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ORIGINAL RESEARCH

An application framework of digital twin and its case study

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Abstract
With the rapid development of virtual technology and data acquisition technology, digital twin (DT) technology was proposed and gradually become one of the key research directions of intelligent manufacturing. However, the research of DT for product life cycle management is still in the theoretical stage, the application framework and application methods are not clear, and the lack of referable application cases is also a problem. In this paper, the related research and application of DT technology are systematically studied. Then the concept and characteristics of DT are interpreted from both broad sense and narrow sense. On this basis, an application framework of DT for product lifecycle management is proposed. In physical space, the total-elements information perception technology of production is discussed in detail. In the information processing layer, three main function modules, including data storage, data processing and data mapping, are constructed. In virtual space, this paper describes the implementation process of full parametric virtual modeling and the construction idea for DT application subsystems. At last, a DT case of a welding production line is built and studied. Meanwhile, the implementation scheme, application process and effect of this case are detail described to provide reference for enterprises.

Keywords Digital twin · CPS · Digital twin system · Application framework

1 Introduction

The manufacturing industry in China is facing huge of competition pressure, with the development of science technique and the economic. The manufacturing mode, manufacturing process and manufacturing approach are undergoing significant changes. Product manufacturing has experienced the large-scale automatic manufacturing mode and digital manufacturing mode, and is now gradually transforming to the manufacturing mode of *Integration of informatization and industrialization*. With the development of advanced mechanical technology, electrical technology and information technology (Damm 2017), especially the rapid development of virtual simulation technology and data acquisition technology as well as the digital factory, digital twin (DT) was emerged and developed.

Although the research and application of DT spring up continuously, the systematic research on DT is rare and many issues are to be explored. First, the concept and content of digital twins are lack of accurate, unified definition and description. On the one hand DT was considered as an object (Grieves 2014; Haupert et al. 2017a, b), including a set of virtual information model and data. And on the other hand it was considered as a technology or means (Tuegel et al. 2011; Tao et al. 2017a, b, c; Zhuang et al. 2017; Reifsnider and Majumdar 2013), such as simulation method. Second, many technologies such as cyber physical systems (CPS) and digital shadow have been proposed and DT has relevance with these concepts. The confusion caused by these concepts will hinder the development of DT. It is necessary to study the relationship between them. Finally, DT application is still in its infancy. For one thing it is more applied in product design, operation and maintenance phase, but less in production and testing. Especially it lacks a complete application framework and reference solutions.

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2 The concept, characteristics and literature review of digital twin

Based on the current research, this section explains the DT concept and characteristics from narrow sense and broad sense. The relationship between DT and other concepts is analyzed. Then the application status of DT is reviewed.

2.1 The concept, characteristics of digital twin

Glaessgen and Stargel (2012), Grieves (2014), Tao et al. (2017a, b, c) and Zhuang et al. (2017) all have a unique understanding or definition of DT. Although the understanding or definitions are different, they all integrated the idea of product lifecycle management (PLM) into DT.

2.1.1 Digital twin in the narrow sense

In a narrow sense, the DT is a set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level. At its optimum, any information that could be inspected from a physical manufactured product can be obtained from its DT (Grieves and Vickers 2017). The concept came from the idea of twin, which limits the DT to the set of virtual information that corresponds to physical products. So the technology to build DT is also known as DT technology (Zhuang et al. 2017). The meaning of DT in the narrow sense is equivalent to that of the digital shadow proposed by European academic institutions. It has the characteristics of virtual, dynamic, polyphysical, multi-scale, integrative, computability and ultra-realistic (Zhuang et al. 2017). In the narrow sense, the DT will visualize the product data with extremely high degree of quasi-reality according to the physical world throughout the product life cycle, especially in the design, production, operation and maintenance.

In short, DT in the narrow sense solves the problem of "how to simulate the physical products realistically".

2.1.2 Digital twin in the broad sense

In a broad sense, DT is an integrated system that can simulate, monitor, calculate, regulate, and control the system status and process. It has the characteristics of individualization, high efficiency and highly quasi-real. In addition, DT is developed by data acquisition, virtual manufacturing technologies, based on the control, computation and communication units.

There are three main components in the DT system, the physical space, the digital space and the information processing layer that connects two spaces. The system has the characteristics of data-driven, intelligent perception, virtual-reality mapping (Tao et al. 2017a, b, c) and cooperation interactive.

In the industrial applications, compared to the traditional manufacturing system, DT in the broad sense has a large number of distributed computing devices, more complete data system, more perfect data acquisition and transmission system, and more extensive product tracing and control network. It can realize the systematic, comprehensive and real-time control of logistics, capital flow and information flow, effectively coordinate and optimize all business activities within the system.

Conceptually, the DT in the broad sense is a kind of CPS, they both realize the fusion of virtual space and physical space. However, in the comparison, the DT system focuses more on data and models with ultra-high fidelity simulations, which is one of its notable features. DT is a new paradigm of future information system. In the future, MES, SACADA and PLM maybe developed into a new pattern with DT as its kernel, and those systems become DT application subsystems (DTs).

In conclusion, the concept of DT has two senses, broad sense and narrow sense. The DT in the broad sense belongs to the CPS but has a higher fidelity degree. The DT in the narrow sense is part of the DT system that describes physical products and is equivalent to the digital shadow.

2.2 The application status of digital twin

Social, individual, intelligent, service-oriented (Tao et al. 2017a, b, c), green and other manufacturing characteristics have become the development requirements and trends of future manufacturing industry. Therefore, realizing the interaction between human, machine, objects and environment in simulation model and manufacturing process have gradually become vital for manufacturing system. And the DT is one of the best ways to realize the communication and interaction between physical space and virtual space (Grieves 2014). It is also a possible direction for future manufacturing workshops, and it will raise the next wave of simulation, modeling and optimization (Rosen et al. 2015). Moreover, DT is not only a complete model of physical products, but also a data interconnection system for physical products and virtual models.

