame rate, and field of view, require systematic optimization based on the specific characteristics of the printing platform to ensure compatibility with the target inspection requirements.

Following image acquisition, subsequent image processing algorithms serve to transform raw data into actionable intelligence for defect identification and decision-making. Conventional workflows typically involve preprocessing operations (e.g., noise reduction, contrast enhancement), feature extraction, and classification modules. Recent advancements have integrated deep learning architectures such as convolutional neural networks (CNN) and modified U-Net variants, significantly enhancing defect detection accuracy and operational robustness. Notably, the research team led by Yuanbin Wang developed a CNN-based framework enabling efficient and high-precision defect identification and categorization for FDM-printed components[2], while Wang Fang et al. proposed a dual-neural network approach for pre-printing material defect detection in DLP printing processes, which has been successfully deployed in industrial production lines [8]. Furthermore, state-of-the-art machine vision systems now incorporate closed-loop control mechanisms capable of real-time printing suspension, dynamic parameter adjustment, and automated alert generation, thereby establishing intelligent feedback loops within additive manufacturing workflows.

2.2 Sensor data-driven monitoring approaches

Data sources for identifying 3D printing process anomalies can be categorized into two primary modalities: imaging data and sensor-derived measurements. Sensor-based monitoring technologies provide foundational support for anomaly detection and control feedback through real-time quantification of critical physical parameters during printing operations. Commonly deployed sensors include accelerometers, thermal cameras, thermocouples, ultrasonic transducers, and current/pressure sensors [9].

In practical implementations, different sensor configurations exhibit distinct advantages and limitations depending on specific printing methodologies and defect typologies. Notably, fused filament fabrication (FFF) processes achieve a success rate of approximately 80%, significantly lower than other additive manufacturing techniques, with nozzle clogging accounting for a substantial proportion of failures [10]. Alexander Isyanov et al. [10] demonstrated a diagnostic approach by integrating three accelerometers into FFF printers, where Fast Fourier Transform (FFT) analysis of acquired vibration signatures enabled real-time detection of nozzle obstruction. Empirical results revealed that sensor proximity to the nozzle crucially impacts signal fidelity, with closer-positioned sensors generating more stable and interpretable datasets.

In selective laser melting (SLM) processes, thermal stresses emerge as the primary governing factor responsible for quality anomalies including part deformation, porosity, and crack formation. Notably, Benjamin Urich et al. [11] developed a predictive framework combining thermal imaging camera data with physics-informed neural networks (PINN), enabling in-situ detection of thermally induced defects. This innovative methodology synergistically integrates real-time thermal gradient measurements with constitutive material models, demonstrating 92% prediction accuracy in identifying stress concentrations that precede macroscopic failure. The system's capability to correlate transient thermal histories with defect nucleation mechanisms provides critical insights for closed-loop thermal management in high-precision metal additive manufacturing.

2.3 New type monitoring

Exclusive reliance on machine vision, infrared sensors, or acoustic monitoring systems results in monochromatic data streams, inherently compromising comprehensive defect prediction capabilities essential for industrial-scale production. No singular sensing modality can holistically monitor product quality or preemptively mitigate defects across the entire manufacturing lifecycle. To address this critical limitation, multimodal sensor fusion architectures have emerged as a transformative solution. A representative advancement is the deep learning framework developed by Vigneashwara Pandiyan's research consortium [12], which synergistically integrates four distinct sensing channels: back-reflection (BR), visible light, infrared (IR), and structural acoustic emission (AE). Post-training validation demonstrated exceptional operational performance in laser powder bed fusion (LPBF) applications, achieving 98% prediction accuracy for real-time process state monitoring with a latency of 0.5–4 milliseconds, thereby enabling sub-layer defect intervention during metal additive manufacturing cycles.

Building upon multisensor fusion architectures, technological advancements have catalyzed the emergence of virtual-physical integrated modeling paradigms, notably embodied in digital twin technology. This approach constructs high-fidelity digital replicas of physical manufacturing systems to enable real-time detection, simulation, prognostics, and process optimization. A pioneering implementation by Lequn Chen et al. [13] developed a multisensor-fused digital twin (MFDT) framework for quality prediction in laser-directed energy deposition (LDED) processes. By integrating heterogeneous data streams from optical cameras, acoustic microphones, and thermal imagers, the MFDT system achieved 96% prediction accuracy with a 4.4% false alarm rate through deep learning (DL)-based multimodal feature fusion, surpassing conventional single-sensor monitoring approaches in both precision and operational reliability. This breakthrough demonstrates the MFDT's exceptional capability as a robust in-process quality assurance solution for energy beam-based additive manufacturing technologies.

Beyond external multisensory monitoring approaches, recent research has extended to intrinsic self-sensing capabilities within advanced materials. Continuous carbon fiber-reinforced polymer composites (CCFRPCs) demonstrate inherent piezoresistive properties enabling autonomous structural health monitoring without auxiliary sensors. Anand Sankar M et al. [14] engineered a resistive network by embedding carbon fibers

within a PLA matrix, where mechanical deformations (e.g., tensile strain) induce measurable resistivity variations, thereby achieving real-time damage detection. This embedded monitoring paradigm eliminates the need for external sensor integration, significantly reducing system complexity and operational costs. Experimental validation demonstrates over 90% accuracy in fracture event identification under cyclic loading conditions [6], establishing CCFRPCs as a transformative solution for in-situ integrity assessment in smart composite manufacturing.

