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Digital Twin-Based 3D Printing Monitoring

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Abstract

This paper proposes a digital twin-based 3D printer and model monitoring method, aiming to address the shortcomings of the current digital twin technology, which can only perform one-dimensional monitoring. The core of the research lies in constructing a comprehensive 3D printer digital twin model covering geometric, physical, and data models, to realize an all-round mapping of 3D printers. In addition, this paper proposes a monitoring method based on the improved YOLOv5 and Long Short-Term Memory (LSTM) network, which is capable of tracking and analyzing the status of 3D printing models and devices in real-time to achieve multi-dimensional monitoring of the printing process. Through experimental verification, the proposed method shows good feasibility and effectiveness, and can significantly improve the monitoring capability and response speed of the 3D printing process. The research results provide new ideas and solutions for the future development of intelligent manufacturing and promote the in-depth application of digital twin technology in the field of 3D printing.

Keywords

Digital Twin; 3D Printers; YOLOv5; LSTM.

1. Introduction

With the in-depth promotion of Industry 4.0, digital twin technology[1] is reshaping the intelligent system of manufacturing through dynamic mapping and real-time interaction between physical entities and virtual models. The technology through the sensor data acquisition, multi-physical field modeling, and machine learning algorithms, constructed from product design, and manufacturing to operation and maintenance of the entire life cycle of the digital mirror, has been in the aerospace, automotive manufacturing, and other fields show a strong prediction and optimization capabilities.

At the same time, 3D printing technology[2], by its layer-by-layer manufacturing principle, breaks through the design constraints of traditional subtractive manufacturing and has been widely used in the molding of complex structural parts, personalized customization, and other fields. However, the technology still faces challenges such as difficult optimization of process parameters, weak real-time monitoring of forming defects, and insufficient precision in product performance prediction. The deep integration of digital twin and 3D printing provides a new path to solve the above problems.

Current research on digital twin for 3D printing focuses on process monitoring and process optimization. In digital twin-based 3D printing process monitoring, Gaikwad[3] integrated simulation, on-site sensing, and machine learning of the 3D printing process to accomplish real-time monitoring of the 3D printing process and constructed a digital twin applied to real-time feedback and monitoring of 3D printing. Gunasegaram[4] addressed the problem of chaotic and poorly reproducible manufacturing processes in metal 3D printing and constructed a digital twin to proactively through real-time control commands to control the process within a certain range, thus injecting certainty into the printing process. Yavari[5] constructed a digital twin for LPBF-type 3D printing by combining in-situ molten pool temperature measurements with a graph-theory-based thermal simulation model to monitor the formation of defects in LPBF parts online. Rachmawati[6] addressed the fused deposition molding (FDM) 3D printer fault detection problem, proposed a new method for sensor data-driven fault diagnosis, and constructed a digital twin for fault detection in FDM 3D printers. In digital twin-based 3D printing process optimization, Zou[7] addressed the challenge of measuring and mitigating the residual strains generated during the 3D printing and manufacturing of metal powders by proposing a digital twin method that fuses modeling results with distributed fiber optic sensor measurements for the study of additive manufacturing processes. Knapp[8] addressed the fact that 3D printed molded parts cannot currently be scientifically based on the selection of the underlying process variables, and can only be optimized through iterative experiments to optimize the shortcomings, a digital twin system for the 3D printing process was established to make predictions. Reisch [9] addressed the problem of process instability leading to production scrap due to poor part quality by proposing an intelligent manufacturing system that can compensate for previously generated defects utilizing a digital twin system. Xu [10] proposed a hybrid digital twin-driven lightweight composite additive manufacturing deformation evolution and perception prediction method to improve the manufacturing quality of irregular lightweight composites in aerospace engineering.

However, through the above research, it is found that the current 3D printing digital twin is not able to do the simultaneous monitoring of 3D printing equipment and 3D printing models. To address the above shortcomings, we propose a digital twin-based 3D printing equipment and model monitoring method, the digital twin model includes a geometric model, physical model, and data model, using the improved YOLOv5 to monitor the printing model, and using LSTM to monitor the equipment operation status. By establishing a digital twin closed-loop system with online diagnosis and parameter self-correction capability, we provide a reliable collaborative monitoring paradigm for intelligent manufacturing.

2. 3D Printing Digital Twin Model Construction

2.1. Geometric Model Construction

In this paper, the construction steps of the high-fidelity geometric model for the 3D printer are shown in Fig 1. To achieve highly accurate modeling of the 3D printer geometric model, accurately draw the parts, the choice of SolidWorks modeling, and the use of Blender for post-processing of the part model.

