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Research on Biomimetic Additive Manufacturing Technology Based on Digital Twin

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Abstract

Biomimetic additive manufacturing (Biomimetic 3D printing) is an emerging technology based on the principle of biological growth and forming to design the biological-like complex structure and biomimetic function of three-dimensional solid structure, and the use of 3D printing technology to realize the processing and manufacturing of components. Digital twin enables the full-cycle optimization and enhancement of biomimetic additive manufacturing by establishing an accurate and dynamic linkage between the physical process and its virtual counterpart. It analyzes the characteristics and problems of existing additive manufacturing technology; Combined with the existing research progress, based on the physical model and data driven perspective, the development status and existing problems of digital twin theory in additive manufacturing process are introduced. The concept and development status of biomimetic additive manufacturing were discussed. The technical framework and challenges of biomimetic additive manufacturing technology driven by digital twin system are put forward to provide reference for the development and application of biomimetic additive manufacturing technology.

Keywords

Additive Manufacturing, Biomimetic Additive Manufacturing, Physical Model, Data-Driven, Digital Twin

1. Introduction

Additive manufacturing (AM), also known as 3D printing technology, has grown rapidly in the past 30 years [1]. It is now regarded as a highly strategic and transformative direction in advanced manufacturing. Unlike the traditional processing technology dominated by equal and reduced materials manufacturing, 3D printing technology employs a bottom-up fabrication strategy. It deposits materials layer by layer to build components from the ground up. Because it is free from the constraints of traditional manufacturing methods, 3D printing technology makes manufacture complex structural parts possible, and has been applied in aerospace, biomedicine, automobile industry, art design, etc. And national defense and other fields have broad engineering application prospects [2]. As one of the most important branches of additive manufacturing technology, metal additive manufacturing is a new technology used to manufacture high-performance metal components. Based on digital model file model, metal additive manufacturing uses dedicated software and numerical control system to melt and stack raw materials such as special metal powder/wire by laser and other energy sources. Currently, the main metal additive manufacturing technologies include: Selective Laser Melting (SLM), Selective Electron Beam Melting (SEBM), Laser Engineering Net Shaping (LENS), Electron Beam Free Form Fabrication (EBF), Wire Arc Additive Manufacturing (WAAM), and Ultrasonic Additive Manufacturing (UAM), etc. The corresponding technical characteristics are listed in **Table 1**. For a long time, there have been three problems restricting the rapid development of the additive manufacturing field: first, how to minimize the production cycle and cost of product design, second, how to optimize the quality of product design, and third, how to maximize the production efficiency in the manufacturing process. Additive manufacturing process has the natural property of "digital". From differential additive product design to integral material accumulation molding, from quantitative manufacturing parameter selection to digital process path planning, data and algorithms generated in additive manufacturing process are the core digital assets, such as online accumulation of additive process data package, additive industrial control algorithm based on path optimization, etc. Consequently, digital-driven additive manufacturing method has gradually become a new manufacturing mode universally recognized and applied. Among them, GE and Siemens put forward the concept of digital twin (DT). It is to integrate the technical means of digital manufacturing and intelligent manufacturing, realize the seamless connection between the virtual digital world and the real world, and form a dynamic optimization process of information interaction and data fusion concerning manufacturing decision-making, execution and control. Recent systematizations highlight integration architectures, data orchestration, and real-time constraints for DT-enabled AM [3].

At present, the principal challenges hindering the development of metal additive manufacturing technology can be summarized into the following categories [4]: 1) insufficient fabrication accuracy that fails to meet high-precision design requirements, 2) pronounced anisotropy inherent to layer-by-layer deposition, and 3) unstable mechanical performance of fabricated components. In addition, there are still great challenges in *in-situ* real-time observation of temperature field, liquid flow state, micro-structure evolution and mechanical property

Table 1. Technical characteristics of metal additive manufacturing.

Type	Thermal Source	Advantages	Disadvantages
Selective Laser Melting (SLM)	Laser	The forming parts have fine grain, uniform structure and are suitable for processing various complex shapes of work pieces, and their mechanical properties are almost close to the level of forgings	Spheroidization in the forming process and thermal stress have great influence on forming precision
Selective Electron Beam Melting (SEBM)	Electron Beam	With the characteristics of high efficiency and low thermal stress, it is suitable for the molding and manufacturing of high performance metal materials such as titanium alloy and titanium aluminum base alloy	Vacuum is needed for a long time before molding, and the printing environment requires high requirements. Due to the electron beam cannot be gathered to very fine, the molding accuracy needs to be improved.
Laser Engineering Net Shaping (LENS)	Laser	It can realize the forming of multi-metal and heterogeneous materials, especially in large parts and parts with multi-metal materials	The precision of forming is low, only some simple parts can be formed, and it is difficult to form parts with cantilever structure
Electron Beam Free Form Fabrication (EBF)	Electron Beam	Fast forming speed, good mechanical properties, can print large non-standard parts	The large work piece surface tolerance, the special equipment and vacuum system required are more expensive
Wire Arc Additive Manufacturing (WAAM)	Arc	High forming efficiency, low equipment cost, flexible manufacturing form, good performance of the formed parts	In the process of welding, the weld shape and the transition mode of droplet are not easy to control, and the forming process is easily affected by other factors, which leads to the accumulation of defects
Ultrasonic Additive Manufacturing (UAM)	ultrasound	High deposition rate with material utilization, low Residual stress	Because the frequency of the ultrasonic generator is generally 20 kHz, it is easy to make the work piece resonant, so that the welding quality is reduced, and the support structure cannot be automatically placed or removed, and the manufacturing progress is limited by the numerical control accuracy

changes in metal additive manufacturing. Quantitative information such as warping and distortion of parts and coarse columnar grains, holes, keyholes and cracks in micro-structure during metal additive manufacturing cannot be fully revealed by simple experimental means, and it will also consume a lot of time. These significantly increase the design cost of products. Consequently, digital manufacturing technologies are expected to provide essential theoretical and technical support for addressing these limitations. Focusing on the above problems, this paper firstly introduces the current applications and development status of digital twin technology in the field of additive manufacturing, discusses the digital twin additive manufacturing technology based on physical model and the digital twin additive manufacturing technology based on data driven. Building on these analyses, the paper proposes a research idea of biomimetic additive manufacturing based on digital twin and concludes with a forward-looking discussion on future developments in this emerging field.

