Research on Digital Twin Modeling Method of Electrical Equipment Spraying Production Line Based on Kalman Filter

Ke-Xin Yang, Zhi-Wen Xia, Yi-Fei Wang, and Li-Jun Jin
College of Electric and Information Engineering, Tongji University, Shanghai, China
Email: {1930679, 1932901, 1552442, jinlj}@tongji.edu.cn

***Abstract*—Digital twins can promote the upgrade of enterprise products through predictive analysis of production lines, operation optimization and intelligent regulation. Based on an improved adaptive filter algorithm, this paper introduces filter convergence criteria on the basis of Sage-Husa filter, which can suppress filter divergence, improve filter accuracy and stability, and propose a digital twin modeling of electrical equipment spraying production line Methods, a unified logical structure of the intelligent spraying production line is constructed, and its twin model is uniformly described, and the digital expression of the physical production line, the acquisition of characteristic data, and the fusion processing analysis are realized. Finally, the application scenarios and actual cases of the digital twin model of the intelligent production line are analyzed, which provides a solution for the realization of the digital twin of the enterprise production line.**

***Index Terms*—digital twin, production process, twin model, model architecture, Sage Husa algorithm**

I. Introduction

Nowadays, the demand for intelligent production of enterprises is higher and higher. Higher standards are put forward in TQCSE (time, quality, cost, service and environment). Digital representation of physical entity production process and the integration of manufacturing physical space and information space are the core problems of intelligent manufacturing. Digital twin is an effective way to solve this problem. Nowadays, digital twin technology has been widely studied and applied in many fields, such as production process, equipment operation and maintenance, modeling and communication.

Digital twin is a virtual entity that creates physical entities in a digital way. By means of historical data, real-time data and algorithm models, it can continuously improve production efficiency, minimize failure rate, shorten development cycle and realize the whole life cycle management of enterprise production, All aspects of situation awareness, and the immersive experience of the whole scene. At the theoretical level, Tao Fei puts forward the concept of digital twin workshop, and studies the key scientific problems of the Information Physics fusion in the workshop [1]. Baojinsong and others have studied the digital definition of product and process information, and the digital twin modeling of resources. In technical aspect, greyce proposes a digital modeling method and a general data interaction method based on AML [2]; Delbruger proposes a framework of virtual factory space location and navigation based on information model, which solves the problem of human and robot motion path in virtual factory [3].

Sage Husa adaptive filtering algorithm can filter the observation data recursively [4]. At the same time, the statistical characteristics of system noise and observation noise can be estimated and corrected in real time by time-varying noise statistical estimator, so as to restrain the filtering divergence and improve the filtering accuracy [5].

The above research has laid a theoretical and technical foundation for the application of digital twin in production line, but there is still a lack of systematic solutions for twin model construction, twin data acquisition and data fusion processing. Therefore, in order to realize the digital twin of the production process and optimize the production process, based on SAGE Husa adaptive filtering algorithm, this paper puts forward the construction method of the digital twin model of the production line, studies the production scheduling scheme of multi-objective optimization, and verifies it through an example [6].

II. Digital Twin System Architecture of Production Line

The production line has multiple elements and processes. Based on the five dimensional structure of digital twin, the digital twin system of production process is shown in Fig. 1.

Physical entity layer is the actual production line, including production equipment, energy information and scheduling, inspection information, etc.; The twin model layer is composed of twin data and virtual model, in which the virtual model is the mapping of the object entity of the production line, and the twin data is generated by the entity of the production line to realize the virtual mapping, real-time interaction, decision analysis and other functions of production activities in the digital space; Through the real-time mapping of twin model in the digital space, the functional application layer

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realizes all aspects of three-dimensional real-time monitoring and visual display, fusion analysis of twin data in the interactive process, and realizes the intelligent production management and control of the production line, and iterative optimization of production, scheduling and decision-making [7].

The access, data type analysis and format of multi-type devices are not unified. Currently, the commonly used multi-source data acquisition technology is OPC-UA. The real-time mapping of production operation realizes the functions of multi equipment action drive, work piece position change, fault warning and scheduling planning through real-time data.