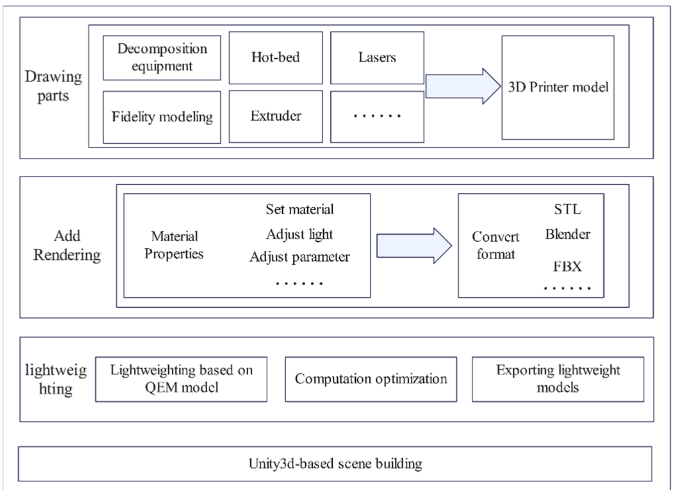

Fig 1. Geometric model construction process

Before modeling the 3D printer in SolidWorks, it is first necessary to collect the real data of the 3D printer to determine the size and location of each component. Subsequently, the physical solid model components are drawn in SolidWorks. The individual parts are assembled into an assembly and exported to STL format. To ensure the realism of the geometric model, appropriate material properties should be added to the geometric model for model rendering. Import the STL model file into Blender for post-processing. Select a renderer such as Cycles, Eevee, or Workbench, and adjust the rendering setup parameters, including output resolution, rendering quality, shadows, reflections, and other parameters, to achieve the best rendering effect. When rendering, the light casting and shadow effects, material texture and reflection effects, as well as the rendering resolution and output format are things to pay attention to ensure that the final rendering meets the requirements for practical use.

To improve the operation efficiency and quality of the twin model, this paper uses the Quadratic Error Metrics (QEM) algorithm to lighten the 3D model of non-critical elements. By reducing the geometric elements on the model surface and collapsing the triangular elements on the model surface, the number of geometric elements of the model is significantly reduced while maintaining the appearance characteristics of the device model.

Import the lightweight and rendered 3D printer model into the Unity3D engine. In Unity3D, build a virtual factory scene based on the actual size and relative position data of the 3D printer equipment model.

2.2. Physical Model Construction

The device operating parameters need to be determined by reading the contents of the G-code file during the printing process. At the same time, to better display the operating status of the printer and to display and monitor the printing process, the behavior of the 3D printing device should be constrained in addition to the relative motion of the printer parts when constructing the geometric model mentioned above. With the help of Unity 3D for motion configuration, the behavioral constraint flow of the printer is shown in Fig 2.

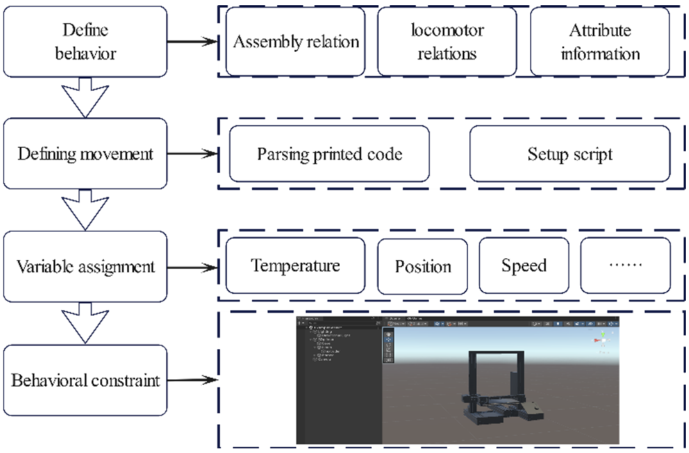

Fig 2. Behavioral constraint process

Based on the geometric model, check whether the part model is correct or not, the movement of the printer is mainly X-Y-Z, in which the extruder carries out the movement in the X direction, the print plate carries out the movement in the Y direction, and the crossbar carries out the movement in the Z direction together with the printhead. In Unity 3D, according to the object's parent-child relationship, the extruder is set as a child object of the crossbar, so that the printhead can move up and down with the crossbar, and the printhead can move left and right.