2. Additive Manufacturing Technology Based on Digital Twin

Digital twin technology is an emerging technologies that integrates artificial intelligence, machine learning, the Internet of Things, and cloud computing to support product design and development. The proposal of digital twin technology in the field of manufacturing can be traced back to NASA's Apollo program in 1969 [5]. In 2003, Grieves first introduced the digital twin concept, describing it as a system composed of a physical entity, a virtual counterpart, and the bidirectional connections between them, though without providing its specific definition [6]. In 2013, the US Air Force Department proposed the concept of digital thread based on modeling and simulation tools [7] and described it as follows: Digital twin is to make full use of physical model, sensor update, operation history and other data, integrate multi-disciplinary, multi-physical field, multi-scale, multi-probability simulation process, complete mapping in virtual space, so as to reflect the whole life cycle process of physical equipment. Digital Thread, as a standardized and integrated data framework, constitutes the essential prerequisite and enabling foundation for building credible and sustainable digital twins. Until 2015, digital twin technology was rapidly developed by large commercial companies such as GE, Siemens and Dassault, and its concept was widely accepted [8]. Since then, various related studies based on digital twin technology have been gradually carried out, and more and more manufacturing enterprises are beginning to pay attention to and incorporate digital twin technology into the whole manufacturing cycle. Nevertheless, due to the relatively late start, the integration of digital twin technology into the field of additive manufacturing for cross research remains in an early developmental stage [9]. Research paper publications over the past five years are shown in **Figure 1**.

2.1. Digital Twin Additive Manufacturing Technology Based on Physical Model

Digital twin technology based on physical model can completely associate the physical model with the digital model, incorporating all relevant physical information into computational analysis. As the physical model is updated or modified, the corresponding digital model autonomously captures these changes, thereby facilitating real-time analysis, feedback, and predictive assessment of the physical system [10].

In 2017, Knapp *et al.* [11] of Pennsylvania State University constructed a twin model of 3D geometric structure for the deposits in the process of laser directed deposition additive manufacturing. Based on this model, they predicted key metallurgical and mechanical parameters of the product, including cooling rate, temperature gradient, curing rate, secondary dendrite spacing and Vickers hardness. As the **Figure 2** show, inspired by the same, Yi *et al.*, Technical University of

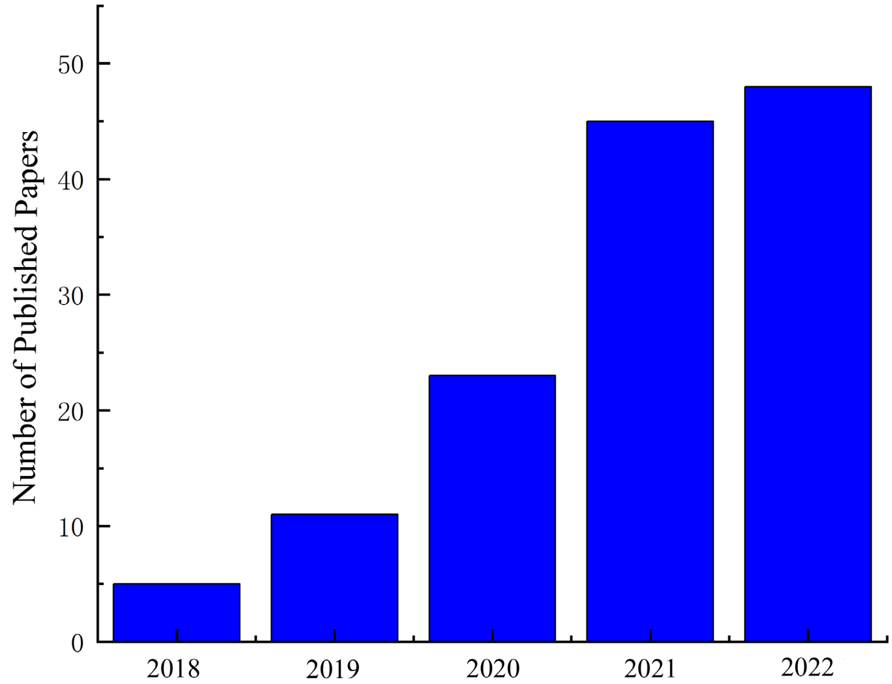

Figure 1. Web of Science statistics of publication status of research papers on additive manufacturing technology based on digital twins.