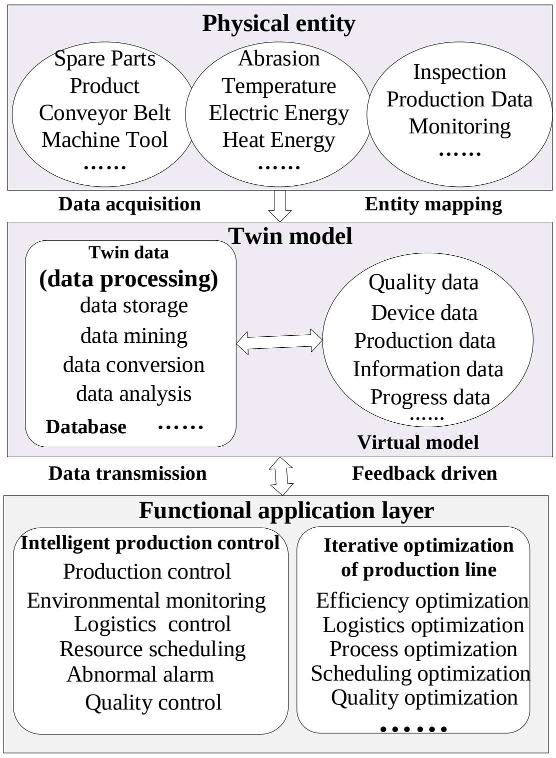

Figure 1. Architecture of production process digital twin system.

III. MODELING AND IMPLEMENTATION OF MULTI FACTOR DIGITAL TWIN IN PRODUCTION PROCESS

A. Twin Modeling of Multi Factors in Production Process

In the manufacturing process, multi factors mainly include materials, equipment, personnel and production environment. Therefore, the digital twin model of production process can be described as follows:

$$DT_{UV}=\left\{DT_{eq},DT_{pr},DT_{pe},DT_{en}\right\} \tag{1}$$

where: DT_{UV} is the digital twin model of production line, DT_{eq} is the equipment twin model, DT_{pr} is the product twin model, DT_{pe} is the personnel twin model, and DT_{en} is the environment twin model.

Production line equipment is responsible for processing, transportation and storage of products and materials, such as industrial robots, special processing equipment, AGV, etc. in order to complete the real mapping of twin model to physical entity, the model must first ensure that the three-dimensional size, behavior and entity height are consistent. At the same time, in order to obtain real-time data, the twin model needs to establish virtual real communication control interface; In order to complete its behavior, it is necessary to define related virtual services. Therefore, the definition of equipment digital twin model is as follows:

$$DT_{eq}=\left\{FM,VR,CI,VS\right\} \tag{2}$$

where:

(1) FM (Functional Model): According to the physical equipment, the corresponding function twin model is established to ensure the consistency of geometric size, physical structure relationship and motion characteristics.

(2) VRCI (VR Communication Interface): In order to realize data interaction and real-time data driving between models, twin model should establish communication signal interface based on running driving data. PLC, PFID and HTTP interface are used to communicate with entities in real time.

(3) VS (Virtual Service): The organic connection and operation of functional model need the support of various virtual services. It includes the realization of equipment function, signal processing, guidance of model behavior, constraints of operation rules, etc [8].

For products/components, in different process stages, products have different geometric shapes, accompanied by order, coding, quality and other life cycle information; The information can be stored in the virtual label of each product in the digital space through the information data interface, and the evolution of the geometric state of the product/component can be driven according to its process data. Therefore, the definition of product/component digital twin model is as follows:

$$DT_{pr}=\left\{SM,II,SS\right\} \tag{3}$$

where: *SM* (Struct Model), *II* (Information Interface), *SS* (Status Service).

B. Establishment of Twin Modeling of Multi Factors in Production Process

1) Implementation of device twin modeling

The twin modeling of key elements in the production process is shown in Fig. 2, including the sources of driving data, data sources and virtual services [9].