It can meet the prospective demand of product management throughout the lifecycle, so that product design, manufacturing, service and other product lifecycle activities can be carried out efficiently (Boschert and Rosen 2016). Especially in the stage of product manufacturing and service (Tao et al. 2017a, b, c), DT technology can realize real-time monitoring and accurate prediction of products performance, and ensure the consistency of product specifications and requirements. Therefore, it is necessary to study the application of DT system.

In product design phase, NASA and US Air Force apply the DT technology in vehicles development, so they can predict the future performance and status of vehicles by constructing ultra-high fidelity simulation models with the parameters of material properties and Manufacturing defects (Glaessgen and Stargel 2012). Siano et al. (2013) proposed DSEMS to describe the designing method and testing method for presenting its simulation results and verify its effectiveness. And many companies (eg., Autodesk, Siemens) are also interested to use the DT technology to provide a general guidance for the future design (Stackpole 2015).

In process design phase, DT is used to optimize tolerances, locator positions, clamping strategies, welding sequence, etc. to obtain good geometrical quality in the final product (Söderberg et al. 2017).

In product manufacturing phase, PTC aims to achieve real-time interconnection between physical products and virtual models to enhance the flexibility and competitiveness of manufacturing system (Pardo 2015). And cyber-physical system is proposed to optimize energy efficient machining process (Li et al. 2018). With the virtual factory technology, a framework of simulation-based approach is proposed to guide simulation-based plant design and evaluation, optimize plant layout and the production process (Zhang et al. 2018).

In product operation and maintenance phase, the US Air Force Research Laboratory applies the DT to predict aircraft structural life to improve its safety and reliability (Tuegel et al. 2011). Tesla is working on developing a DT for every car it produces, allowing for synchronous data transmission between cars and its factory (Schleich et al. 2017). Li et al. (2017) use the concept of a dynamic Bayesian network to build a versatile probabilistic model for diagnosis and prognosis in order to realize the DT vision to fulfill airframe health monitoring. On the basis of the Gaussian–Bernoulli deep Boltzmann machine (GDBM), Wang et al. (2018) discuss a deep neural network model to optimize the condition prognosis and to predict the future degradation status and remaining service life of a machine.

Besides, Canedo (2016) present a new vision on the industrial IoT lifecycle management and optimization at scale via DT. Rodič (2017) shows a new simulation modelling paradigm by using development of DT based on the widely available sensor technologies. Schleich et al. (2017) propose a comprehensive reference model based on the concept of skin model shapes to describe model conceptualization, representation, and implementation as well as applications along the product life-cycle. Alam and El Saddik (2017) present a DT architecture reference model for the cloud-based CPS to identify various degrees of basic and hybrid computation-interaction modes.

Literature review and application cases related to DT indicated that current research and application of DT is still in its initial phase. It is still difficult to use the DT technology to realize synchronous fusion of virtual and physical space in the process of product manufacturing and service. Because multi-scale high-precision simulation model and virtual test model are deficient, the model uncertainties quantitative technology is insufficient, predictive precision of sophisticated systems is low, and data acquisition and processing is still difficult. In addition, for industry a complete application framework is also needed to solve the problem at the system level.

3 Application framework of digital twin

Application framework of DT for product lifecycle management consists of three parts, physical space, virtual space and information-processing layer. In the application process, the DT technology can realize the full-physical system mapping, the life-cycle dynamic modeling and the whole process real-time optimization. The bidirectional mapping and interoperability of physical space and virtual space are realized through data interaction. Intelligent decision is realized through iterative optimization and regulatory interaction between two spaces. The application framework of DT is shown in Fig. 1.

3.1 Physical space

The physical space is a complex, diverse and dynamic production environment, which consists of people, machines, material, rules and environment. Resources layer includes all kinds of objects related to product development and manufacturing, such as production resources (production line equipment, etc.), product data resources, computing resources (high-performance computing clusters, etc.) and software resources. All kinds of objects are separated and distributed in different places, and they are needed to be connected by IOT technology. Then the data of physical world will be collected, integrated and used for optimization.

Taking manufacturing workshop as an example, intelligent sensor and communication equipment are used to collect and transmit multi-source heterogeneous data, including equipment attributes, status, process, fault, disturbance, etc. These data will be collected by digital devices and transferred to the network. In addition, according to the feedback instructions from virtual space, related physical devices will also make timely intelligent reaction. The mapping (direct mapping and indirect mapping) between data and device

