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An Efficient Big Data-Driven Scheduling Algorithm Models for Cyber Physical Systems Based on a Cloud Platform

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ABSTRACT

In this paper, we study big data-driven Cyber–Physical Systems (CPS) through cloud platforms and design scheduling optimization algorithms to improve the efficiency of the system. A task scheduling scheme for large-scale factory access under cloud–edge collaborative computing architecture is proposed. The method firstly merges the directed acyclic graphs on cloud-side servers and edge-side servers; secondly, divide the tasks using a critical path-based partitioning strategy to effectively improve the allocation accuracy; then achieves load balancing through reasonable processor allocation, and finally compares and analyses the proposed task scheduling algorithm through simulation experiments. The experimental system is thoroughly analysed, hierarchically designed, and modelled, simulated, and the experimental data analysed and compared with related methods. The experimental results prove the effectiveness and correctness of the worst-case execution time analysis method and the idea of big data-driven CPS proposed in this paper and show that big data knowledge can help improve the accuracy of worst-case execution time analysis. This paper implements a big data-driven scheduling optimization algorithm for Cyber–Physical Systems based on a cloud platform, which improves the accuracy and efficiency of the algorithm by about 15% compared to other related studies.

INDEXTERMS: Industrial robotics, cloud platform, bigdata, CPS, AADL.

I. INTRODUCTION

The new generation of information and communication sys- tems represented by the Internet, cloud platforms and big data is developing rapidly, and a wave of re-industrialization is rolling worldwide. What is this generation of information and communication systems brings is a deep and fundamental change, which has completely changed the production methods, industrial systems, an even business models of traditional manufacturing industries [1]. Manufacturing is a reflection of the country’s comprehensive strength has well as international competitiveness, which is not only an impor- tant element in deepening structural reform on the supply side an promoting high-quality economic development ,but also an important grasp for building a resource-saving and environment-friendly society, and an objective requirement for building a strong social is t modern country in anall-round

Theassociateeditorcoordinatingthereviewofthismanuscriptandapproving it for publication was Po Yang. way [2]. As global economic integration continues to develop in a deeper direction, the United States, Germany, and China have put forward new strategies such as ‘‘Industry 4.0’’ in line with the national conditions of each country, combining the development of industrial technology and intelligent information in each country and coincidentally clarifying the CPS is the core of intelligent manufacturing [3]. The CPS is an embedded system that deals with the physical and information environment, its information side model connects one or more control units and interacts with the real world under human guidance while collecting and processing data from sensors and actuators, and the interaction between data processing and other physical or digital systems is the basis of the CPS [4]. Based on the numerous sensors and actuators, they form the basic functional logic unit of the CPS and are responsible for performing the most basic monitoring and control functions of the CPS [5], [6]. In the case of Industry 4.0, for example, the idea is not only to use the CPS to promote information and intelligence within the factory, but also to use