(1) Processing equipment

Processing equipment includes CNC machine tools and special equipment. Firstly, the 3D geometric model is constructed according to the equipment entity, and then the digital space is imported and the precise positioning is made according to the physical location. Secondly, the motion structure is established, and finally the processing behavior, fault behavior, cooperation behavior and so on are realized on the basis of the motion structure. The implementation of behavior needs to use the corresponding virtual service program to drive the model to complete the functional response to different signals. FM function model includes three-dimensional model of processing equipment, position information and behavior information. Its vrci virtual real communication interface includes translation, rotation joint data interface, tool action signal interface, machine door action signal interface and equipment status interface. Vs virtual service includes motion control and signal processing service, according to the real-time data obtained from the physical space, update the action and status of the processing equipment [10].

(2) Logistics equipment

Logistics equipment includes AGV, conveyor belt, etc. AGV includes translation and rotation actions on the plane and various load shifting functions. Conveyor belt is used to realize the flow of goods, and coordinate with sensors to realize the position control of goods. FM function model includes three-dimensional model, location and behavior information. Vrci virtual and real communication interface includes spatial position data interface, load shifting action signal interface, start/stop signal and sensor signal interface, etc. vs virtual control service includes motion control and signal processing services to update the operation and status of logistics equipment.

(3) Storage

The three-dimensional warehouse is composed of static shelves, pallets, shuttles and stackers, which are responsible for the execution of actions. Through the processing of inventory information and scheduling information, it realizes the delivery of parts and the delivery of finished products. According to the actual inventory information, the warehouse location goods are dynamically adjusted, and the action execution is controlled according to the actual scheduling data. FM function model includes three-dimensional model, location information and its behavior. Vrci virtual real communication interface includes drive data interface, inventory information interface, ex warehouse / in warehouse information interface and warehouse status interface. Vs virtual control service includes stacker scheduling service, inventory management service and signal processing service to realize the action and status update of three-dimensional warehouse [11].

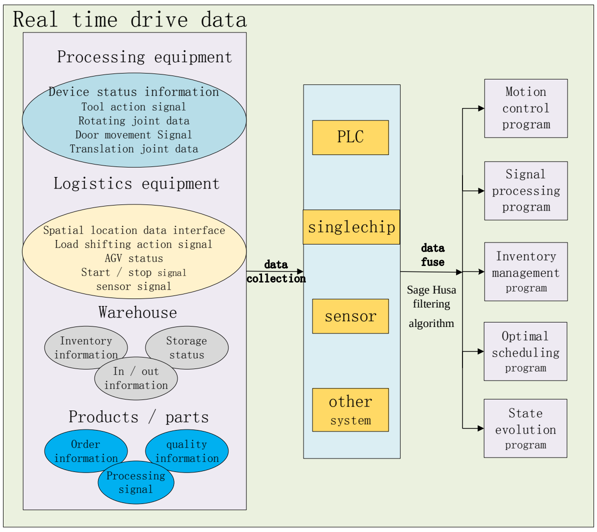

Figure 2. Digital twin modeling of key elements in production process.

2) The realization of twin modeling of product/component

The twin modeling of product/part is realized by geometric model and virtual production information of different process stages. The geometric shape changes with the production process, and the order, coding, quality and other life cycle information of the product are displayed in virtual tags. According to the twin model defined, II information data interface obtains other system orders, quality information, and processing signals in PLC. SS state evolution program drives geometric shape change and virtual label information update [12].

3) Implementation of information fusion algorithm

Kalman Filter (KF) is an optimal autoregressive data processing algorithm, which is mainly used to solve the estimation problem in linear system. Let the equation and observation equation of the dynamic system be as follows:

$$x_k = A_{k-1,k} x_{k-1} + B_{k-1,k} u_{k-1} + w_{k-1} \tag{4}$$

$$z_k = H_k x_k + v_k \tag{5}$$

x_k is the system state vector at k, $A_{k-1,k}$ is the state ransition matrix from time k-1 to k. $B_{k-1,k}$ is the input system control matrix from time k-1 to k. z_k is the observation vector of time k. H_k is the observation matrix at k, w_k is the dynamic noise at k, v_k is the observation noise at k. If the estimated state and dynamic noise satisfy equation (4), and the system observation and observation noise satisfy the conditional assumption of equation (5), then the estimation and solution process of time k observation x_k is as follows:

Pre estimate:

$$\hat{x}_k^- = A_{k-1,k} x_{k-1} + B_{k-1,k} u_{k-1} \tag{6}$$

Calculation of pre estimated covariance matrix:

$$P^-_k = A_{k-1,k} P_{k-1} A^T_{k-1,k} + Q \tag{7}$$

The calculation of Kalman gain matrix:

$$K_k = P^-_k H_k^T \left[H_k \cdot P^-_k \cdot H_k^T + R \right]^{-1} \tag{8}$$

$$Q = B_{k,k-1} \left[u_k \cdot u_k^T \right] B^T_{k,k-1}, R = v_k \cdot v_k^T \tag{9}$$

Update estimates:

$$\hat{x}_k = \hat{x}_k^- + K_k \left[z_k - H_k \cdot \hat{x}_k^- \right] \tag{10}$$

The calculation of the covariance matrix after updating:

$$P_k = \left[I - K_k \cdot H_k \right] P_k^- \tag{11}$$

Recursive loop computation:

$$x_{k+1} = \hat{x}_k, \; p_{k+1} = p_k^- \tag{12}$$

Equations (6) to (10) are the basic formulas of Kalman filter. Kalman algorithm is a recursive prediction-correction method, divided into time update equation and measurement update equation. Under the given initial value x_0 and P_0, according to the observation value at k

time, the state estimation at k time can be calculated recursively, and the state prediction can be calculated recursively by repeating each step [13].

Combined with the accuracy and stability of filtering, Sage Husa filtering algorithm is used when filtering under the condition of convergence; Strong tracking Kalman filter is used when the filter has divergence. Therefore, it is necessary to use the convergence of filtering to judge whether the filtering is divergent before filtering. The convergence criterion is as follows:

$$\tilde{Z}_{k+1} = Z_{k+1} + H_{k+1}\hat{X}_{k+1,k} \tag{13}$$

Formula (3.12) contains the sum of squares of the new sequence, and the variance matrix of the new sequence is used to describe the error size information.

$$E\left[\tilde{Z}_{k+1}\tilde{Z}_{k+1}{}^{T}\right] = H_{k+1}P_{k+1,k}H_{k+1}{}^{T}P_{k+1} \tag{14}$$

So the convergence criterion is as follows:

$$\tilde{Z}_{k+1}\tilde{Z}_{k+1}{}^{T} \le \gamma Tr\left[H_{k+1}P_{k+1,k}H_{k+1}{}^{T}P_{k+1}\right] \tag{15}$$

When the above formula is true, sage Husa adaptive filtering is used. If it is not true, the filtering error exceeds the predicted value γ Strong tracking Kalman filter is used to enhance the ability of mutation state tracking.

IV. Real Time Data Acquisition of Physical Entities in Production Process

A. Data Communication Network Architecture Based on OPC UA

The interface protocol of each equipment in the production line is different. At present, the mainstream equipment supports OPC protocol. In order to solve the problem of heterogeneous physical entity data acquisition in production line, this paper proposes a data communication network architecture of production process digital twin system based on OPC UA, as shown in Fig. 3.

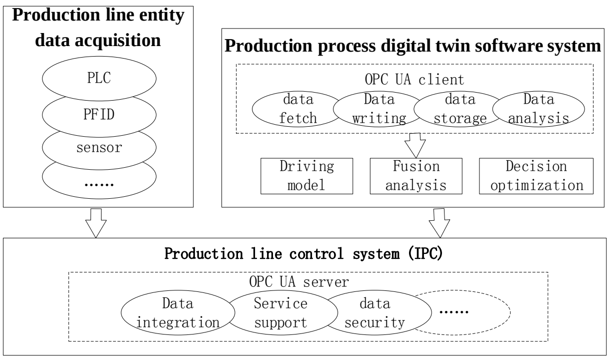

Figure 3. Data communication network architecture of production process digital twin system.

The UA server is placed in the production control system of the production line, and the field devices are connected through the fieldbus or industrial Ethernet to obtain the IO port data, so as to realize the data acquisition of the bottom devices of the production line. Through data conversion, management and logic operation, it provides services for UA clients. The production process digital twin system obtains real-time data from the server for data reading, writing, storage, analysis and calculation, drives the element model, updates the real-time production data of each element, and carries out intelligent analysis and decision-making [14].