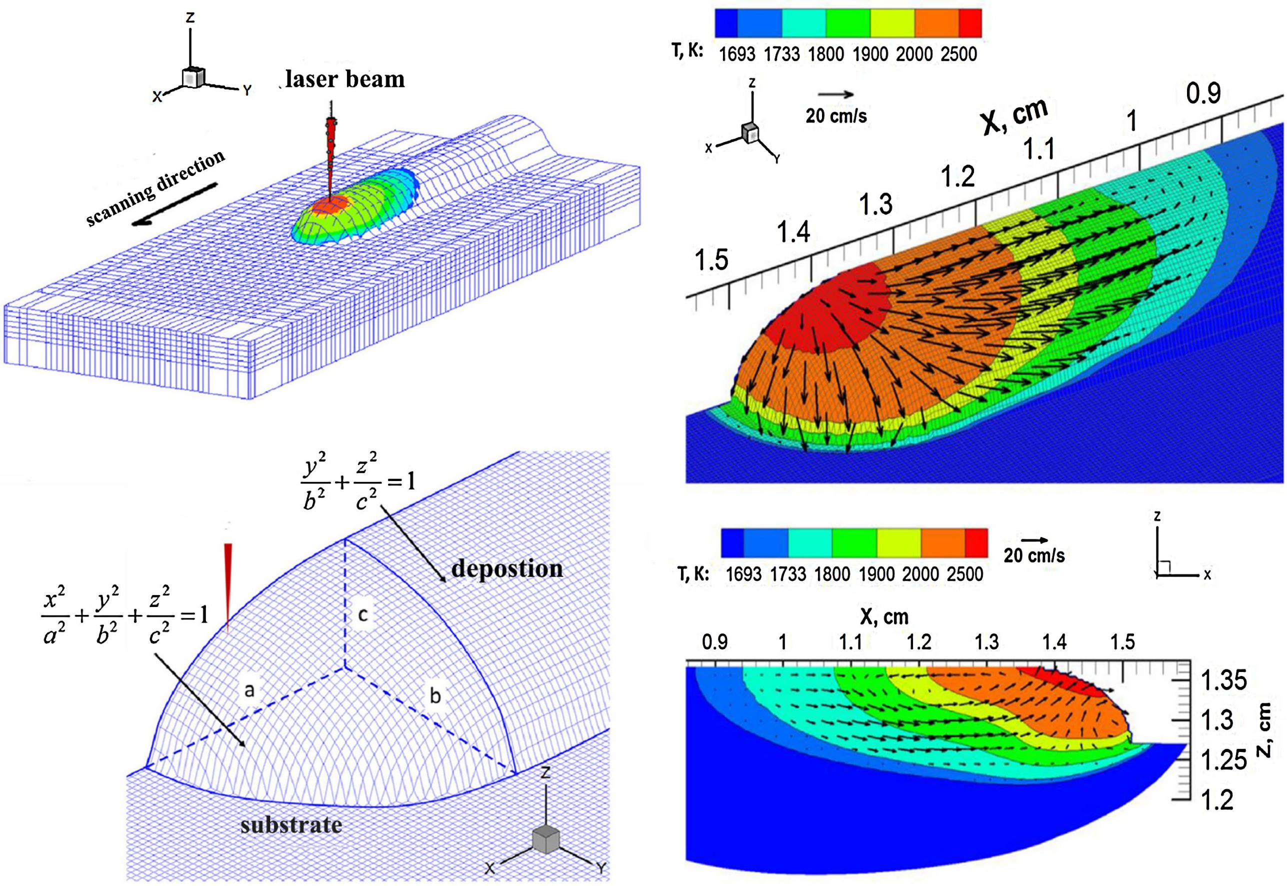

Figure 2. Metal additive manufacturing molten pool prediction based on digital twin [11].

Kaiserslaatten, Germany, used machine learning and augmented reality technology to establish a digital twin model of extrusion 3D printer. They replaced the geometric structure of parts with the accumulated small cylinder (**Figure 3**), and constructed augmented reality technology based on digital twin by using four process indicators such as power consumption and manufacturing cost [12].

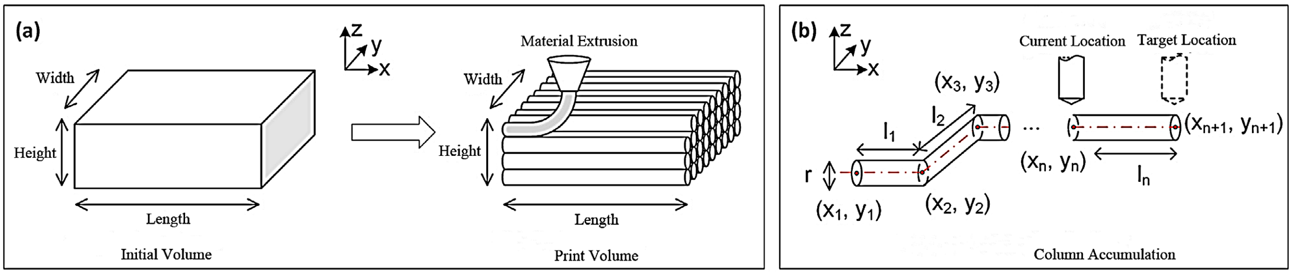

Figure 3. Parametric model of the printing process [12]. (a) Print the approximate model of the part; (b) The cylinder accumulation process.

Yavari *et al.* from the University of Nebraska in the United States, based on the temperature field model in the melting process of laser powder bed, arranged coaxial sensors on the laser printing equipment to obtain the actual temperature of the melting pool, and combined with the graph theory method to modify, finally established a digital twin model on the mechanism of additive manufacturing, so as to realize the rapid prediction of the internal temperature change of printed products. And in situ defect prediction is realized [13].

Lu *et al.*, Georgia Institute of Technology, USA, used stress sensing to detect temperature changes in additive manufacturing process and established a digital twin model (as shown in **Figure 4**). Then the temperature model corresponding to printed products could be updated in real time on the premise of reducing the actual number of measurements [14].

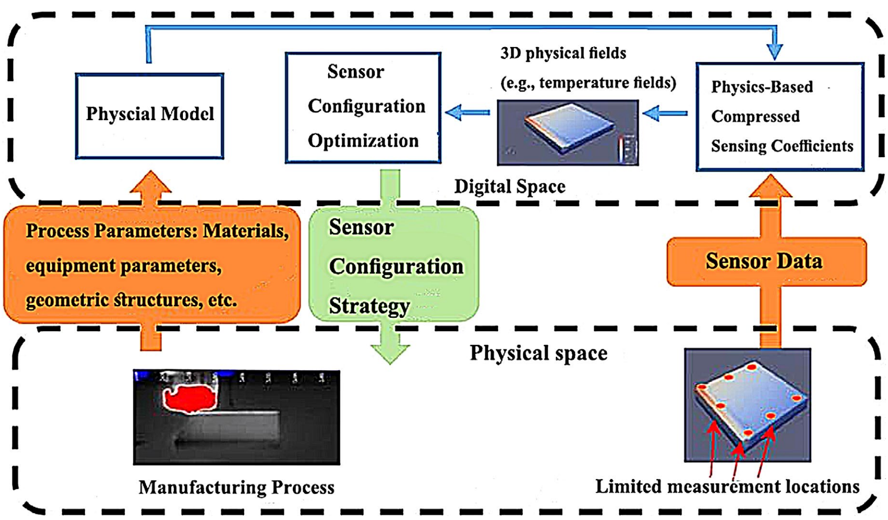

Figure 4. Digital twin additive manufacturing technology framework based on physical compressed sensing technology [14].

Nath *et al.* [15] of Vanderbilt University took into account the uncertainty of the model and the variability of process parameters, and adopted the alternative model of two stages to construct the digital twin model of the whole manufacturing process. The effectiveness of the whole twin model was verified by using the collected data in the physical space manufacturing process, and the digital model was used to optimize the process parameters, as shown in Figure 5.