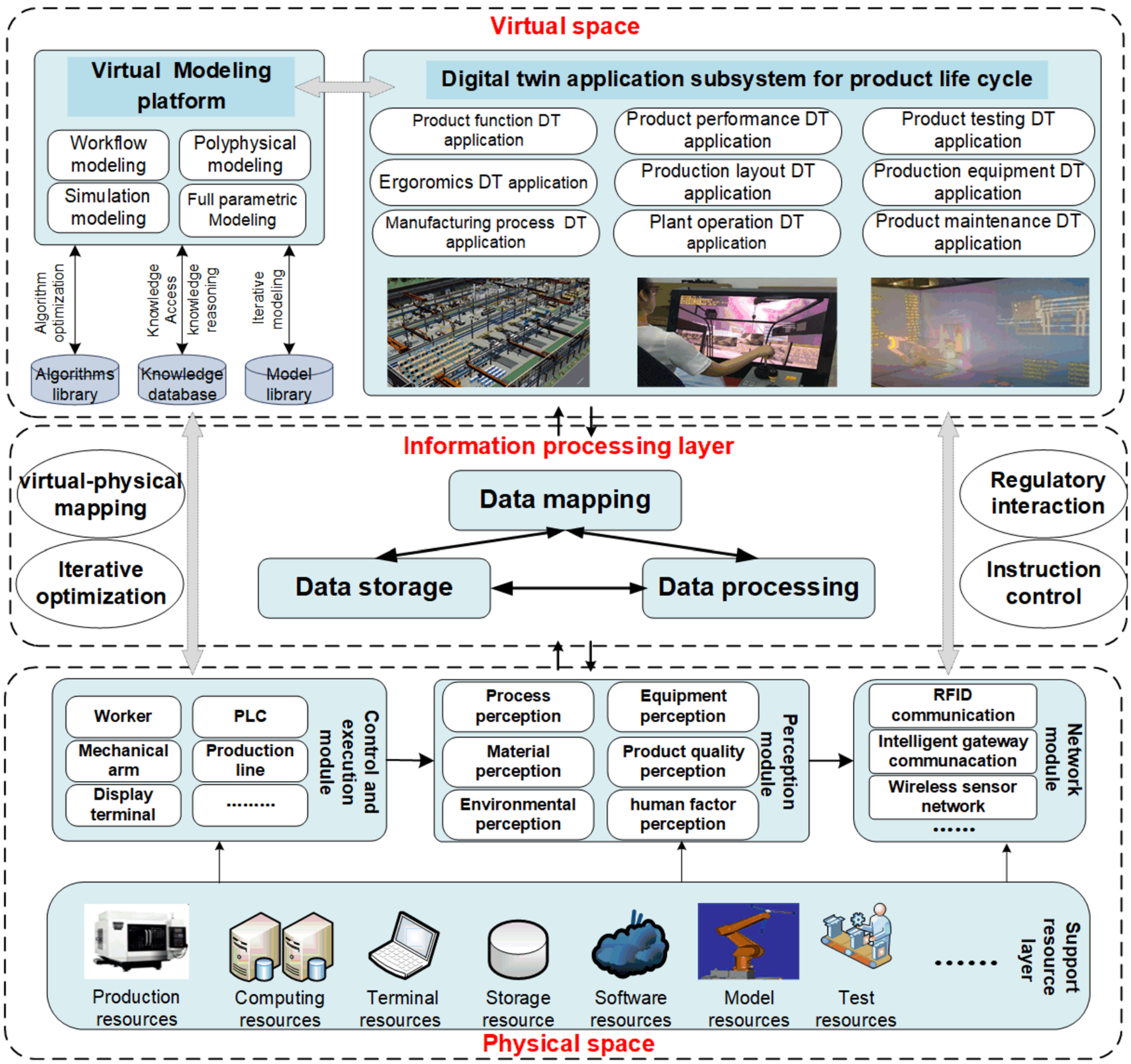

Fig. 1 Application framework of digital twin technology

attributes makes the interaction between the physical and the digital space possible.

At the implementation level, the core of physical space construction is mainly the total-elements information perception of physical production.

As shown in Fig. 2, the total-elements information perception technology of physical production mainly includes four levels, the physical layer, the technology layer, the data layer and the system layer. The perceived objects of the manufacturing process include the manufacturing status of parts, environment, logistics, equipment, and labors. Taking manufacturing process flow and control flow as the main line, perception includes status perception, location perception and manufacturing quality perception. Through the barcode or QR code, RFID, IPC, positioning system, PLC and sensors, various status information will be accessed in real-time. The real-time status data has to be integrated with information management system, such as PDM, ERP, and MES. In addition, the mapping relationship between data and device attributes has to be established for the total-elements perception.

3.2 Information processing layer

The information processing layer is the channel connecting physical space and virtual space, the bidirectional mapping and interoperation of physical space and virtual space are realized through the data interaction in this layer. There are three main function modules of this layer, data storage, data processing and data mapping (Fig. 3).

