Research On Virtual Monitoring Method Based On Digital Twin Smart Factory

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Abstract

In the context of the widespread application of the Internet of Things, big data, artificial intelligence, and cloud computing, intelligent manufacturing has become a development trend in the manufacturing industry. The foundation of intelligent manufacturing is the interconnection between physical space and digital space, and digital twin is the best way to achieve the fusion of physical space and digital space. This article is based on the digital twin of the intelligent factory production line, and studies the visualization monitoring technology of multi-source heterogeneous data in the production process of the assembly line. Ultimately, a virtual monitoring method for smart factories based on digital twin is proposed. To validate the feasibility of the proposed method, the Unreal Engine 4 software was used to establish a virtual monitoring system for smart factory digital twins, and the effectiveness of the method was verified, providing a reference for further realizing real-time monitoring of digital twin smart factories.

Keywords

Digital Twin, Smart Factory, Unreal Engine 4, Monitoring

1. Introduction

With the development of the new generation of information technology, manufacturing industry is undergoing a transformation from the physical world to the information world, realizing the interconnection and intelligent operation of the physical world and the information world, which has become the trend of the world's industrial development. An important part of intelligent manufacturing is the automated assembly line. With the widespread use of automated assembly lines, the production needs of large-scale products can be met and the economic efficiency of enterprises can be significantly improved. However, the traditional workshop monitoring methods mainly rely on manual records, 2D reports, and configuration monitoring, resulting in poor real-time and visualization. For example, manual records are error-prone, time-consuming, and do not provide real-time status information. Although two-dimensional reports and configuration monitoring have some visualization, they lack intelligent analysis and feedback mechanisms, which limit the ability of shop floor managers. Therefore, to address these issues, more and more companies are adopting next-generation information technology-based intelligent monitoring systems to manage automated assembly lines. These systems utilize technologies such as IoT, cloud computing, big data, artificial intelligence, and digital twins to achieve real-time monitoring, data collection and analysis, and rapid feedback and adjustment of the assembly line. Among them, digital twins feature high fidelity, multi-physics and multi-scale mapping. They establish a virtual entity that reflects the actual physical object in the virtual space, and are able to monitor the assembly line comprehensively in the virtual space with a strong sense of realism and immersion.

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2. Related Work

For the various data generated during the operation of the assembly line, a monitoring system is needed to store and manage the data and solve the problems such as untimely data interaction and low visualization. Many scholars at home and abroad have conducted research and practice on this. Although certain results have been achieved, there are generally problems such as high threshold of system development, low development efficiency, poor system portability, and single monitoring method, which cannot reflect the workshop manufacturing status well. For example, GuangYuan Zhou et al [1] researched the key technology of production workshop visualization and monitoring for the problems of backward management, lagging information and low visibility in manufacturing workshops. Chao Yin et al [2] studied the implementation technology of visualization and dynamic monitoring of workshop production execution based on Flexsim. Li Zhi et al. [3,4] designed a real-time monitoring system for manufacturing workshops based on the analysis of the current status of workshop monitoring and discrete enterprise workshop data types. Niki Kousi et al [5] proposed a 3D rendering of the digital workshop with the functions provided by ROS and combined with multi-sensors and CAD models, and used multi-sensors to collect real-time workshop data, and implemented a physical and virtual communication system in the framework of ROS. physical and virtual communication was achieved under the framework of ROS. In recent years, Digital Twin has gained wide attention in smart manufacturing [6,7,8]. With its high fidelity, multi-physics, and multi-scale mapping [9,10,11], digital twin also has great potential in areas such as monitoring and simulation of industrial equipment and monitoring and management of smart factories [12,13,14]. Adriano Fagali et al. proposed an industry 4.0 system for real-time monitoring and control of 5-axis CNC machine centers by mobile devices [15].Ahmad H. Sabry et al. proposed proposed a fault diagnosis method based on an accurate mathematical model of the reference power model [16] for monitoring the performance of industrial robotic systems. JiaCheng Xie et al.deeply integrated VR monitoring system with data and video monitoring system [17] to achieve real-time transparent presentation of operating conditions and remote intelligent coordination control. Liu et al [18] proposed a digital twin architecture driven by digital twin technology for the production process in the workshop. This architecture enables the digitization modeling and real-time monitoring of the workshop production process, allowing for real-time collection, storage, processing, and analysis of production data, thereby optimizing the production process and improving production efficiency and quality. Zhao et al [19] presented a data-driven multi-dimensional 3D visualization mapping method based on the workshop's operational logic modeling and analysis. This method integrates multi-source and heterogeneous data to build a digital twin of the production workshop and presents it in 3D visualization form, enabling real-time dynamic monitoring of the workshop production. The previous monitoring system had shortcomings in terms of visualization, interactivity, and blind spots, making it difficult to comprehensively and intuitively monitor and manage the robot production process. This paper proposes a virtual monitoring method based on a digital twin smart factory, which uses the UE4 (Unreal Engine 4) engine and 3D point cloud data to construct a 1:1 three-dimensional virtual space of the real physical space, and real-time maps physical units to virtual units. UE4 has a powerful rendering engine that can render realistic lighting and shadow effects, making the digital twin more realistic. Through real-time data transmission, the working status of robots on the production line can be remotely monitored in the three-dimensional virtual space, enabling transparent and intuitive monitoring of the production line, ultimately achieving a fusion of the virtual and real worlds.