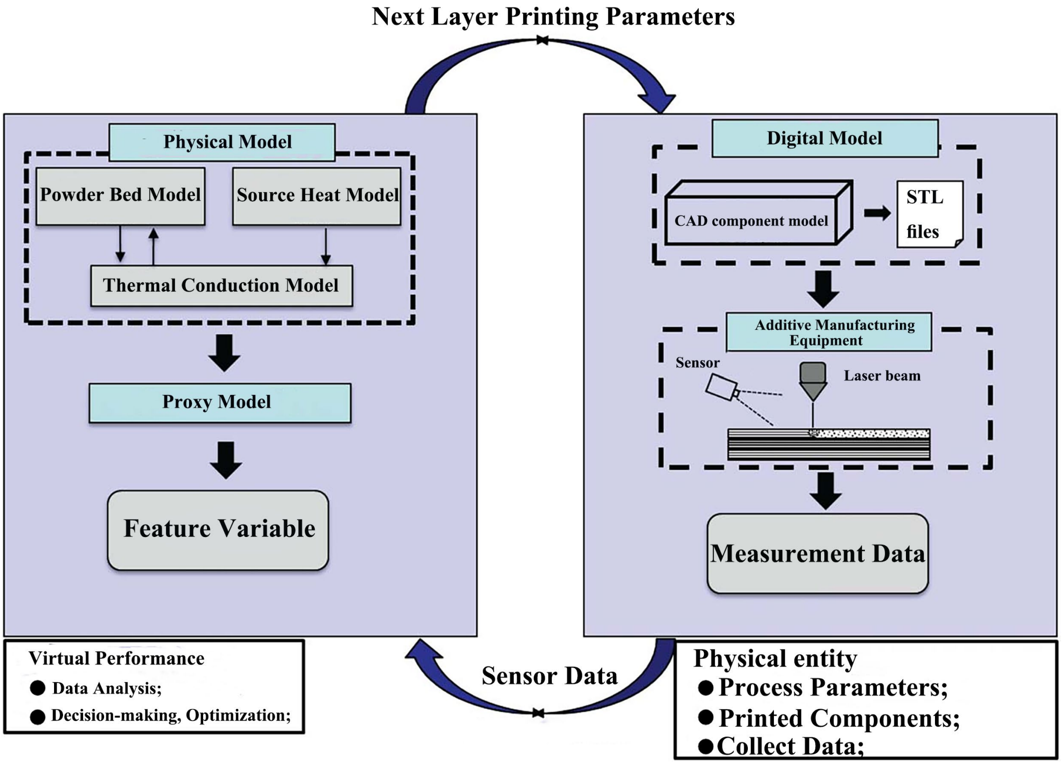

Figure 5. Block diagram of laser powder bed melting process based on digital twin [15].

2.2. Data-Driven Digital Twin Additive Manufacturing Technology

Data-driven digital twin technology operates by organizing, analyzing, and mining large volumes of data, subsequently abstracting the underlying physical-entity problems into graph-based representations to construct solvable reduced-order models. Common methodological approaches include neural networks, machine learning algorithms, and response surface methodologies, etc.

In 2019, Mandolla *et al.* [16] from the Polytechnic University of Bari, Italy, used blockchain technology to build a digital twin model of the additive manufacturing process, which uses distributed node consensus algorithms to generate and update data models aimed at identifying and monitoring the entire manufacturing cycle of parts.

In 2021, Gunasegaram *et al.* [17] from the Australian Organization of Science and Industry established a digital twin model by constructing a reduced order model. Aiming at the uncertain factors existing in the additive manufacturing process, the data model was trained by machine learning method to replicate the metal additive manufacturing process in the physical space in the virtual space, as shown in Figure 6. Similarly, liu *et al.* [18] from Cardiff University proposed a collaborative data management framework based on digital twin, which adopted the method of cloud digital twin technology and edge digital twin technology to realize intelligent detection, control and optimization. The data model in the process of metal additive manufacturing was divided into the following in detailClass (Figure 7): 1) Design parameters; 2) Processing parameters; 3) Process characteristic

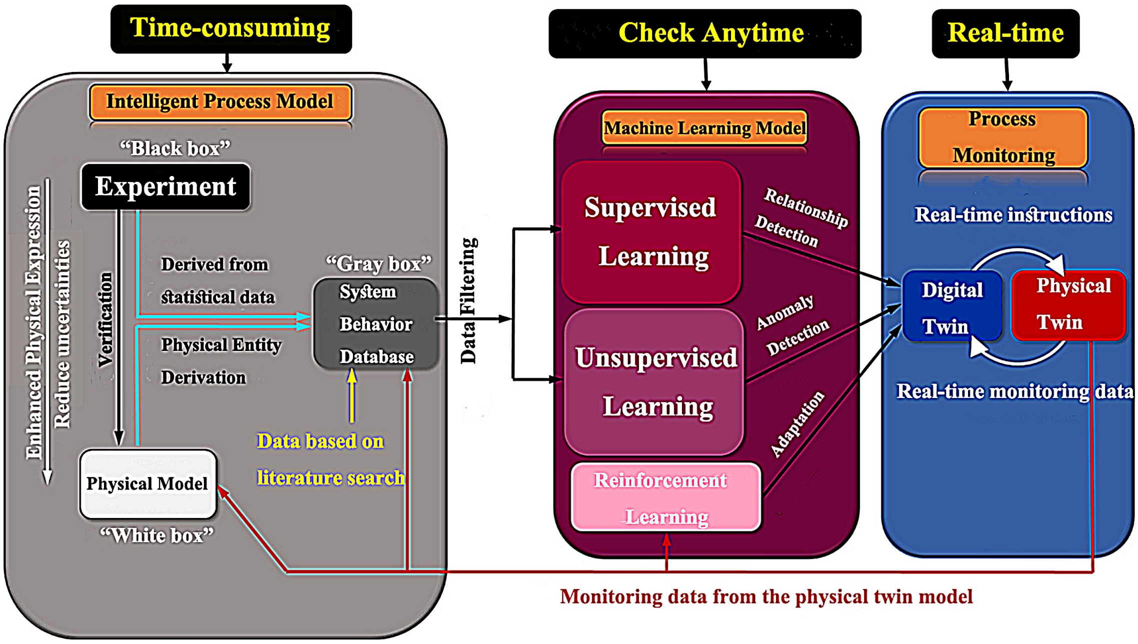

Figure 6. Simple process flow of technological process system based on digital twin [16].