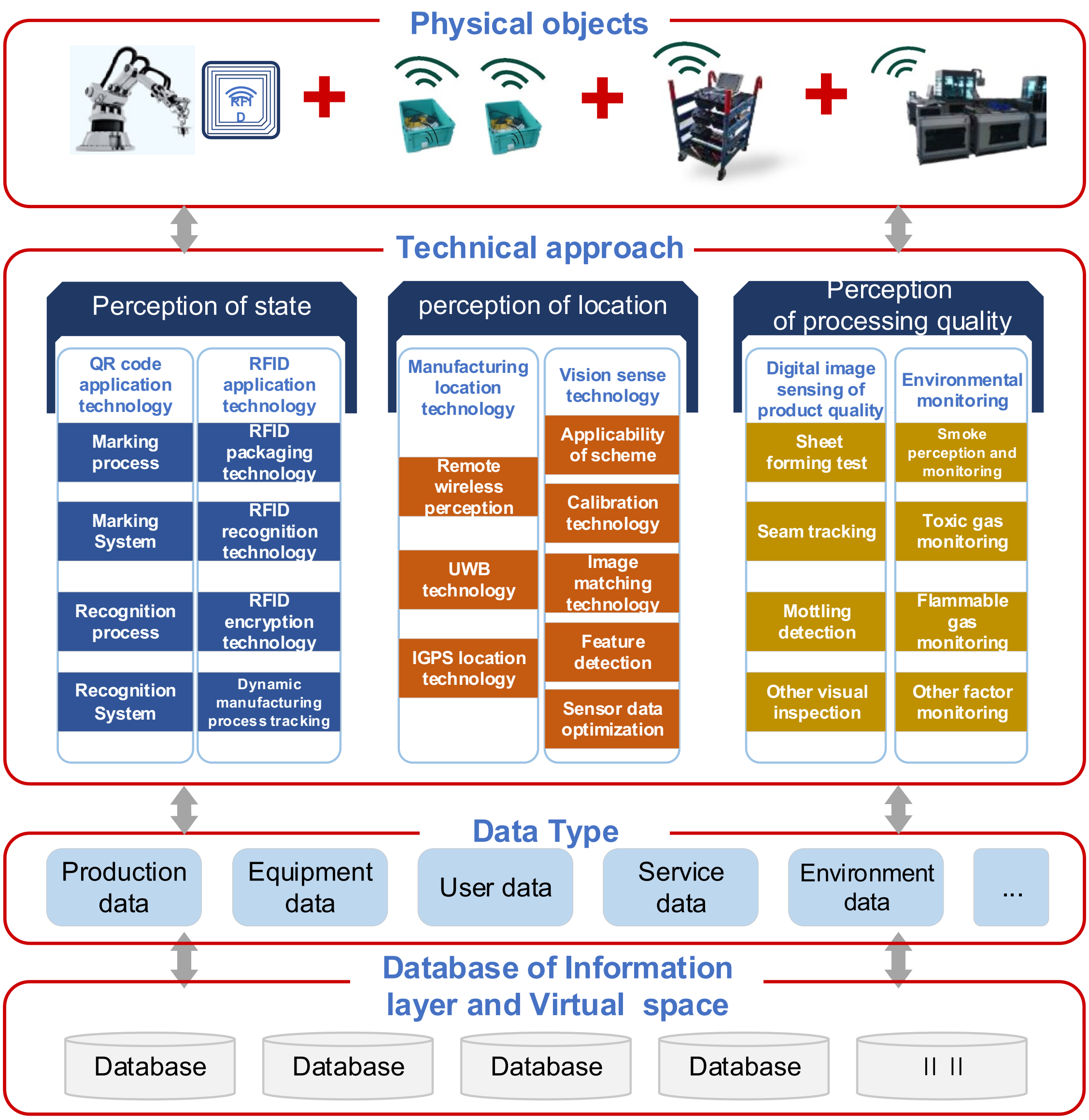

Fig. 2 Total-elements information perception frame for workshop

3.2.1 Data storage

The data that needs to be stored in this layer mainly consists of two parts, data from physical space and data from virtual space.

The data from physical space mainly includes production data, equipment data, material data, labor data, service data, workshop environment data, etc. The data from virtual space mainly includes simulation data, evaluation and prediction data and decision data.

3.2.2 Data processing

Data processing in this layer consists of four steps: data acquisition, data preprocessing, data analysis and mining, and data fusion. Data source includes the different database of MIS, PLCs, and manufacturing systems. The raw data is collected by ODBC interface and other technologies. Then sets of raw data are preprocessed, and the procedure mainly includes the rule-based data cleaning, data structuring, and primary clustering (Zhang et al. 2016). Thus, the noise in

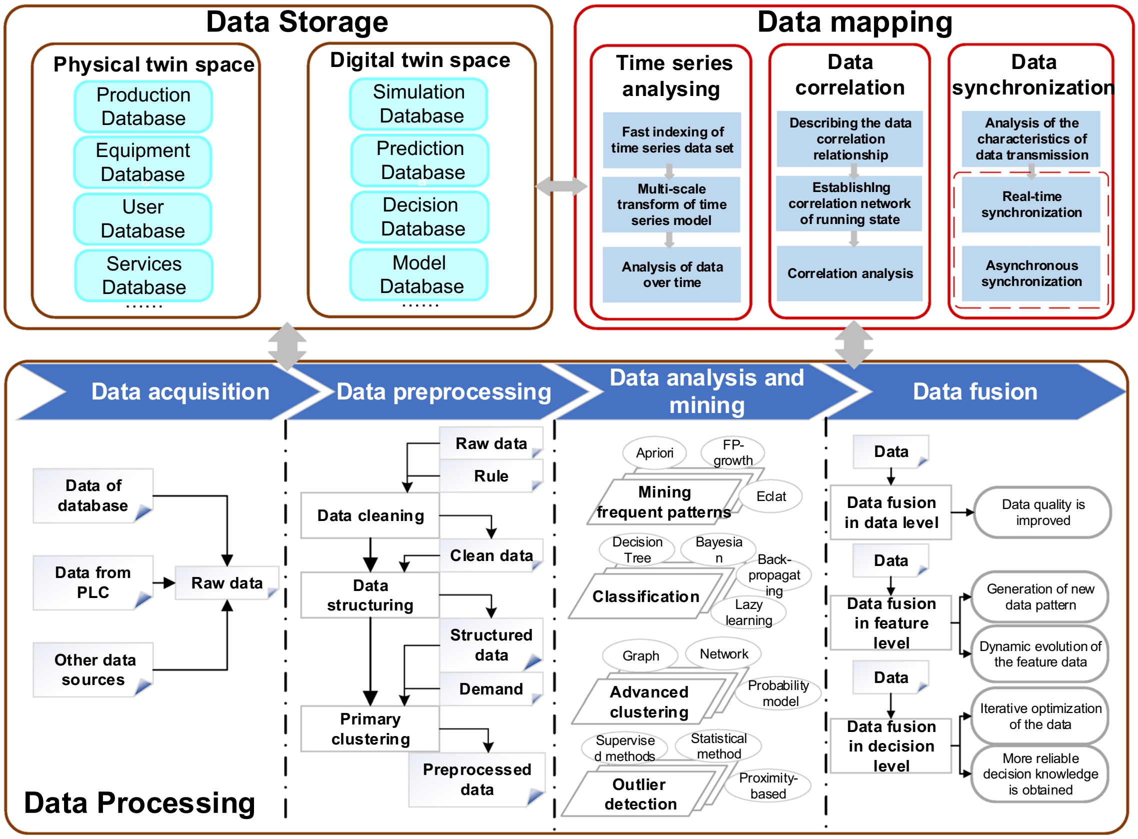

Fig. 3 Information processing layer

raw data is eliminated, and the accuracy, completeness and consistency of data are improved. Then sets of clean data are analyzed and mined. The normal procedures of target oriented data analysis include frequent patterns mining, classification, advanced clustering, and outlier detection. On the basis of data acquisition, preprocessing, analysis and mining, multi-level data fusion from feature level and decision level is possible. Thus, the quality and dimensions of data are improved.