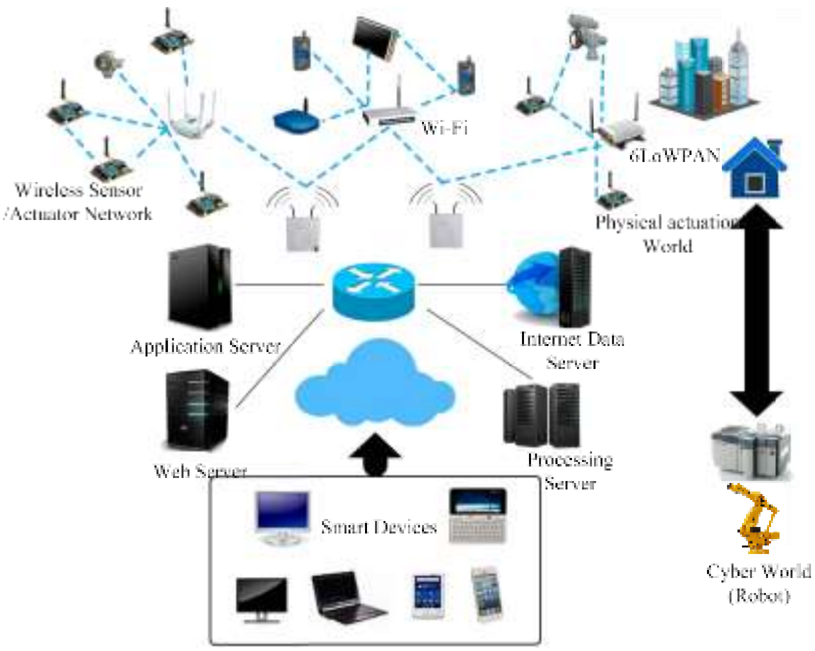

FIGURE1.IndustrialrobotCPSenvironmentawareness.

The IoT system as a basis for external expansion to connect the relevant services outside the factory and ultimately to contribute to the information and intelligence of the entire industrial chain. The key to realizing CPS is to realize the mutual perception, understanding, and integration of people, machines, and things in an interconnected environment [7]. As industrial development enters a new era, information technology represented by big data, cloud computing, and other technologies continues to develop, and artificial intelligence has made breakthroughs and applications. As shown in Figure 1, a high degree of automation and intelligent integration has become synonymous with the future of the industry, and industrial robots have been better integrated into the current industrial sector, making the application of industrial robots an effective guarantee to enhance the level of industrial production technology in the future [8]. The industrial robot industry is growing in China as a result of rising labor costs, and in some advanced manufacturing industries, industrial robots are utilized to replace manual labor in the production process [9]. With the continuous development of technologies related to industrial robots, the role of industrial robots is no longer to simply replace people but to combine environmental conditions and work more flexibly with people, but at this stage, there are deficiencies and shortcomings in the interplay between industrial robots and people [10]–[13]. The interworking of industrial robots and humans means that they are closely coordinated in the same environment, which means that the mutual perception, understanding, and integration between humans and robots is achieved while ensuring safety [14]. As robotics research continues to grow.

It is important to look at achieving closer collaboration between robots and humans, and this research has become one of the popular elements in achieving smart manufacturing, as well as being part of Industry 4.0. Key to Industry 4.0 is CPS technologies and intelligent automation technologies, which also include robotics [15]. As industrial robots continue to deepen their technological strength, combined with microprocessors and artificial intelligence, they are interacting more closely with people at work and in life, and this is facilitating an increasing role for industrial robots in smart manufacturing [16]–[18]. In the real-world of industrial production, manufacturing companies face many challenges in their pursuit of market performance and efficiency and meeting customer needs. These challenges are also present in industrial production for the involvement of industrial robots [19]–[22]. To improve market performance and meet customer needs, and ultimately to achieve the best possible functioning of the company, it is necessary to increase productivity through the good use of human resources, capital, and technical equipment, as well as the continuous application of multiple combinations of technologies [23]. The concept of Industry 4.0 was spawned by major technologies such as CPS, and the continuous development of these technologies has advanced Industry 4.0 technologies to ever greater depths. When evaluating innovative technology applications in manufacturing companies, the results usually include both safety and human factors in the system [24].

The operator to visualize the status of the robot [25]. As the real-time state of industrial robots is constantly sensed, the way they interact with society largely improves their performance. Under CPS, industrial robot systems are studied and improved through the interaction between robots and society, and the improved systems not only improve the functioning of the robots themselves but also deepen the communication and collaboration between robots and humans. Robot programming technology is the universal basis for communication between humans and robots, and to promote mutual awareness, understanding, and integration between humans and robots, there is a need to strengthen the information-sharing aspect of robot programming technology [26]. At this stage, real-time programming and control of robots require a high level of programming skills [27]. Therefore, this paper studies the big data-driven CPS modeling method for industrial robots based on a cloud platform, and applies the motion monitoring and control system of industrial robots as the main body in intelligent manufacturing, with emphasis on the interaction and integration of robot Cyber models and physical entities, and realizes the application of information technology when industrial robots are involved in the production. The establishment of a CPS based motion monitoring and control system for industrial robots realizes the interaction between the Physical system and the Cyber system at the industrial robot level, providing important theoretical research significance and application value to better realize human-machine integration and promote better transformation and upgrading of the manufacturing industry [28]–[30].