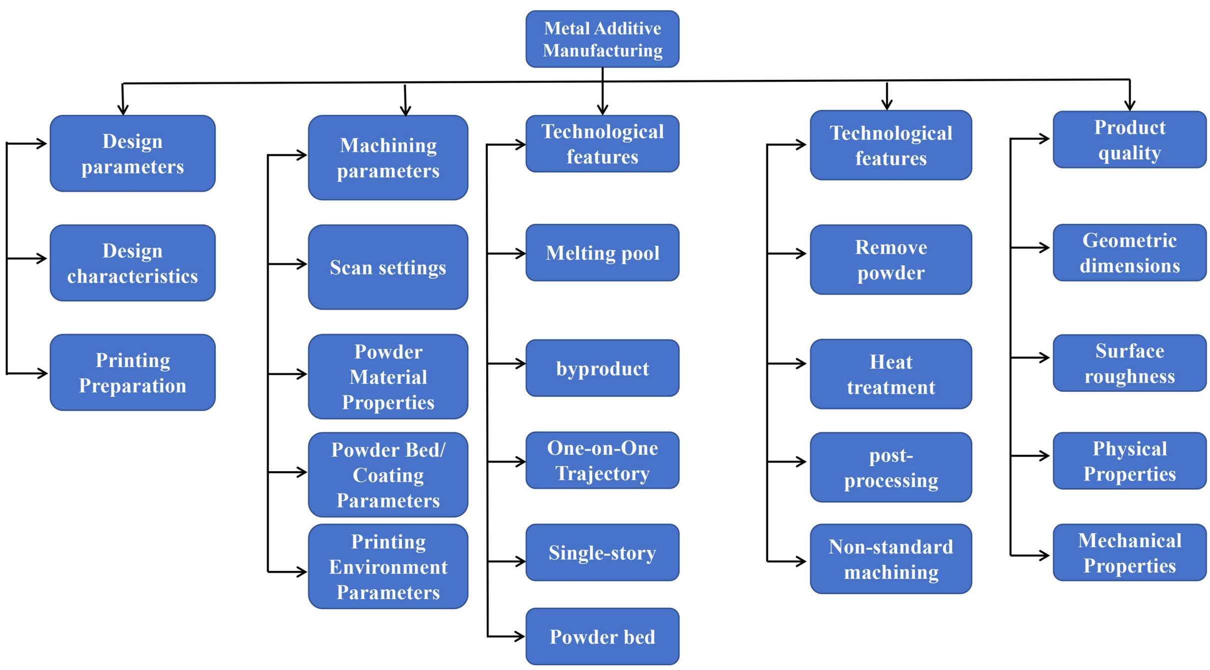

Figure 7. Metal additive manufacturing data model structure [18].

parameters; 4) Post-processing parameters; 5) Product quality parameters.

Klingaa *et al.* [19] of the Technical University of Denmark explored the influence of the flowing gas inside the 3D printing chamber on the product quality. They used the response surface method to construct a twin model, and compared the product quality (surface roughness, void, channel diameter, etc.) with the printing chamber. The internal gas flow rate, pressure, and oxygen content establish a response relationship. Studies have shown that the oxygen content has a greater impact on the printing quality of the product during the manufacturing process.

3. Biomimetic Additive Manufacturing Technology

Biomimetic additive manufacturing is the process of constructing additive manufacturing technology based on the principle of biological growth and forming, or the process of additively manufacturing biologically complex structures and their products according to biomimetic design rules [20]. During the evolution and optimization of natural organisms for hundreds of millions of years, whether it is a complex porous structure with light weight and high strength, or a multi-dimensional laminated structure with alternating strength and toughness, it is completely accumulated point by point through the energy-saving and material-saving green "manufacturing" method grow. Organisms use a variety of building units to form multi-level and multi-dimensional structures such as gradients, topologies, and hierarchical orders, and use the most reliable, efficient, and economical methods to achieve light and strong, strong and tough, self-adaptive, and self-repairing beyond engineering materials. It is known as the main blueprint for designing and manufacturing the next generation of high-performance structural materials [21]-[23]. At present, the research on biomimetic additive manufacturing mainly focuses on biomimetic additive manufacturing technology based on structural design and process.

3.1. Biomimetic Additive Manufacturing Technology Based on Structural Design

In the process of biological evolution, unique materials and structures have been formed, and advanced performances beyond engineering materials such as light and strong, strong and tough, adaptive and self-repairing have been realized. Additive manufacturing for biomimetic structure design mainly focuses on shape simulation and performance simulation [24]. The scope of shape simulation can include the microscopic and macroscopic structures of organisms, while performance simulation is mainly reflected in the functional and mechanical properties of organisms. For example, Connors of the University of Cambridge, inspired by the structure of fish scales, additively manufactured materials from non-overlapping squares to complex scale structures with overlapping and interlocking features, which can be used for armor and other equipment with ultra-high impact resistance and protection capabilities [25]. Nicholas *et al.* [26] of the University of

California, Riverside found that the "elbow" of the mantis shrimp is composed of densely packed organic and inorganic phases in an interpenetrating bicontinuous network structure, and forms a low-angle grain boundary (1.5˚), these low-angle grain boundaries reduce the formation free energy of this inorganic network and provide excellent toughness at the interface, thus endowing the mantis shrimp with strong impact resistance. Du *et al.* [27] from Nanjing University of Aeronautics and Astronautics designed and additively manufactured a novel lattice structure by observing the microstructure of the beetle's forewing, and can achieve a high density of more than 97% under optimized process parameters. It is found through experiments that the lattice structure exhibits good elastic deformation ability, uniform plastic deformation ability and fatigue and damage resistance. Figure 8 shows the typical biomimetic structural design mentioned above and its corresponding performance attributes.