3.2.3 Data mapping

Data mapping supports the synchronous mapping of physical data and virtual workshop operation based on the data storage module and data processing module. It mainly including three parts, data time-sequence analysis, data correlation and data synchronization.

The core of data time-sequence analysis is the mining algorithm with sequence mode. According to the characteristics of the data, a time-sequence data model is built for the multidimensional and heterogeneous data, to reveal the evolution rules of manufacturing data. There are three key points in this phase, fast index of data sequence set, multi-scale transforming of time-sequence model, and time-varying regularity analysis.

Data correlation is realized by using complex network and data mining algorithm. Through the definition of data relation, and correlation rules of different data from the physical and virtual objects, the workshop data network is built for the workshop status analysis and he mapping between the physical and virtual DT system.

There are two modes for data synchronization, real-time synchronization and no real-time asynchronous. The core of the real-time synchronization is to connect simulation model controller with the physical PLC controller, and the controller can be verified by the virtual test system. In no-real-time asynchronous data transition, the intermediate database is used as temporary storage in data transmit to the virtual space.

3.3 Virtual space

3.3.1 Working mechanism of virtual space

The virtual space consists of two parts, the virtual environment platform (VMP) and the DT application subsystem (DTs) for product lifecycle management. The VMP is built to establish a unified 3D virtual model for application and to provide an operating environment for algorithms library. There are interactions between VMP and DTs. VMP provides various virtual models for DTs, including polyphysical model, workflow model, simulation model, etc. DTs accumulates various models, methods and historical data that are created during the operation into VMP. In virtual space, the modeling of physical objects is available by obtaining the attributes of the virtual model from the database, and the feedback of 3D models will be stored in the database by using corresponding interfaces. In the DT system, the real-time and historical data of 3D virtual models and physical products are combined to drive the DTs running synchronously. Meanwhile, the DT, as the real mapping of physical entities, can not only realize the visualization of products, but also realize the simulation of complex systems. When conflicts and disturbances occur in physical space, virtual models can be tested in real time or even predict them, and feed the information back to the physical space.

Take the workshop as an example, the construction of virtual space mainly includes the modeling of full parametric virtual workshop and the construction of DT application subsystems.

3.3.2 Full parametric virtual modeling of workshop

On the base of physical workshop prototype, the high precision digital simulation models of all kinds of equipment, labors, fixtures, tools, products and other workshop elements are established. And based on UML and other information modeling methods, the mapping information model for total-elements of workshop is established. Then, the information model and the simulation model are integrated and correlated, to synchronize the operation information of the workshop, and to provide a basic environment for the 3D simulation of workshop status.

The implementation process of full parametric virtual modeling includes four steps: analysis of a specific workshop system, construction of the information model, construction of the simulation model and the fusion of models, as shown in the Fig. 4.

1. Analysis of a specific workshop system

Based on multidimensional analysis of the composition of the workshop, the workshop system can be decomposed into several subsystems including workshop physical layout, material inventory, production quality, equipment maintenance and other subsystems. On this basis, the information of modeling objects, such as internal equipment, labor and materials, is analyzed and the properties of each object and their relation are determined.

2. Construction of the information model

First, the meta-models of physical objects are established by analyzing the data structure of entity object and its relation. According to the full parametric modeling method, the expression of all kinds of information involved in the model is defined to ensure the completion of meta-models. Then the consistency check of the sub-model of the same layer is implemented. And the horizontal integration of the same hierarchical model is established. Meanwhile, the low-level sub-models are integrated into the high-level domain information model. As a result, the global information model is implemented.

3. Construction of the simulation model

The key to construct the simulation model is to define the behavior logic for physical objects. Take the workshop DT as an example, the entity status, activities and events that causes physical changes are defined. Then, the behavior logic of entity models is built by taking process flow and other processes as the main line.

4. Fusion of models

The full parametric information models and the high accurate simulation models should be integrated to ensure the correct relationship of multi-level dimensions. The accuracy and consistency of the final model should be checked.

3.3.3 Construction of digital twin application subsystems

Based on the requirements and application targets, the DT application subsystems for product life cycle are built with knowledge fusion, data management, algorithm optimization, status evaluation and prediction, plan and instruction release and other functions. They can realize product function analysis, product performance prediction, product testing, ergonomics analysis, production layout planning, equipment status prediction, process implementation analysis, plant operation optimization, and product maintenance prediction, etc.

4 Case study

4.1 Background

In order to improve product quality and production efficiency, a DT system of welding production line using the DT technology was built, based on the physical production line of an equipment factory.