3. Methodology

3.1. Framework of digital twin system

The digital twin creates a virtual system that corresponds to the physical system. A virtual system is a complete mapping of a physical system, reflecting the operational state of the physical system. Using this virtual environment, a 3D visual monitoring system is established to provide transparent and comprehensive monitoring of the physical system. In this paper, referring to the digital twin five-dimensional model [20], the proposed digital twin smart factory virtual monitoring system is divided into five layers. As shown in Figure 1, they are physical layer, transport layer, information processing layer, virtual layer, and application layer.

The physical layer serves as the base of the entire framework, encompassing the production site environment, and comprising various devices such as robots, control cabinets, and sensors. Specifically, robots consist of robotic arms and AGVs, where the latter plays a vital role in completing the entire production efficiently by connecting different equipment to accomplish transportation tasks between different robots. On the other hand, the robot arm is the primary component that accomplishes operations by planning the end of the robot arm's trajectory to achieve tasks such as painting, assembly, welding, handling, among others. Sensory data is obtained from sensors that collect operational data from various robotic devices. Uploading this real-time data to upper-layer devices via the transport layer forms the foundation of data needed to construct the virtual layer and drive it.

The transport layer plays a critical role in enabling seamless communication between the physical and virtual layers. It serves as a bridge that allows data to flow between different platforms and systems in both directions. By transmitting operational data from sensors in the physical layer to the virtual layer through the transport layer, real-time data mapping between the two layers is achieved. Additionally, the transport layer enables the physical layer to receive commands or data from the virtual layer, thus establishing a bidirectional connection between the two layers. This layer is responsible for ensuring smooth and efficient data transmission, which is essential for creating a responsive and accurate virtual monitoring system.

The information processing layer plays a critical role in the digital twin smart factory virtual monitoring system. It processes, transforms, and fuses data collected from various sources to generate valid data that can drive the digital twin. Data processing includes data cleaning, filtering, and normalization, as well as fusing data from multiple sources to generate accurate and comprehensive data. Additionally, as the coordinate system of the robot and the coordinate system of UE4 are different, conversion at the information processing layer is required to drive the digital twin correctly. To achieve this, the information processing layer establishes a coordinate system conversion algorithm that can convert the data collected in the physical layer into data that can drive the virtual layer effectively.

The virtual layer is a crucial component of the digital twin smart factory virtual monitoring system as it provides a realistic mapping of the physical layer, reflecting its static and dynamic characteristics. It comprises a realistic model and all available data about the physical layer, synchronized with the physical layer. The virtual layer can be divided into two parts: twin data and twin model. The twin model accurately depicts the characteristics of entities in the physical layer, including location, geometry, material, color, subordination of entities, kinematic characteristics, and more. Through real-time data mapping, the twin model reflects the state of physical entities and enables monitoring of the physical layer. The twin data is sourced from the physical layer and is processed and stored as a data source to drive the twin model. Together, the twin model and twin data make up the virtual layer, providing a comprehensive and accurate representation of the physical system.

The application layer is the interface between the user and the system. The main functions of the application layer are 3D visual monitoring and operation status reproduction. The 3D visual monitoring function provides real-time monitoring and displays the operating status of the robot in 3D, including the speed, acceleration, angle, torque, and other parameters of each axis of the robot. Compared with traditional manual monitoring or video monitoring, the 3D visualization monitoring mode is more intuitive and interactive, enabling the user to monitor the scene through scene roaming in all directions without any dead angle. The operation status reproduction function enables the user to review the historical operating status of the robot and perform post-analysis, making it easier to identify any issues or areas for improvement.