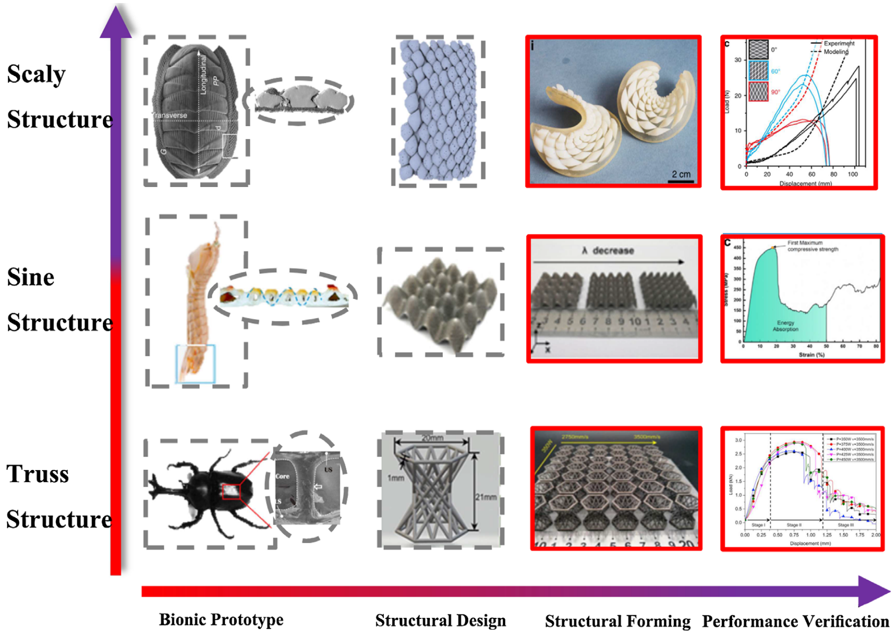

Figure 8. Biomimetic structure design [25]-[27].

3.2. Biomimetic additive Manufacturing Technology Based on Materials and Processes

The International Organization for Standardization and the American Society for Testing and Materials have listed two types of laser additive manufacturing mainly for metal materials, namely laser powder bed fusion technology based on powder diffusion, and laser directed energy deposition technology based on powder spraying. Among them, laser is used as an energy source to melt metal powder and manufacture parts layer by layer, and metal powder materials can be divided into single material, composite material and multiple materials [24].

3.2.1. Single Material

Powder materials commonly used in laser additive manufacturing technology include: nickel-based alloys, stainless steel and alloy steel [28]-[30]. The characteristic properties of metal materials can often enhance the performance of biomimetic structures in additive manufacturing. Zhang Zhihui from Jilin University *et al.* [31] based on NiTi alloy materials and used a unique orbital rotation scanning laser 3D printing method to obtain a biomimetic NiTi structure material with a tensile deformation of 15.2%, which is the largest tensile deformation of NiTi alloys reported internationally at present. Elongation (**Figure 9**). In addition, some aluminum-based alloys with high strength have been proposed by some scholars in recent years, such as Al-Mg-Sc-Zr [32], Al-Mg-Si-Sc-Zr [33], and Al-Mn-Sc [34]. However, due to the large differences in the material properties of different types of metal powders during processing, such as high aluminum-oxygen affinity, laser reflectivity and low absorption rate, poor thermal conductivity of titanium alloys, etc., these material properties will be Significantly affect the processing quality of biomimetic products, so it is necessary to reasonably and appropriately select the corresponding environmental parameters and process parameters.

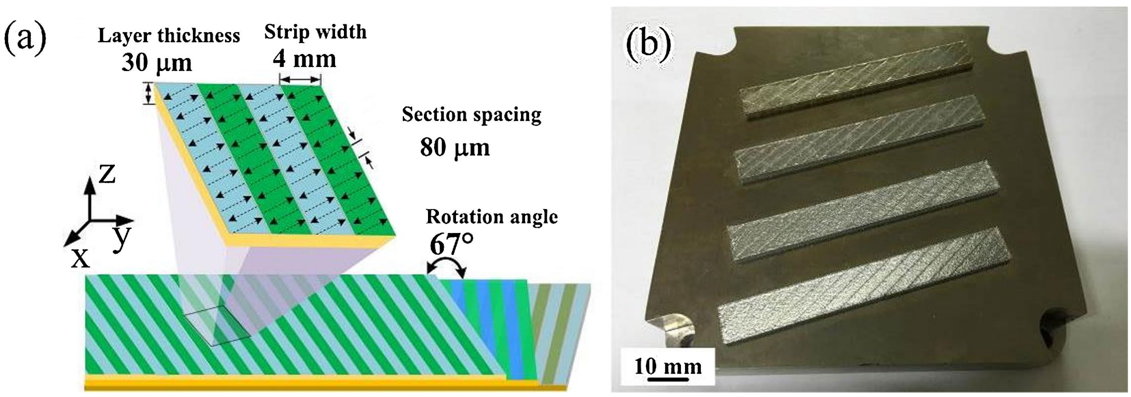

Figure 9. (a) Schematic diagram of laser scanning method [31]; (b) 3D printed nickel-based tensile sample based on selective laser melting technology [32].

3.2.2. Composite Material

Composite materials suitable for laser additive manufacturing are materials composed of two or more components with different chemical and physical properties [35], and can enable biomimetic structures with high performance and versatility. Currently, composite materials used in laser additive manufacturing technology include *in-situ* reinforced composites [36], particle-reinforced composites [37]-[40], and carbon-reinforced (including carbon nanotubes [41], graphene [42]) Composite materials, as shown in **Figure 10**. However, in laser additive manufacturing of composite materials, the metal powders are easily affected by issues such as powder agglomeration, low flowability, and uneven dispersion. These factors can lead to local voids, insufficient fusion, and cracking, which in turn severely degrade the performance of the biomimetic component. Up-to-date LPBF defect-monitoring surveys synthesize sensing routes and mitigation strategies for AMMCs, offering guidance for interface control and lack-of-fusion prevention [43]-[45].