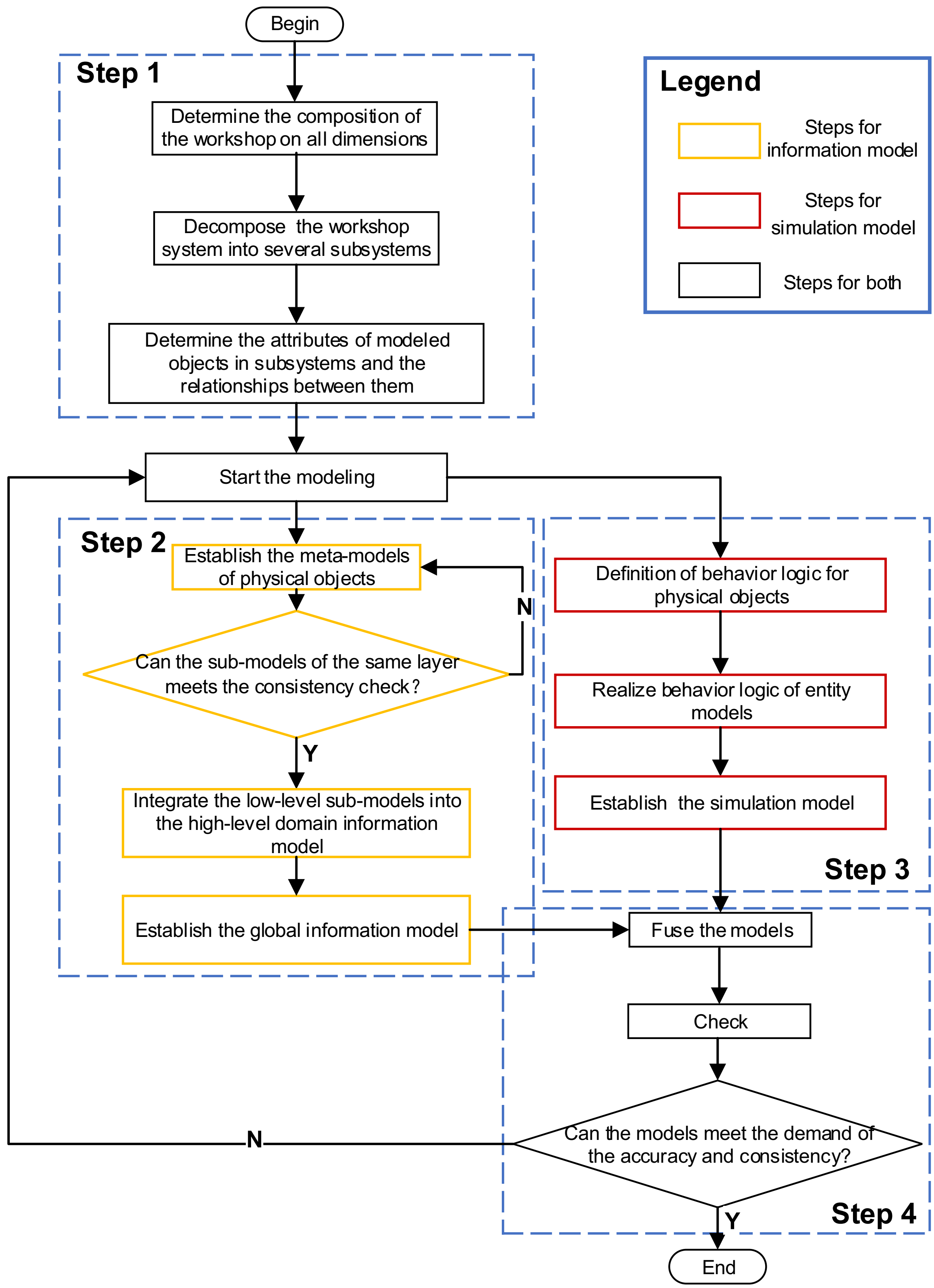

Fig. 4 The implementation process of full parametric virtual modeling

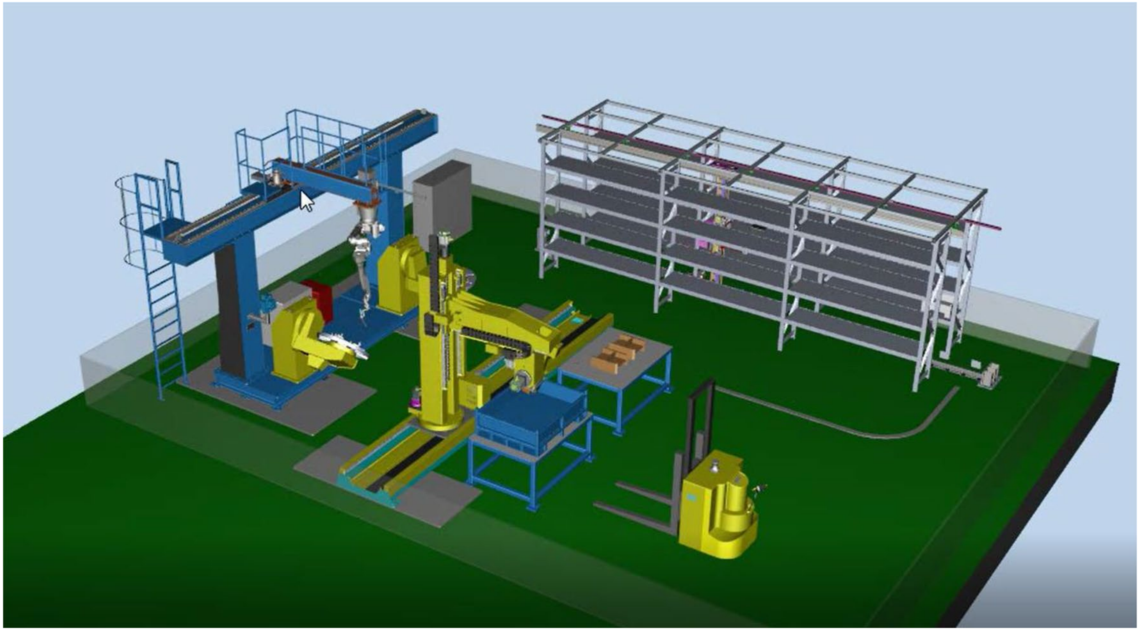

Fig. 5 3D model of welding production line

The virtual model of the welding production line was built and real-time data of production line monitoring was collected to achieve the mapping and interaction between real-time data and models. Therefore, it can form the real-time interaction between the physical welding production line and the virtual welding production line consistently. Based on that, the operation time and the production cycle of each station are analyzed, and the real-time status warning during the production process is realized. Figure 5 shows the virtual model of the welding production line of the factory, from left to right, there are the welding machine for weld assembly, the transporter for the delivery of finished parts and the multi-layered warehouse for the storage of the finished parts.

4.2 Modeling of the welding production line

The DT model of welding production line contains 3D geometric model, physical model and kinematic model. The geometric model uses lightweight triangular mesh data to describe the shape and size of the device. The physical model defines the mechanical state and thermodynamic state of the device in parametric data. The kinematics model defines kinematic pairs of devices for describing connection between the components of the device. Correspondingly, monitoring data is divided into physical data and motion data. The physical data corresponds to the specific parameters of the physical model. When the physical data received, the system directly displays the data and records the data in the database for the historical data analysis and optimization. The kinematic data corresponds to the specific parameters of the kinematic model. When the kinematics data received, the system sends the data to corresponding device, updates all components positions in the device by kinematic pairs. Finally, geometric model of each device is updated in 3D scene to realize the real-time 3D monitoring process.

4.3 Information perception and data acquisition

The objects of data acquisition are mainly industrial robots on the production line. The industrial robot has multi-DOF and pretty high speed of movement. Its driving components

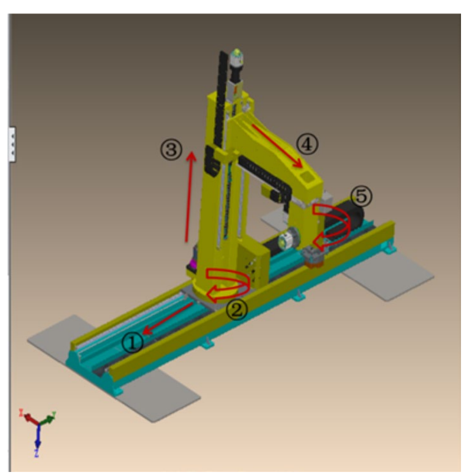

Fig. 6 Analysis of kinematic pair

are mostly installed on the mobile frame, such as the arm and the turntable. In order to drive digital model in virtual environment in real time, it not only needs to obtain real-time status data of equipment in physical space, but also needs to pre-define the information of motion pair of 3D model. As shown in Fig. 6, there are three prismatic pairs and two revolution joints in the carrier robot.