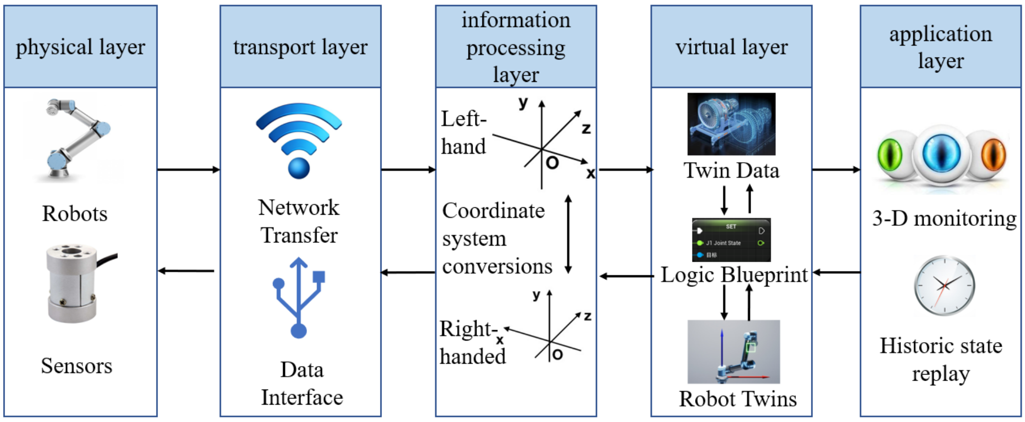


Figure 1: Digital Twin Monitoring System Framework

3.2. Building virtual spaces in UE4

UE4 is a powerful engine for simulating various virtual scenes. It is known for its powerful screen rendering capabilities and easy-to-use blueprint programming. In the digital twin smart factory virtual monitoring system,UE4 is used to create a virtual environment that is mapped to the twin data and synchronized with the physical environment. This allows the 3D model in the virtual environment to run synchronously with the real equipment and display the equipment operation information. To construct the virtual space in UE4, both static and dynamic objects need to be created. Static objects are those that do not move in the production environment, such as walls and floors. Point cloud data is generated from these static objects using radar scanning and then imported into UE4 using Point Cloud Support. The size and position of static objects are obtained from the point cloud data, and then secondary editing is performed in UE4 to create a more realistic layout. To further enhance the realism of the virtual layer scene, light sources can be added to the scene and objects can be rendered. Dynamic objects in the virtual environment include various types of robotic arms, AGVs, and conveyors. For AGVs and conveyors, there is no complex hierarchy, so only the geometric model, physical model, material, and color are modeled in 3Dmax software and then imported into UE4 using the Datasmith plug-in. Robotic arms, on the other hand, have a complex hierarchy of components, including the base, swivel, large arm, small arm, small arm bar, wrist, and end flange. The kinematic arm hierarchy is described in UE4 so that the virtual model corresponds to the physical entity characteristics.

(a)

(b)

Figure 2: Virtual environment construction: (a)Physical space.; (b)Virtual Space

3.3. Robot end trajectory visualization

Robot end trajectory visualization is the process of presenting the robot end trajectory graphically. The end trajectory visualization provides an intuitive understanding of the robot's working state and motion trajectory, which helps to analyze and optimize the robot's motion planning and control. In UE4, a particle system can be used to present the visualization of the robot end trajectory. First, create the particle system, set the shape, size and color of the particles, and then, attach the particles to the end-effector of the robot through the Spawn Emitter Attached function in order to make the particle effect move along the trajectory of the robot's end, as shown in Figure 3.