3 Closed-loop control systems

In 3D printing systems, offline or online analysis of monitoring results provides critical insights into product quality and defect characteristics. However, the true industrial value lies in leveraging this information to dynamically optimize printing processes through closed-loop control mechanisms, thereby enhancing both production efficiency and output reliability. Establishing robust real-time control architectures capable of adaptive parameter adjustment and rapid anomaly response is, therefore, paramount to achieving intelligent manufacturing objectives.

The essence of closed-loop control resides in real-time calibration of key process parameters (e.g., scan velocity, laser power, material feed rate) based on multisensory feedback. Widely adopted control strategies encompass PID algorithms, adaptive control systems, and fuzzy logic controllers. A representative implementation by Lu et al. [14] demonstrated the efficacy of YOLOv4-based real-time defect detection integrated with closed-loop parameter correction during carbon fiber-reinforced polymer (CFRP) additive manufacturing. This system autonomously identified defective patterns within the initial two printed layers, diagnosed erroneous process parameters, and implemented corrective actions that eliminated over 85% of defects in subsequent layers, significantly improving dimensional accuracy while reducing material waste and post-processing costs.

The rapid evolution of artificial intelligence (AI) has further revolutionized closed-loop control paradigms. Contemporary AI-driven feedback systems employ deep reinforcement learning and predictive analytics to continuously monitor printing dynamics, detect deviations from target parameters (e.g., extrusion temperature, deposition speed), and execute preemptive adjustments with second latency [15]. Such intelligent control frameworks not only minimize defect propagation but also enable energy-efficient operations.

4 Challenges

Despite significant advancements in 3D printing monitoring and control technologies, persistent challenges hinder their widespread industrial implementation, primarily manifested in insufficient detection accuracy, control latency, limited system generalizability, and prohibitive operational costs.

4.1 Defect identification & in-process monitoring challenges

The inherent complexity of defect typologies and morphological variability during printing processes poses fundamental limitations. In fused deposition modeling (FDM) and comparable technologies, dynamic surface quality variations induce unstable diagnostic signatures [2, 9]. Furthermore, the scarcity of defect samples in production environments exacerbates data imbalance issues, compromising detection accuracy [8]. While high-resolution imaging and multisensory data fusion enhance diagnostic capabilities, they concurrently escalate computational loads, degrading real-time performance [4, 12]. Sensor deployment is further constrained by spatial limitations and process-induced interference, rendering optimal positioning and calibration critical yet unresolved challenges [10, 12].

4.2 Closed-loop control system limitations

Current implementations predominantly operate in "monitor-dominant, control-secondary" modes, lacking robust autonomous adjustment mechanisms [4, 15, 16]. Control strategies exhibit excessive dependence on material-specific properties, path-planning algorithms, or equipment configurations, severely limiting cross-platform adaptability [13, 16]. Sensor-to-actuator latency—encompassing data processing, decision-making, and mechanical response—further impedes real-time control precision, particularly in high-speed printing scenarios [15].

4.3 AI & Digital twin implementation barriers

While AI-enhanced systems and digital twins demonstrate theoretical promise, their industrial adoption faces multifaceted obstacles. Deep learning models require extensive domain-specific training data, exhibiting poor adaptability to equipment heterogeneity, material variations, and environmental fluctuations [5][13][15]. Multimodal data fusion (e.g., thermal, mechanical, and optical signals) necessitates precise temporal synchronization and feature alignment, demanding substantial computational resources and customized development for reliable digital twin construction.

4.4 Material-process interaction complexities

Emerging challenges arise from advanced material systems, exemplified by continuous fiber-reinforced composites prone to voids, delamination, and interfacial debonding—defects governed by intricate multiscale mechanisms with limited controllability [4][6][15]. The pronounced parameter disparities across materials and equipment platforms further obstruct the standardization and transferability of monitoring-control frameworks.

5 Conclusion

The integration of real-time monitoring and control technologies into 3D printing production has not only significantly improved the quality and stability of the printing process but also facilitated the precise realization of personalized manufacturing and complex structures. Through machine vision, sensor technology, and digital twins, operators can track various anomalies in real time during printing, enabling early defect prediction and remediation, thereby greatly optimizing production efficiency and material utilization.

However, despite notable academic progress, industrial applications still face numerous challenges. For example, efficiently processing large-scale real-time data, achieving precise fusion of multi-source data, and enhancing the system's real-time responsiveness require further research. Additionally, while various monitoring technologies have distinct advantages, ensuring their stability and accuracy in extreme printing environments remains a critical focus for technological breakthroughs.

Future advancements in real-time monitoring and control for 3D printing will trend toward higher intelligence and stronger system integration. Continuous progress in artificial intelligence, particularly deep learning, will further improve the precision and reliability of monitoring technologies. The integration of multimodal sensors and digital twin technology will enable more intelligent process control, allowing dynamic adjustments based on real-time feedback data during printing. Concurrently, advancements in edge computing will enhance local rapid decision-making for real-time data processing and feedback, improving overall system response speed and accuracy.

Furthermore, as 3D printing applications expand, achieving universal monitoring and control across different printing processes and materials has become key to enhancing technological generality and reducing costs. Future development of lightweight, cost-effective, and highly adaptable monitoring and control systems will enable the widespread adoption of 3D printing in diverse industrial applications. In summary, real-time monitoring and intelligent control for 3D printing are advancing rapidly. In the coming years, with technological innovation and interdisciplinary collaboration, 3D printing will play an increasingly vital role in smart manufacturing and personalized production.

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