The key data collected in this case are as follows:

The device data is described in OPC protocol specification on an OPCUA (OPC Unified Architecture) server which provides data services. Robots are connected to the server to collect the monitoring data in the unified description method. When the 3D monitoring system turns on the monitoring mode, a connection is established between the system and OPCUA server. All monitoring data points in the current monitoring project are read and send to the OPCUA server as a subscription data list. After that, an independent monitoring thread is started to receive the real-time monitoring binary data list sent by the OPCUA server in blocking mode. Received data is parsed and put into the monitoring data buffer. When the virtual scene is updated, the monitoring data is taken out from the data buffer and send to the corresponding device (Table 1).

In the process, taking advantage of interface data to acquire the key data mentioned above, OPCUA and Socket communication mode are mainly adopted. Wide area network (WAN) adopts OPCUA communication mode, which has high reliability and safety, while local area network (LAN) adopts Socket communication mode to ensure better transmission efficiency (Figs. 7, 8).

Table 1 The key data of welding production line

Equipment	Data types	Count
Welding machine	Translation of mechanical arm	6
Welding machine	Rotation of mechanical arm	3
Welding machine	Rotation of welding table	2
Transporter	Rotation of mechanical arm	2
Transporter	Translation of mechanical arm	3
Multi-layered storehouse	Translation	3
	Total	19

4.4 Process of data real-time mapping

After the objects and the methods of data acquisition are ascertained, the workflow of real-time data mapping is determined. It includes two steps, the first is using our own 3Dlayout to build the virtual environment according to the realistic physical model, and the other is DT application system development based on OPCUA, which can fulfill real-time virtual-physical mapping. 3Dlayout is used to generate the virtual simulation environment of welding production line and generate the file of scene layout for DT application system. The DT application system in this case is mainly used in the realization of the real-time mapping between physical production line and the virtual production line. Then the monitoring and status warning of the production process are realized based on the real-time visualization of physical state data.