B. Data Acquisition Model Construction and Field Data Acquisition

The UA server connects with the control unit of the field device to obtain the underlying data. The construction of data acquisition model is based on the data acquisition object of twin system, and adopts the modeling method of object and node, as shown in Fig. 4. The whole equipment module is composed of controller, joint and end effector. The controller includes power status, working temperature and I / O port control signals; The joint includes motor speed, voltage, current, temperature and other parameters; The actuator contains action signals, etc [15].

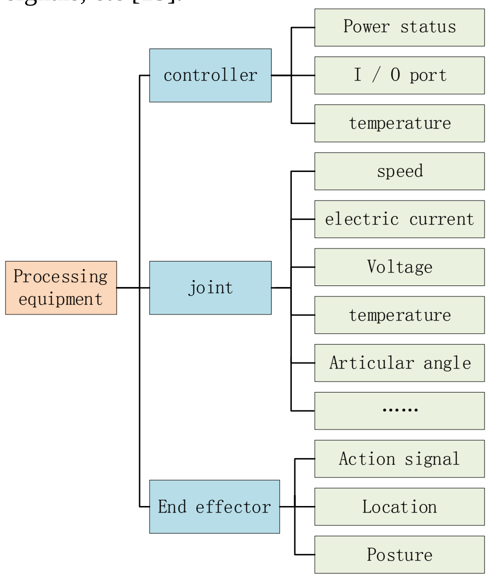

Figure 4. Data acquisition model of processing equipment.

The construction of other heterogeneous elements data collection model is similar. When the UA server is running, it integrates the source data of various elements in the production process, and provides service interface for the client; Twin system as OPC UA client, all the simulation variables (attributes or signals) of the model are organized in the form of the same node hierarchical relationship, and the field device node data is obtained by traversing the server. That is to establish a connection variable pair between the simulation variable and the server variable one by one to complete the subscription of the client to the server node data. Because part of the signals in the production system are in the form of short pulses, the polling mode is easy to cause the signal changes can not be captured, and the client updates when the variables change, so as to improve the response speed of the twin model to the signal. Through the above methods, the real-time acquisition of field data by twin model is realized [16].

V. Real Time Mapping of Production Run

A. Mapping Subject

The mapping of digital space to physical space is the basis of the virtual and real interactive application of digital twin technology. Mapping and interaction are mainly divided into five parts: product, equipment, personnel, system and environment.

B. Drive Data Logic Coordination

The signal logic of the digital space is different from the signal logic of the physical system. In order to use real-time data to drive the highly realistic operation of the model, various methods of logical processing of data and signals are required [17].

The driving data in the digital space can be divided into 4 categories: motion driving data, action signals, status data, and instruction data. The logical structure of real-time mapping is shown in Fig. 5. After processing the drive data of the physical space, it acts on the twin model. Various virtual service programs in the digital space realize the products, equipment, personnel, and environment in the virtual space in a multi-threaded parallel manner [18]. And the mapping of the system. On this basis, full three-dimensional monitoring of the production process and twin data analysis are realized, thereby further optimizing production and intelligent management and control [19]. The running process of real-time mapping in digital space is as follows:

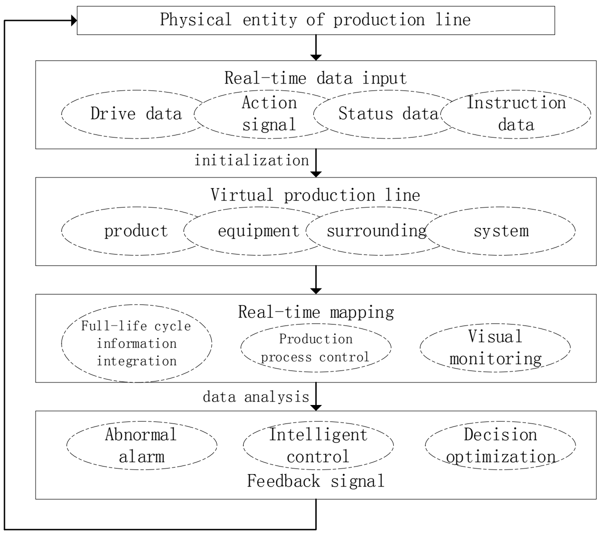

Figure 5. Real-time mapping box for production runs.