The configured model is inserted into the script, and the G-code file is parsed using the Java language to obtain the coordinates of the corresponding positions of the printheads and to enable the printer model to perform the movement of the predetermined trajectory by causing the printheads to reach the position indicated by the value of the X-coordinate, the printing platform to reach the position indicated by the value of the Y-coordinate, and the crossbar to reach the position indicated by the value of the Z-coordinate.

2.3. Data Model Construction

In the 3D printing process, the digital twin is based on the OPC UA communication protocol to acquire real-time information from multiple heterogeneous data sources such as 3D printer controllers and sensors during the 3D printing process in a standardized, secure, and efficient manner. After information collection, the collected heterogeneous data from multiple sources are converted to JSON format.

After the classification process for the characteristics of multiple data types of 3D printers, considering the two main directions of the application of the collected data: historical traceability and real-time prediction, two storage modes of temporal and relational databases are constructed respectively. Relational databases are mainly used to store structured data, which usually have a fixed format and can be efficiently operated using SQL queries. In the digital twin, the device status, task data, and operation records of 3D printers are usually managed using relational databases.

Temporal databases are a class of databases specifically optimized for processing temporal data and are suitable for data that needs to be recorded and queried about time. In the 3D printing process, data such as temperature, pressure, and printing speed are usually temporal data, which continue to change over time, and are therefore well suited for storing using temporal databases. In this paper, we use InfluxDB to store temporal data, which can provide more efficient storage and retrieval, especially when the amount of data is large, fast queries are required, and the data changes over time, temporal databases can provide better performance.

To ensure the scalability and flexibility of the digital twin system to adapt to future needs and to reduce the tight coupling relationship between modules, this paper adopts an event-driven approach, as shown in Fig 3.

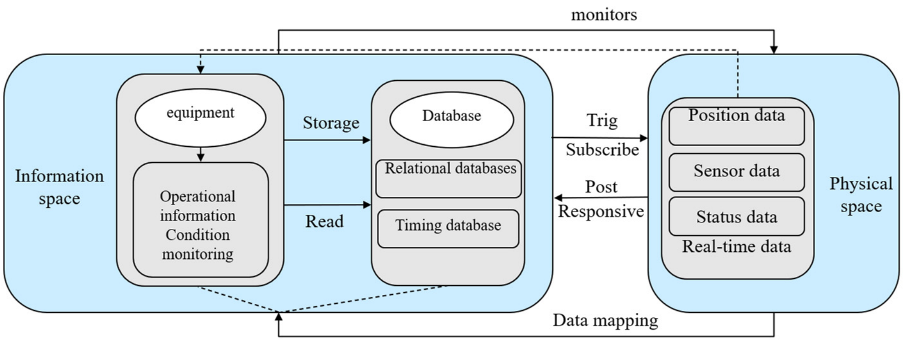

Fig 3. Work data management and mapping methods

The architecture is based on an event triggering, subscribing, publishing, and responding mechanism that enables different modules to register and respond to specific events as needed without deep integration or dependence on the internal logic of other modules. In the event-driven architecture for 3D printing, modern communication and data transfer technologies are used through message queues (Rabbit Message Queue, RabbitMQ) to achieve efficient data management and processing. When certain events or data on the production line are updated, the OPC UA server publishes the relevant information into the RabbitMQ message queue. Handlers subscribed to these messages can then immediately access the information and respond accordingly. With event capture and transfer, the system can capture event data in

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real-time from various data sources. Once an event is captured, the event-driven architecture routes and processes the event based on its type, content, and source.

3. 3D Printing Monitoring Based on Improved YOLOv5 and LSTM

3.1. 3D Printing Model Inspection based on Improved YOLOv5

Surface defects (e.g., warpage, cracks, excessive buildup) and structural anomalies (e.g., mis-layering, material inhomogeneity) are common problems in the 3D printing process. Considering the computational power requirement, efficiency of target monitoring, and stability in the industrial meta-universe, the target detection algorithm YOLO-V5 [11] in deep learning can be utilized to achieve real-time monitoring and classification of these problems. The ShuffleNetV2 lightweight network model is used to replace the CSPDarknet53 in the YOLO-V5 model as the backbone network to construct the improved YOLO-V5 network model.

The improved YOLO-V5 model algorithm discards the Focus layer, avoids using slice operation several times, and reduces cache occupation and computational processing burden. The 3D printing monitoring process based on the improved YOLO-V5 is shown in Fig 4.