II. CPSARCHITECTUREMODELDESIGNFORBIGDATA- DRIVENROBOTSBASEDONCLOUDPLATFORM

A. AHIERARCHICALMODELOFROBOTCPSMODELING SYSTEMARCHITECTUREFORCLOUD-BASED SMARTFACTORIES

Robotic Smart factory architectures are complex and interdisciplinary, and their overall inclusion of several different layers of CPS control systems with a hierarchy of scale by the hierarchy is one of the key reference factors for smart factory modeling. This paper will introduce three levels of CPS-based on the CPS system scale division of the Information Physics Systems White Paper, which gradually expands from a cell-level robotic CPS system to an SOS-level holistic CPS system.

The unit-level CPS system is the smallest unit of the CPS that is indivisible and whose peculiar physical devices already contain sensors, actuators, and interactive controls. Unit-level CPS is primarily represented as a single functional unit that contains the feedback processes for state sensing, autonomous decision-making, and data closure of the complete CPS system [31]. It also has a communication function. In a smart factory, each industrial robot is a unit-level CPS system. System-level CPS integrates multiple unit-level CPS devices into a complete system based on certain tangible distribution rules through industrial bases, connection protocols, and Ethernet connection. Based on the condition-aware information of the multiple unit-level CPSs, the data flow through the multiple unit devices by using the industrial network bus to share device information and work together [32].

This enables self-determination and self-optimization of the combined devices. System-level CPS heterogeneously integrates and processes data from several distinct unit-level CPSs, interconnecting them and providing unique functions such as collaborative control, monitoring, and diagnosis. Interconnection is the key to system-level CPS and determines the degree to which the units of a system-level CPS can work together. Monitoring and diagnostics use the HM Worker (human-machine interface) to monitor the status of unit-level CPS equipment within the system in real-time and to comment on the operating status of unit-level CPS equipment [33]–[36].

In a smart factory, each robot workshop is an example of system-level CPS. The actual production process includes multiple robots working together in the workshop, for instance in the final assembly workshop, where the robot arm uses the robot’s positioning information to determine the position and obtain material for model assembly.

SoS-level CPS converges and connects the diverse system-level CPSs, mainly through a unified cloud management platform. The focus of industrial SoS-level CPS is on an intelligent service cloud platform. In a smart robotic factory, the different overall data are stored in the lower workshop CPS system components [37]. Using the intelligent cloud platform for the unified management and integration of these distributed data, can either make individual manipulation actions of the unit-level CPS through the integrated cloud platform or analyze and utilize all or part of the workshop sensory data through distributed computing and big data analysis capabilities, which can achieve it.

Based on the platform-level data flow, the production scheduling scale order of each workshop can be adjusted to complete the closed-loop feedback of CPS at the SoS level [38]. Based on the big data-driven industrial cloud platform CPS data collection layer, data processing layer, data storage layer, the architecture is mainly based on data use as a layering system, divided into big data decision analysis layer as well as the data application layer, as shown in Figure 2.

In a smart factory system, the data sensing and collection layer consist of numerous robot cells and various sensors that collect operational logs and environmental information.

The robot transmits its logs and other information to the upper layer, which then aggregates the results and brings them to the robot in the field, forming a complete sensing and feedback system process [39].

The data processing layer is the transit layer that connects unit-level CPS systems to industrial system-level CPS. The key to the data processing layer is to provide data sharing and interconnection as well as heterogeneous data integration, which provides the foundation for information interaction in scholarly production CPS systems. OPCUA is the most rapidly developing standard and specification for the