It mainly includes three stages of initialization, real-time mapping and data processing. Due to the uncertainty of the system startup time, the twin model first needs to be initialized from multiple dimensions when the system is running to match the physical space state. After the digital space is synchronized and initialized, multi-dimensional real-time mapping of products, equipment, environment and production processes is carried out according to the driving data. In the real-time mapping process, statistics are performed on the operating data of the digital space, and various data are integrated and analyzed, including alarms for abnormal production, production decision-making, etc., so as to optimize and control the physical production line [20].

VI. Application Example of Production Line Digital Twin System

A spraying production line for electrical parts uses digital twin technology based on discrete system simulation. According to the process flow, logistics logic and actual scheduling rules, a virtual twin line as shown in Fig. 6 is established, and simulation experiments for spraying and testing of parts are carried out to predict the parts. The spraying quality level verifies the rationality of the parts shelf planning in the assembly area after the increase in production capacity. The production process of the entire production line is:

a. Parts in and out of the warehouse
b. Logistics distribution and transmission, parts spraying, and sent to the inspection area
c. Combine image recognition for inspection and acceptance
d. Return unqualified products, repeat the first step
e. The finished products are shipped back to the three-dimensional warehouse.

According to the above process flow and the implementation method of the production line digital twin system proposed in this paper, Solid works and auto mod are used to complete the production line modeling, weight reduction and decomposition. The three-dimensional model of the equipment is assembled in auto mod, the action is set, and the parameters are input according to the unit of the production equipment. The physical equipment is a unit to establish a virtual simulation model in the simulation system. Through OPC UA, the interoperability problems of interface integration and information coordination between different systems are solved, the communication network construction and the data collection of field equipment and other elements are carried out, and finally the three-dimensional monitoring of the production process is realized through real-time mapping. The main implementation process is as follows:

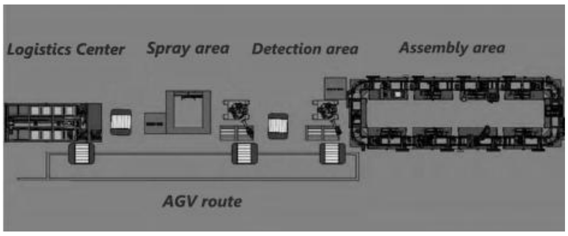

Figure 6. Virtual model production process.

A. Twin Model Construction

The twin model of corresponding function is established according to the physical equipment to ensure the consistency of the twin model and the entity in terms of geometric size, physical structure relationship, and movement characteristics. Solid works is used to complete the production line modeling, weight reduction and decomposition. The three-dimensional model of the equipment is assembled in auto mod, and the action is set. According to the unit input parameters of the production equipment, the virtual simulation model is established in the simulation system with the single equipment as the unit. Establish the internal and external communication control signal interface of the model according to the operating logic and entity data, and realize the data interaction between the models and the drive of external real-time data. Establish virtual services through development and secondary development of scripts to realize equipment operation control, status monitoring, inventory control and data statistics.

B. OPC Data Communication Construction

The digital space is linked with the established UA server through the OPC communication interface to establish data communication variable pairs to realize the real-time data collection of various elements of the production site. The data scanning period is set to 50ms to ensure a short data communication delay.

C. Real-Time Mapping Construction

Use the established virtual service to logically process the data, drive the highly realistic operation of the model with real-time data, realize that the operation status, storage status, and logistics status of the equipment are consistent with the actual production line, and the product RFID reader performs real assembly geometric changes. Through continuous calculation and statistics of the collected data, the key monitoring and statistical data can be visually displayed.