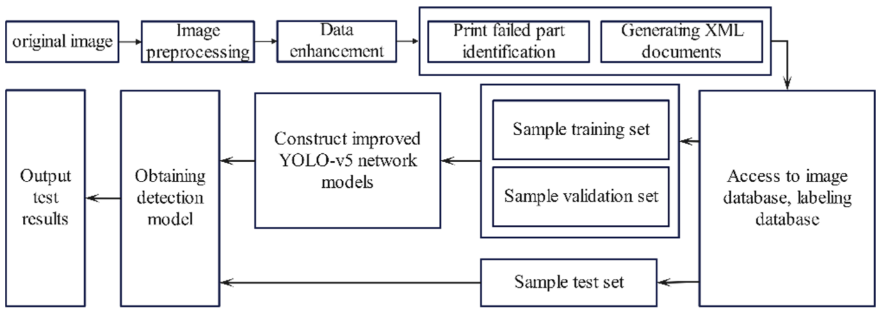

Fig 4. 3D Printing monitoring process based on improved YOLO-v5

3.2. 3D Printer Monitoring Based on LSTM

The LSTM-based 3D printing device monitoring process is shown in Fig 5.

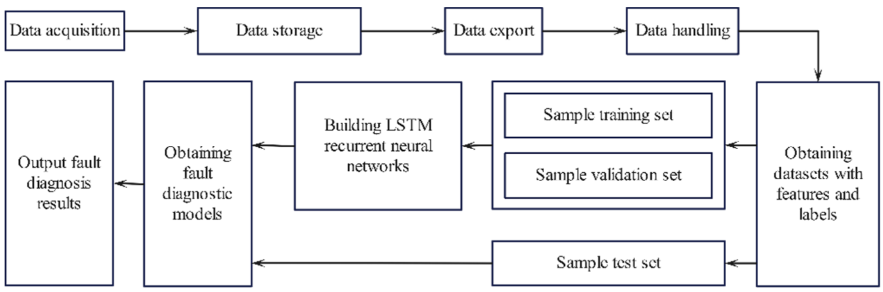

Fig 5. 3D Printer monitoring process based on LSTM

The input data of LSTM comes from the multi-source timing data generated during the operation of the device, which is mainly collected from industrial IoT devices such as temperature sensors, pressure sensors, speed sensors, etc., and is efficiently stored and managed through the timing database. To ensure the validity of the data and the convergence of the model, the study adopts a systematic data preprocessing process: firstly, the raw sensor data are normalized, and the value range of each sensor is linearly mapped to the range between zero and one, to eliminate the magnitude difference and accelerate the model training; secondly, a reasonable time window is set up according to the actual situation and the type of equipment, and the continuous time series data are divided into fixed-length of input samples for model training and prediction.

4. Digital Twin-Based 3D Printing Monitoring Verification

4.1. Digital Twin Model Mapping Accuracy Verification

The final digital twin scenario diagram is shown in Fig 6.

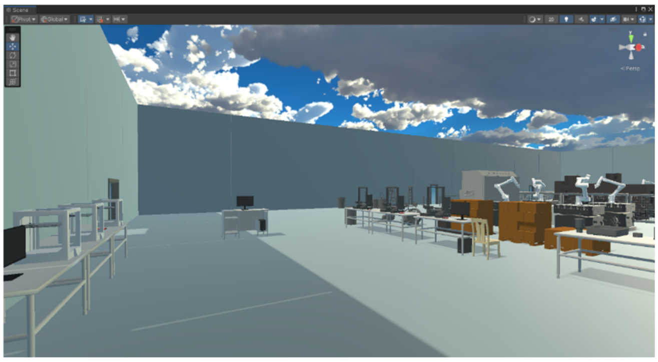

Fig 6. Digital twin virtual scene

After connecting with the 3D printer, the digital twin can synchronize the working status of the 3D printer in real-time, including temperature, printing progress, working position, etc., and the latency is as low as 50ms, as shown in Fig 7.

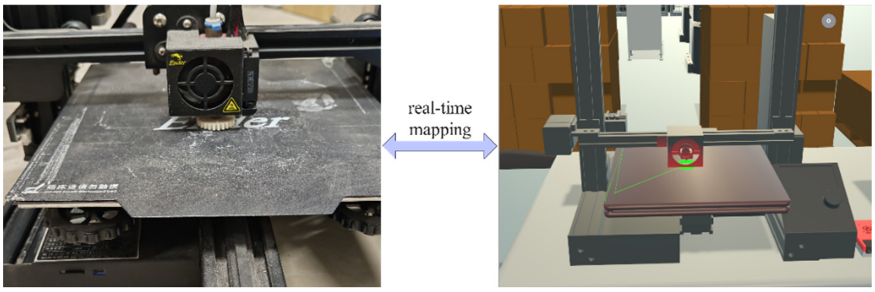

Fig 7. Digital twin and 3D printer synchronization and mapping

4.2. Improved YOLOv5 and LSTM Performance Verification

The improved YOLOv5 and LSTM are trained after collecting the required training data and the training results of the improved YOLOv5 are shown in Fig 8.