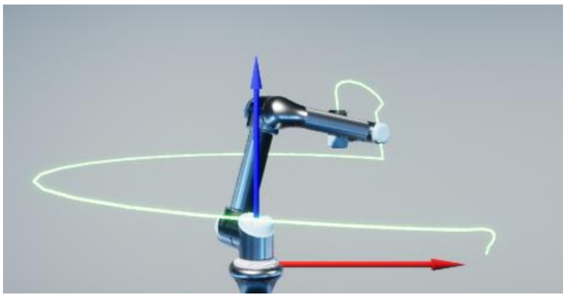


Figure 3: Robot end trajectory particle effect

3.4 Two-way communication method

The physical space and virtual space are on ROS and UE4 platforms respectively, so the barrier between UE4 and ROS needs to be broken. And RosBridge of ROS platform provides JSON interface between ROS and non-ROS platforms to realize the data communication function between ROS and UE4 platforms through various communication methods. ROSIntegration is used in UE4 to connect UE4 and ROS. it uses itself as a client in ROS system and uses ROSBridge as a communication intermediary to connect to ROSBridge server with WebSocket protocol to realize two-way communication between ROS and UE4, and its communication framework is shown in Figure 4. Specifically, ROSIntegration maps ROS topics into the data structure of UE4, enabling users to directly subscribe to ROS topics and process the corresponding data in UE4. It also supports calling ROS services in UE4, and users can create a ROS service client object and specify the service name and service type to call the corresponding services in the ROS system. Overall, ROSIntegration acts as a communication bridge to connect ROS and UE4 organically, allowing users to use ROS functions in UE4 and to control the robot and process data in the ROS system in a more flexible way.

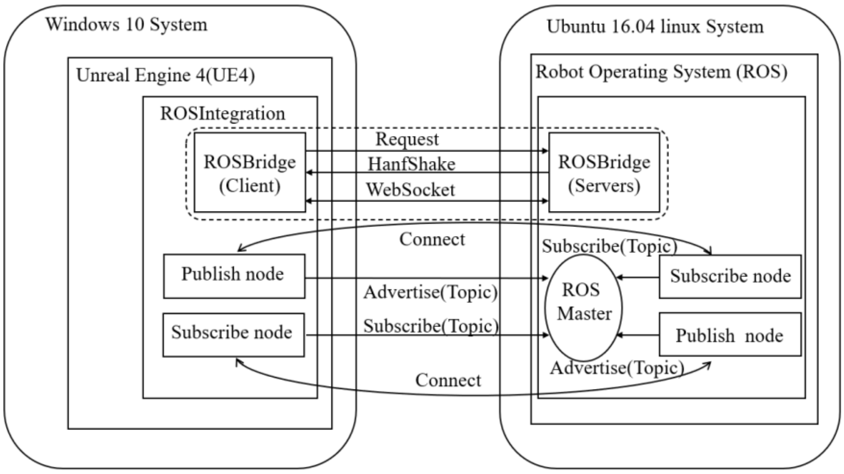


Figure 4: UE4 communication framework with ROS

3.5 Coordinate system conversion of twin data

Twin data is a critical component of digital twins, which includes both the static and dynamic data that build the physical space. Static data encompasses information such as the geometric shape, size, and layout of the device, usually transformed from real-world data captured by sensors. Dynamic data, on the other hand, is the operational data generated during device operation and is a key part of achieving real-time mapping. In this article, the dynamic data mainly comes from the UR5 robot and AGV car.

The twin data of UR5 robot includes current timestamp, joint name, joint position, joint velocity, joint acceleration. The message format of its dynamic data is shown as follows:

```
std_msgs/Header header
  unit32 seq
  time stamp
  string frame_id
string[] name
float64[] position
float64[] velocity
float64[] effort
```

The dynamic digital twin data of AGV includes timestamp, position, and direction in space, with the specific format as follows:

```
std_msgs/Header header
  unit32 seq
  time stamp
  string frame_id
float64[] x
float64[] y
float64[] theta
```

3.6 Coordinate system conversion of twin data

After transferring data between ROS and UE4, coordinate transformation is required because the coordinate systems used by the two platforms are different. In UE4's left-handed coordinate system, the thumb points towards the positive X-axis, the index finger towards the positive Y-axis, and the middle finger towards the positive Z-axis. However, in ROS's right-handed coordinate system, the thumb points towards the positive direction of the X-axis, the index finger towards the positive direction of the Y-axis, and the middle finger towards the positive direction of the Z-axis. Figure 5 shows the coordinate systems used by UE4 and ROS.