D. Data Fusion Analysis

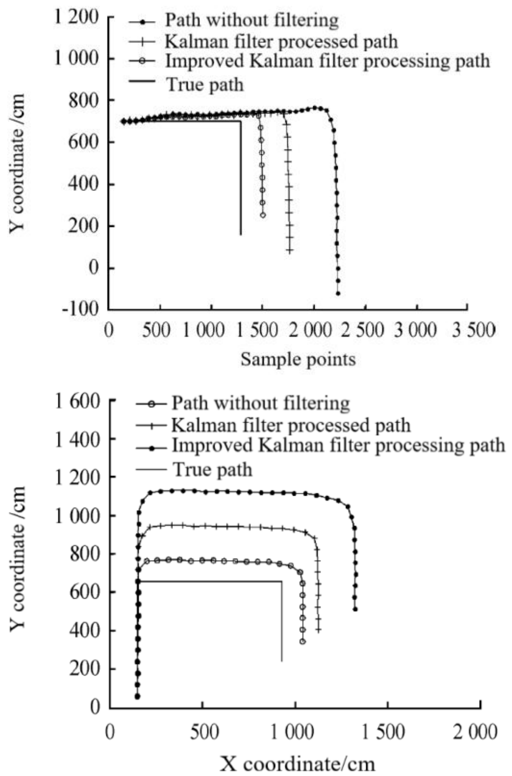

Figure 7. Path results under different filtering processing.

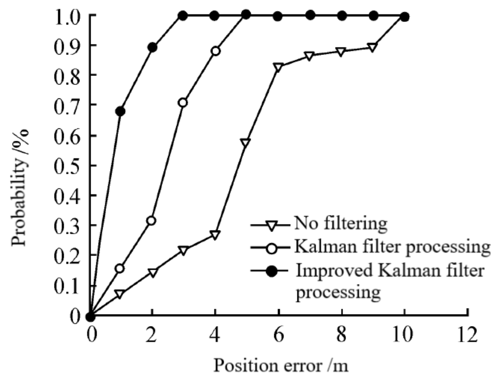

Figure 8. Cumulative probability of position error under different filtering processing.

According to the improved Sage-Husa algorithm, the field collected data is fused and analyzed, as shown in the Fig. 7 and Fig 8 above. Under the sensor's own measurement drift, the positioning path obtained after the acceleration processing by the improved Kalman filter is closer to the real path than the single Kalman filter processing. The positioning accuracy without filter processing is low. After Kalman filter processing, the positioning accuracy within 3m can reach 70.7%. Taking the data processed by the mean filter as a measurement value and then using Kalman filter to perform recursive operation, the positioning accuracy can reach 89.4% within 2m. The error after filtering is smaller than the error of the measured value, and the value after the information fusion algorithm is closer to the true value, which meets the twin requirements.

VII. Conclusion and Outlook

Digital twins can optimize production operations and achieve closed-loop feedback and continuous improvement across the value chain. This article provides a technical solution for the realization of digital twins in the production process of the production line, and studies its key technologies. The digital twin system architecture and technology of the production process proposed in this paper can realize the coupling and interaction of the three modules of the production line automation system, twin model and OPC communication network; the use of OPC data communication network architecture can quickly realize multi-source data collection, and the data service platform can The twin data is fused, analyzed and processed, and the feedback optimization channel of the twin system is also established. On this basis, the real-time obtained twin data will be used in the follow-up to carry out research work such as intelligent production decision-making and virtual-real interactive control based on twin data.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All the authors have contributed to this study equally.

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Ke-Xin Yang was born in China in 1996 and graduated from Tongji University, Shanghai, China in 2019. He is currently studying for a master's degree in the Department of electrical engineering, Tongji University. The main research direction is intelligent manufacturing technology.

Yi-Fei Wang was born in China in 1997. He received the B.S. degree in Electrical Engineering from Tongji University, Shanghai, China, in 2019. He is currently pursuing the Ph.D. degree in Department of Electrical Engineering, Tongji University. His research interests include intelligent manufacturing and machine vision.

Zhi-Wen Xia was born in China in 1997 and graduated from Tongji University, Shanghai, China, in 2019 with a bachelor's degree in electrical engineering. He is currently studying for a master's degree. Department of electrical engineering, Tongji University. His research direction is intelligent manufacturing.

Li-Jun Jin was born in China in 1964. He received the B.S., M.S. and Ph.D. degrees in electrical engineering in 1987, 1997 and 2000, respectively, from Xi'an Jiaotong University (XJTU), China. He held the post of Postdoctoral in Tsinghua University from 2000. He is currently a Professor in Department of Electrical Engineering, Tongji University. His research interests include electromagnetic field theory, power equipment fault diagnosis and high voltage technique.