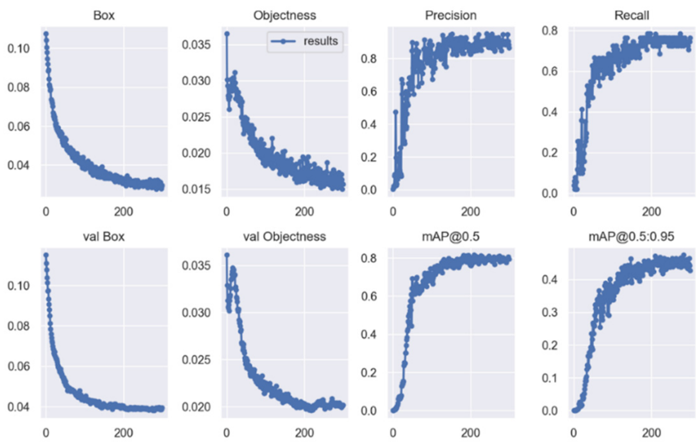

Fig 8. Improved YOLO-v5 training results

The training results show that the improved YOLO-v5 model exhibits good convergence and detection performance during training. The precision and recall curves gradually converge to

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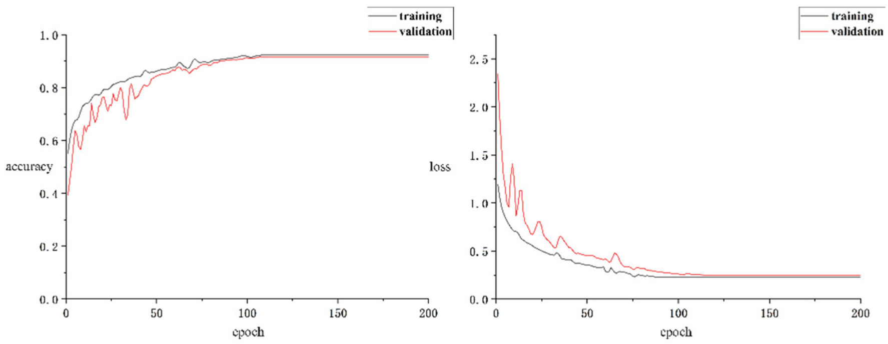
the ideal state, which is lower than that of the large-scale model, but it has a smaller number of parameters and faster inference speed, which is suitable for real-time edge computing scenarios. The training and validation metrics curves are highly synchronized, indicating that the data enhancement strategy and regularization method effectively improve the generalization ability. The overall results show that the optimized model strikes a balance between accuracy and efficiency and is suitable for 3D printing device monitoring tasks.

The LSTM training results are shown in Fig 9.



(a) (b)

Fig 9. LSTM training results

(a) Diagnostic accuracy curve, (b) Diagnostic loss ratio curve

From the figure, it can be seen that the model's accuracy leveled off after 100 iterations and reached 92.0% accuracy on the validation set. The loss curve shows that the model converges after 110 iterations and the final loss rate is 0.25. Therefore, the LSTM network fault diagnosis model can be used for 3D printing equipment fault diagnosis and has high feasibility and effectiveness. The integration of LSTM into digital twin can be used for effective equipment work monitoring of 3D printing equipment.

In summary, the proposed digital twin-based 3D printing monitoring can efficiently monitor the printing model and 3D printer, effectively solving the current digital twin can only be a single dimension monitoring deficiencies.

5. Conclusion and Suggestion

In this paper, a digital twin-based approach for 3D printer and model monitoring is proposed to address the shortcomings of current digital twins that can only perform single-dimensional monitoring. It mainly includes the proposed construction method of the 3D printer digital twin model, including the geometric model, physical model, and data model, and the proposed monitoring method of 3D printing models and devices based on improved YOLOv5 and LSTM. Finally, the feasibility of the proposed method is experimentally verified.

In the subsequent research, the construction method of digital twin for heterogeneous 3D printers will be further conceptualized to improve the reusability of the digital twin models of individual 3D printers, which will in turn promote the intelligent development of the entire 3D printing industry.

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