The key technologies demanded for the application case are lightweight of 3D models, dynamic scheduling of

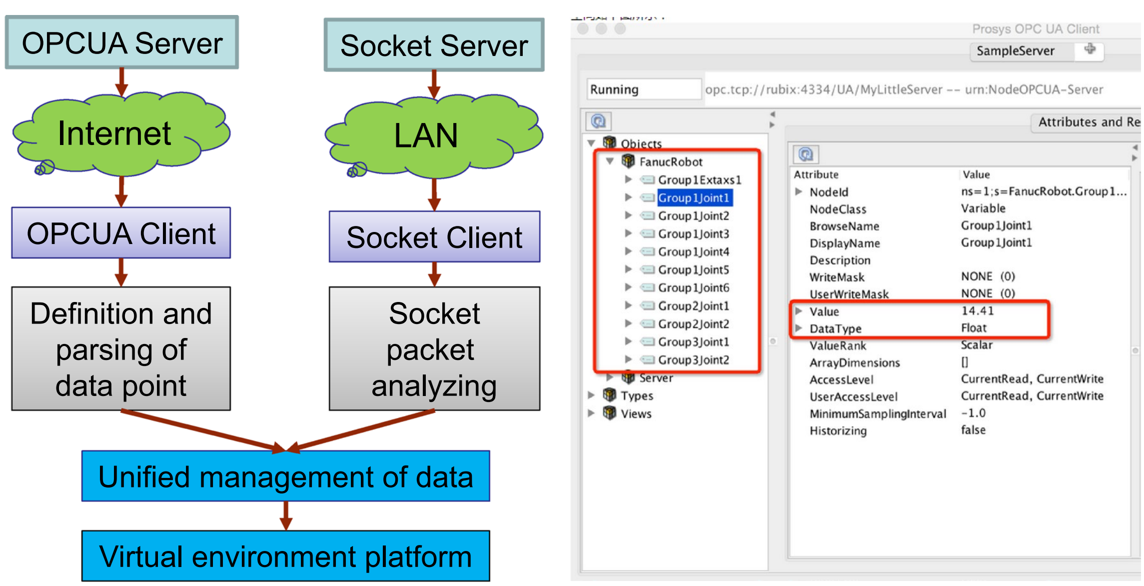

Fig. 7 The development of communication interface

Fig. 8 The process of data real-time mapping

models, layout real-time visualization, etc. And the process involves simplification of triangular mesh model, model smoothing, data real-time exchanging and algorithms In the process of real-time mapping, data, algorithms, models and knowledge are accessed and called via corresponding library, and the mapping results are sent to the interface database finally.

4.5 Application effect

The synchronous operation of virtual manufacturing system is driven by the correlation and integration of physical model and 3D virtual model of the welding production line. Then remote, real-time, visual monitoring of the physical production process is realized. The manufacturing status of the equipment is transparent, the reliability of the operating equipment is interpretable, and the warning for the abnormal state is timely, to ensure reasonable machining process by acquiring and processing the equipment status data and comparing it with standard.

As shown in Figs. 9 and 10, the system can show 19 types of key data of the production line in real time and make sure the delay for real-time online simulation is no more than 1 s. At the same time, the real-time update rate of 4 million piece

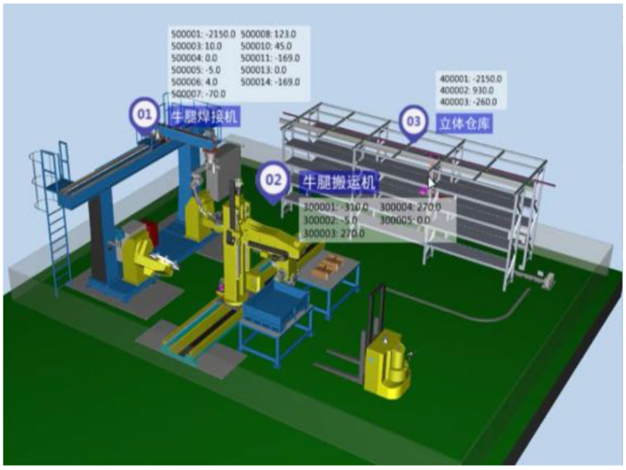

Fig. 9 Data real-time mapping

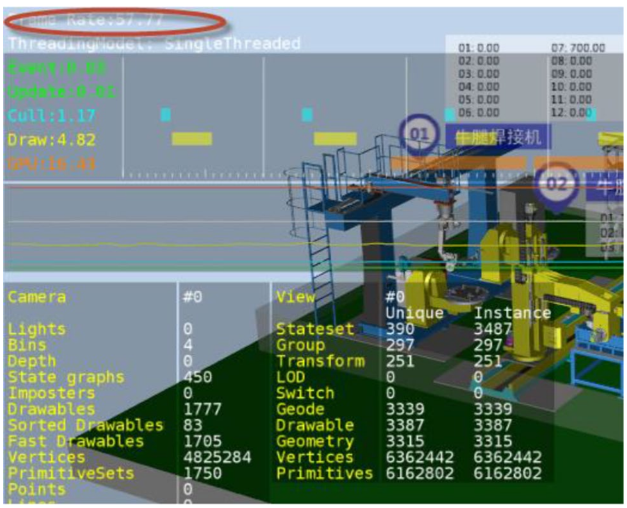

Fig. 10 Data real-time update

models is stable at more than 50 times per second. And this DT system is able to ensure operation efficiency of equipment in production line, as well as provides data for welding quality of product.

5 Conclusion

Digital twin technology is the key technology to realize the fusion of physical models and virtual models, a typical system of cyber physical system for application. This paper proposes both broad sense and narrow sense definition of DT technology after analyses DT related essay and application in detail at home and abroad, ascertaining the relationship between the related concepts. Meanwhile, the application framework and model of DT for product lifecycle management is discussed, which includes physical twin space for total-elements information perception, information processing space for synchronous and asynchronous coupled mapping, and all parameterized DT space. And the total-elements information perception and real-time data acquisition method are discussed. Three functional module structures of information processing layer are given, which are data storage, and data processing and data mapping. Full-parametric virtual modeling and construction flow of DT are also included. Finally, in order to provide references for enterprises, a case of DT system for real-time monitoring is built based on a welding production line.

The application framework of DT technology is given in this paper. In the future, combined with specific application targets and scenarios, further research includes application mode of DT, mapping methods between physical space and digital space, and data synchronization.

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