Because the two platforms, UE4 and the robot, are in different coordinate systems, conversion is necessary for calculations. First, the point in the left-handed coordinate system is transformed into the right-handed coordinate system. Second, rotation is performed based on the rotation matrix in the right-handed coordinate system. Finally, the rotated point is transformed back into the left-handed coordinate system. As shown in Figure 5, the X-axes of the two coordinate systems point in opposite directions. Therefore, the point $P_R(x, y, z)$ in the right-handed coordinate system, represented as $P_L(-x, y, z)$ in UE4, can be expressed as a matrix:

$$P_L = \begin{bmatrix} -x \\ y \\ z \end{bmatrix} = S_T P_R = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} \tag{1}$$

The rotation matrix for the right-handed coordinate system is expressed as follows:

$$R_R = \begin{bmatrix} r_{00} & r_{01} & r_{02} \\ r_{10} & r_{11} & r_{12} \\ r_{20} & r_{21} & r_{22} \end{bmatrix} \tag{2}$$

The rotation matrix converts the points $P_R(x, y, z)$ to $P_R'(x', y', z')$:

$$P_R' = \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = R_R P_R = \begin{bmatrix} r_{00} & r_{01} & r_{02} \\ r_{10} & r_{11} & r_{12} \\ r_{20} & r_{21} & r_{22} \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} \tag{3}$$

The P_R' transformation in the left-handed coordinate system is:

$$P_L' = (-x', y', z') \tag{4}$$

In summary, we can obtain:

$$P_L' = S_T P_R' = S_T R_R P_R = S_T R_R S_T P_L \tag{5}$$

Then the rotation matrix in the left-handed coordinate system is expressed as:

$$R_L = S_T R_R S_T \tag{6}$$

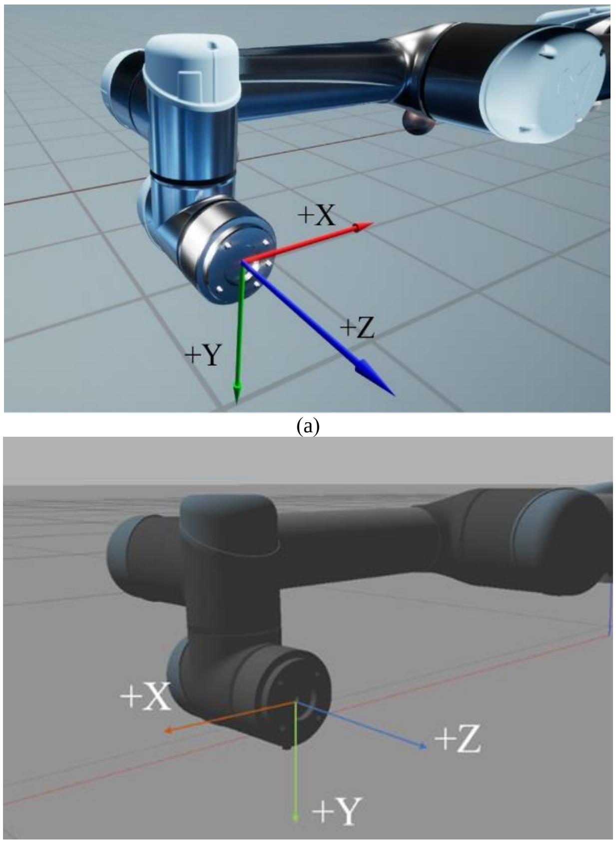


Figure 5: Coordinates system.: (a)Coordinates in UE4 space.; (b)Coordinates in physical robot space.

3.7 Store historical data of the robot

The data collected and transmitted from the ROS-side robot can be categorized into two types: real-time data and historical data. Real-time data is mapped in real-time based on the physical and virtual layers, driving the virtual model to run for comprehensive monitoring and management of the equipment operation site. Storing historical data provides users with a data query function. Users can query the operation status of the equipment within a certain period of time and reproduce the working process of the equipment in the virtual environment. The stored data can be used for post-event analysis, further laying the foundation for future analysis and optimization, and intelligent decision-making using big data. The data serves as the basis for data traceability and error identification when the equipment operates abnormally. The reproduced data includes the robot's joint angle, joint speed, joint acceleration, and joint torque.The details of the fields in the database table are shown in Table 1.

Table 1
Historical data database table

Field name	Primary key or not	Data type	Field meaning
id	Yes	INT	number
angles	No	DOUBLE	jointAngles
velocity	No	DOUBLE	jointVelocity
acceleration	No	DOUBLE	jointAcceleration
torque	No	DOUBLE	jointTorque

4. Experiments and Results

4.1. Experimental environment and equipment

This system development environment is divided into physical space development environment and virtual space development environment. The virtual space is developed based on Windows 10, and MySQL is used as the database software to build the database, and UE4 software is used for the 3D virtual simulation, and SW (SolidWorks) and 3Dsmax software are used for 3D modeling. The physical space is developed on Ubuntu 16.04 linux system, and Robot Operating System (ROS) is used to control the robot and collect its operation data [21]. The specific development environment is shown in Table 2 and Table 3.