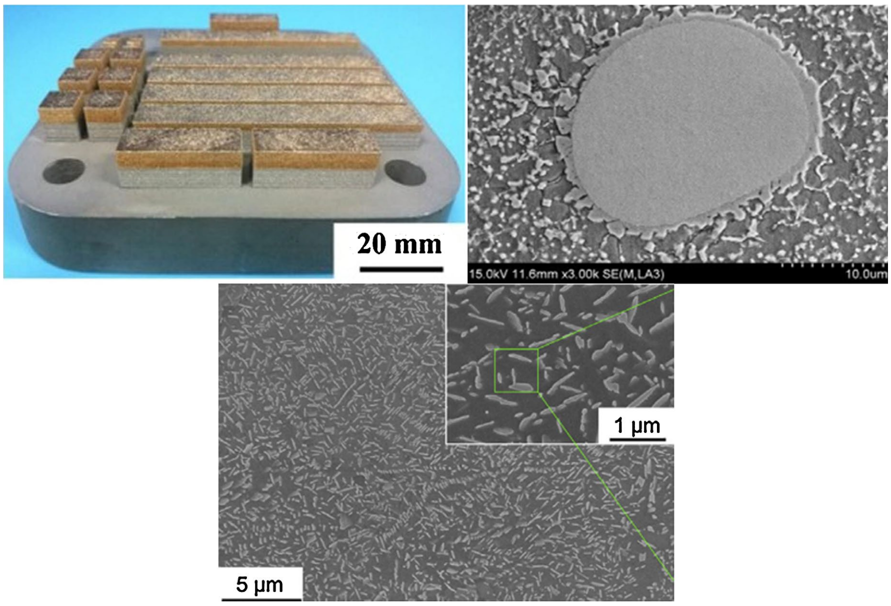

Figure 10. (a) 316L stainless steel/Cu10Sncomposite parts [36]; (b) Scanning Electron Microscopy Particle Enhancement WC/Inconel 718 Composite Microstructure [40]; (c) Scanning electron microscope image of carbon nanotubes/titanium based on selective laser melting [41].

3.2.3. Various Materials

Sometimes the use of a single material or a composite material often cannot fully reflect the excellent performance of biological structures, while the laser additive manufacturing technology based on multiple materials can make the components show different physical or chemical properties in different parts, so it can realize fully replicate the structural properties of organisms [46]-[49]. For example, a scale-horned gastropod snail living in deep-sea hot springs has a three-layer shell structure [48]: the outer layer is mainly composed of iron sulfide; the middle is a thick layer of organic matter; the inner layer is calcified layer. This biological structure can not only resist high temperature, but also resist external impact in high temperature environment. Inspired by this, Gu Dongdong *et al.* [49] of Nanjing University of Aeronautics and Astronautics developed a multi-material 3D printing of Ti_6Al_4V-TiB_2-Ti_6Al_4V based on laser directed energy deposition technology. This material has a low thermal conductivity and therefore has good insulation properties. Thermal properties (**Figure 11**). However, for multi-material laser additive technology, due to the complex interaction between multi-materials in the fusion and curing process, how to make the effective combination of the current layer material and the deposition layer material becomes the main factor affecting the characteristics of the biomimetic structure [50]. Recent surveys on metal multi-material and functionally graded AM emphasize interfacial design, compositional-gradient control, and process-window management as prerequisites for robust bio-inspired architectures [51] [52].

Biomimetic additive manufacturing aims to fabricate components with superior performance by emulating optimized structures and functions found in

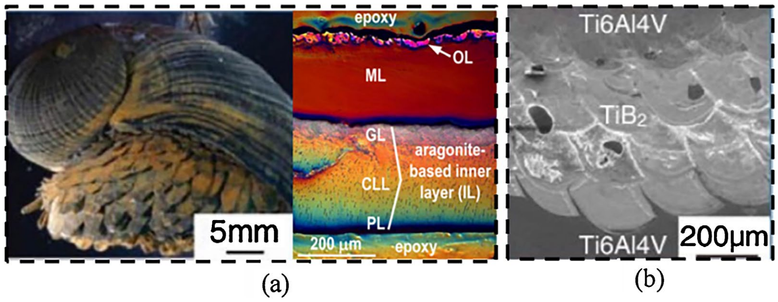

Figure 11. (a) Shell structure of scaly horned gastropod snail [48]; (b) Ti_6Al_4V/TiB_2 biomimetic multi-material structure [49].

nature. This cutting-edge field, however, grapples with a dual-core challenge: on one hand, its design paradigm leans toward extreme complexity, involving the geometric modeling and performance integration of bio-inspired structures across multiple scales, materials, and functional gradients; on the other hand, the corresponding manufacturing process is characterized by high dynamism and inherent unpredictability. Minor fluctuations in process parameters, material behavior, or environmental conditions can readily introduce defects, making it difficult to guarantee forming quality, repeatability, and ultimate performance. Within this context, digital twin technology offers a highly promising solution.

4. Biomimetic Additive Manufacturing Technology Based on Digital Twin

In order to ensure that the geometric structure accuracy, mechanical properties and biomimetic functions of biomimetic products meet the design requirements, optimize design, environment, process and other parameters, and improve design and production efficiency, the biomimetic additive manufacturing technology based on digital twins has important scientific research significance and broad market application prospects. To this end, this paper proposes the basic framework of biomimetic additive manufacturing technology based on digital twins, as shown in **Figure 12**. The framework structure of the entire digital twin system includes four digital twin models, which are the biomimetic design model, the additive equipment model, the processing technology model, and the quality inspection model.

- Biomimetic design model. The biomimetic design model defined based on the physical model includes: material properties, three-dimensional geometric structure, mechanical properties, and biomimetic functional properties. Among them, CAD software is used to model the three-dimensional geometric structure based on the physical entity model, and the material properties, mechanical properties and biomimetic function properties are analyzed by means of simulation software. Finally, the relevant data is classified and stored in the database. The above is the preliminary preparation of the mathematical, physical and chemical process [53].
- Additive device models. The additive device model defined based on the