Table 2
Virtual space development development environment

Hardware Name	Environmental	Software	Environmental
CPU	Intel(R) i5-9300H	Operating system	Windows 10
Hard Disk	500G	Development Language	C++、Blueprint
Memory	16GB	Database Software	MySQL
Video Cards	GTX1650	Development software	UE4、3Dsmax、SW

Table 3
Physics space development development environment

Hardware Name	Environmental	Software	Environmental
Robot	UR5	Operating system	Linux、ROS
AGV	Ant-E300	Development software	Gazebo、Rviz

4.2. Three-dimensional visual monitoring function test

The experimental procedure is to send a motion command from the controller to the robot drive, which drives the robot's motion. The entire operation of the robot is monitored in the monitoring system.

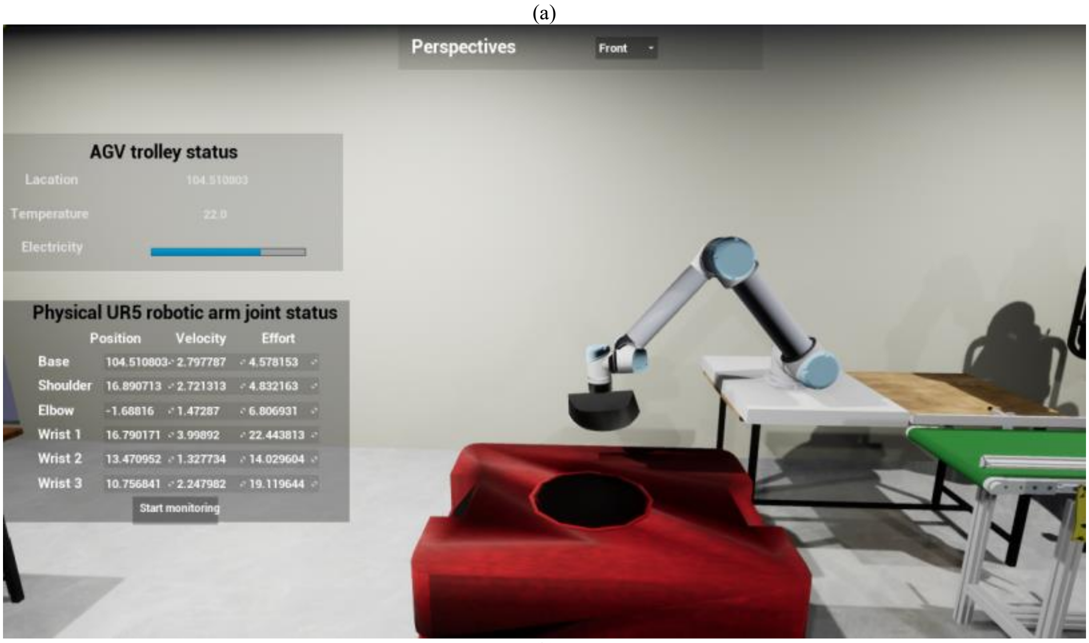
The specific steps of the experiment are as follows：

1. Start the rosbrige_server in Rosbridge to open a TCP server.
2. Click on the Run button in UE4 to connect the monitoring system to the socket server on the ROS side and start the monitoring process.
3. The controller receives the command and then converts it into a drive signal to the driver, which drives the robot's internal motors. movement and the physical robot begins to move.

4. The controller transmits the robot's real-time operational data to the monitoring system via socket communication; it checks the consistency and synchronisation of the model's movement with the actual robot in the monitoring system.

The paragraph describes the results of experiments conducted to evaluate the proposed system's performance in 3D visualization and monitoring of a robot, as presented in Figure 6. The virtual model successfully tracks the robot's movements and displays the real-time operational status of the device entity. The system's interactive features allow users to roam the monitoring scene, adjust the viewpoint distance and angle, and switch the perspective as desired. The experiments also found that the system has no noticeable delay and provides good real-time performance, enhancing its ability to monitor scenes in 3D. Overall, the results demonstrate that the proposed system effectively enables 3D visual monitoring of a robot in real-time, providing a useful tool for users.