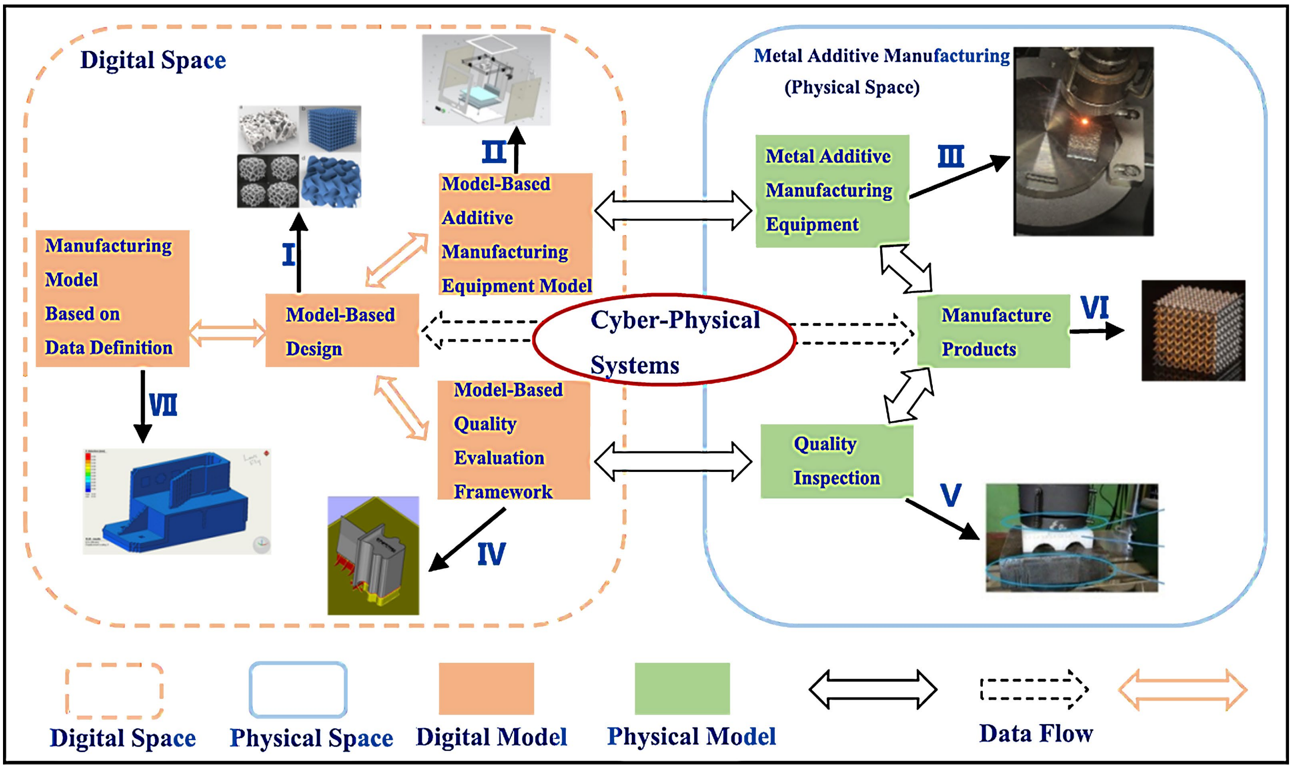

Figure 12. Basic technical framework of biomimetic additive manufacturing technology based on digital twin.

physical model includes: the geometric structure model of the device, the processing parameters of the device, the environmental parameters of the printing chamber, and the operating state model of the device. Among them, CAD modeling software is used to model the geometric structure of the equipment. The processing parameters of the equipment include pre-designed related parameters (such as laser power, printing path, scanning mode, etc.). The above two types of parameters belong to the preliminary preparation of the mathematical, physical and chemical process. The environmental parameters of the printing chamber are dynamic sensing data acquired in real time through the data acquisition device, namely temperature data, humidity data, and inert gas data, etc. The equipment operating status model includes the real-time acquisition of the spatial position status of the laser head, laser power, etc., all of which belong to Real-time information collection and processing flow [54] [55].

- Process model. The data-driven processing technology model includes: additive manufacturing forming mechanism model and process parameter control optimization model. Among them, the use of reduced-order model technology (such as neural network and machine learning, response surface method, etc.) [56]-[58] to construct a data-driven additive manufacturing mechanism model, the selection of relevant data includes the database established based on simulation, the preliminary basic test And database resources obtained by literature review. The data-driven process parameter control optimization model is composed of data sensors and controllers. Its main task is to adjust and optimize the design parameters of equipment and biomimetic products in real time according to the process parameter route created by the mechanism model. The above two models belong to the process of real-time information collection and processing.

- Quality inspection model. Quality inspection models based on physical models include: geometric structure inspection models, mechanical performance models, and function prediction models of biomimetic products [59]. Among them, the geometric structure detection model can reflect the surface roughness, porosity, deformation and crack of the component in time through the data collection of the sensor. The mechanical performance detection model is composed of the simulation database model and the dynamic data collected by the sensor, which can provide real-time feedback on the stress state of the product and predict its mechanical performance. The function prediction model includes biomimetic functions such as product thermal conductivity, impact resistance and deformation ability, and is composed of the previous simulation database model and dynamic data collected by sensors.

These four models, through a dynamic linkage of the data closed-loop, establish an intelligent feedback and optimization system that integrates design, process, equipment, and quality. This integrated framework significantly improves the reliability, yield, and efficiency of the biomimetic additive manufacturing process while effectively reducing associated costs.

5. Conclusion and Outlook

Biomimetic additive manufacturing, which integrates biomimetic design principles with discrete layer-by-layer fabrication, is emerging as a transformative approach in advanced sectors such as aerospace, intelligent manufacturing, and biomedicine. Nevertheless, significant challenges remain, including mismatches between process parameters and design requirements, long development cycles, and high production costs. As an advanced technological framework, biomimetic additive manufacturing based on digital twin leverages physical models, sensor data, and operational histories to integrate multidisciplinary, multiphysics, and multiscale simulations. This integration establishes an accurate and dynamic linkage between physical and virtual domains, thereby enabling optimized product design and process parameterization, enhancing the responsiveness and reliability of manufacturing systems, and reducing both development and maintenance cycles. Despite these advances, numerous critical issues require further investigation. These include the development of fast and accurate dynamic-response twin models; systematic classification, processing, and deep mining of heterogeneous data; efficient data exchange and interoperability among digital twin models; construction of relational models connecting design, process, equipment, functional performance, and quality; and robust evaluation methods and verification frameworks for digital twin models. These areas represent key priorities for subsequent research, crucial for establishing a robust implementation framework for biomimetic additive manufacturing based on digital twin. Addressing these challenges will be essential for fully realizing the potential of digital-twin-driven biomimetic additive manufacturing in next-generation intelligent manufacturing systems.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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