(a)



(b)

Figure 6: Monitoring process: (a)Physical space.; (b)Virtual Space

To demonstrate the real-time capability of the digital twin system described in this article, we have collected the timestamps of four adjacent data points in each of the three stages, with the system runtime as the reference zero point. These timestamps are listed in Table 4.

Based on Table 4, it can be observed that the average time intervals between adjacent data collections for stages A, B, and C are 0.207s, 0.204s, and 0.167s, respectively. This further confirms the excellent real-time performance of the proposed digital twin system in this paper.

Table 4
Historical data stored in the database

Time Period	Timestamp I	Timestamp II	Timestamp III	Timestamp IV	Average interval time
A	96.307s	96.529s	96.776s	96.928s	0.207s
B	550.521s	550.742s	550.922s	551.214s	0.204s
C	1775.486s	1775.675s	1775.815s	1775.987s	0.167s

4.3. Historical state reproduction function test

The paragraph explains the process and results of run state reproduction experiments. During these experiments, the robot's real-time data was recorded while it was in operation. This data was later called from the system's database to reproduce the robot's state and verify whether the reproduced state was consistent with the actual running state. To ensure data accuracy, the historical data was compared with the real-time data sent by the controller. For instance, Table 5 shows an example of historical data fields, J1Angles to J6Angles, representing the received angle values in degrees for each of the six axes, while Table 6 displays the real-time data sent by the controller.

Table 5
Historical data stored in the database

J1Angles	J2Angles	J3Angles	J4Angles	J5Angles	J6Angles
30.091°	6.604°	-112.410°	15.806°	89.999°	-120.091°
30.091°	6.604°	-112.410°	15.806°	89.999°	-120.091°
30.091°	6.604°	-112.410°	15.806°	89.999°	-120.091°
30.091°	6.604°	-112.410°	15.806°	89.999°	-120.091°
30.091°	6.604°	-112.410°	15.806°	89.999°	-120.091°
30.091°	6.604°	-112.410°	15.806°	89.999°	-120.091°

Table 6
Real-time data sent by the controller

J1Angles	J2Angles	J3Angles	J4Angles	J5Angles	J6Angles
30.156°	6.638°	-112.354°	15.798°	89.964°	-120.079°
30.156°	6.638°	-112.354°	15.798°	89.964°	-120.079°
30.156°	6.638°	-112.354°	15.798°	89.964°	-120.079°
30.156°	6.638°	-112.354°	15.798°	89.964°	-120.079°
30.156°	6.638°	-112.354°	15.798°	89.964°	-120.079°
30.156°	6.638°	-112.354°	15.798°	89.964°	-120.079°

The above data was inputted into the formula for mean absolute percentage error, and the calculated error between the replicated state and the actual operating state was only 0.1465%, demonstrating the reliability and accuracy of the data.

$$\mathrm{S_R} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\mathrm{V}_{\mathrm{J}i}-\mathrm{P}_{\mathrm{J}i}}{\mathrm{P}_{\mathrm{J}i}}\right| = 0.1465\% \tag{7}$$

where $\mathrm{S_R}$ denotes the average absolute percentage error between the historical data and the actual run data. $\mathrm{V_{Ji}}$ (i= 1,2,3,4,5,6) is the joint angle of the historical data $\mathrm{P_{Ji}}$ (i= 1,2,3,4,5,6) is the joint angle of the actual run data.

5. Conclusion

This paper describes a novel approach to building a smart factory virtual monitoring system using digital twin technology, which offers several scientific and practical innovations. The proposed system architecture consists of five dimensions, with detailed explanations of the digital twin system components. The use of UE4 to construct the virtual scene provides a more realistic environment than previous virtual monitoring systems, enhancing the accuracy and precision of monitoring operations. The system facilitates real-time data mapping between the physical and virtual space, enabling the monitoring of industrial robot assembly line operations in the virtual environment, which is a significant advancement in digital twin technology. The use of MySQL for storing historical data allows for the reproduction of historical motion states, enabling users to analyze past performance and optimize future processes. Overall, the proposed system offers an innovative solution for monitoring and managing smart factories, improving efficiency, and enhancing overall production processes. The system's advanced features, such as real-time data mapping, digital twinning, and historical data reproduction, provide users with valuable insights into the factory's operations, enabling them to make data-driven decisions and optimize processes, thereby enhancing the practical value of the system.

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