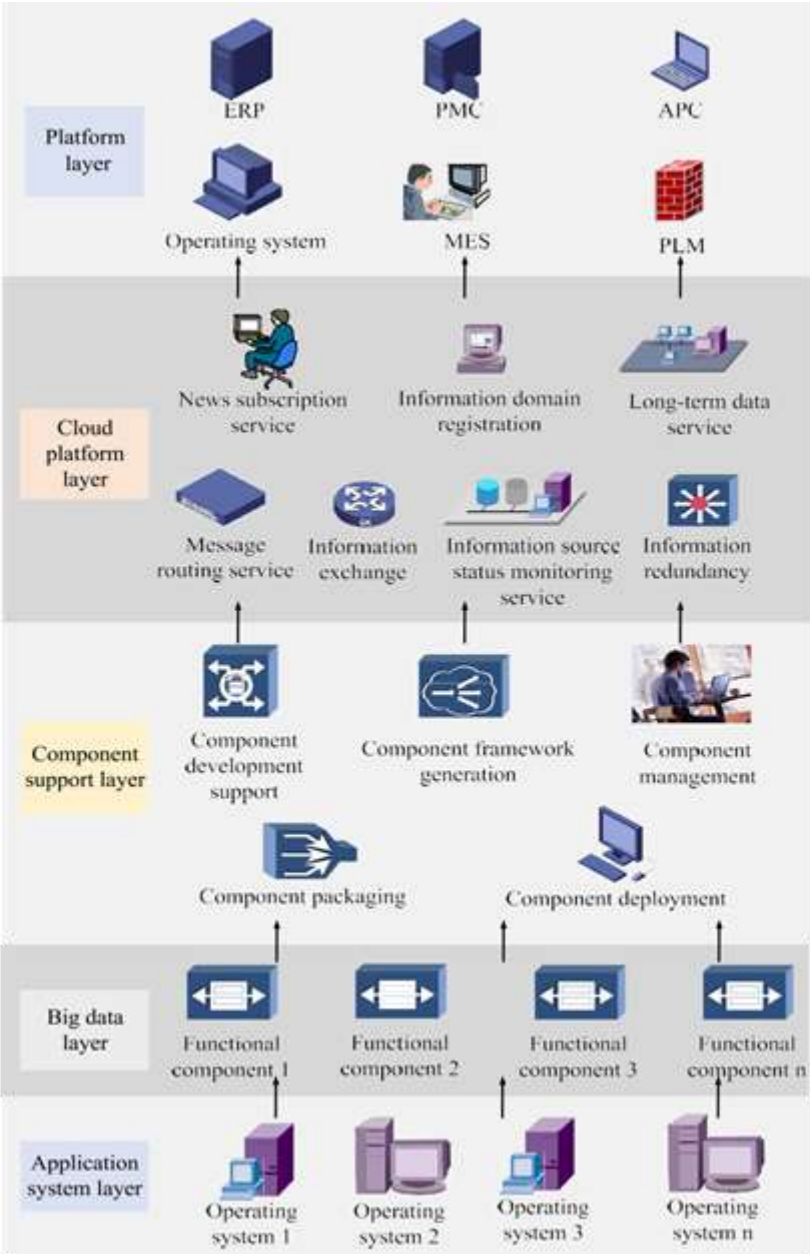

FIGURE2.Bigdata-drivenCPSarchitectureforcloudplatforms.

interconnection of mechanized equipment [40]. The OPCUA specification can be utilized to unify the format of device data collection into a unified specification for storage and processing while enabling interconnection and interoperability between devices. The storage part mainly assumes the role of the industrial robot workshop database, saving important data such as robot operation logs, error logs, or industrial sensor information in the system. It mainly composes of HBase distributed database and Hive data warehouse. The decision analysis layer is the core layer of considerable data processing in the CPS system of the industrial cloud platform [41]. The decision analysis layer uses the Spark big data processing platform for vast data processing and analysis of the data from the lower layer. Data such as industrial image monitoring streams are sent to the Spark real-time processing engine for immediate processing and transmitted to the human-machine interface for monitoring, while the upper layer historical data analysis and robot operation instructions are returned to the upper layer and the industrial robots through the analysis results processed by other Spark components. Its role is essentially that of a decision execution unit for the CPS of a smart factory [42]. The data application layer mainly provides interactive applications for users who utilize the industry cloud platform.

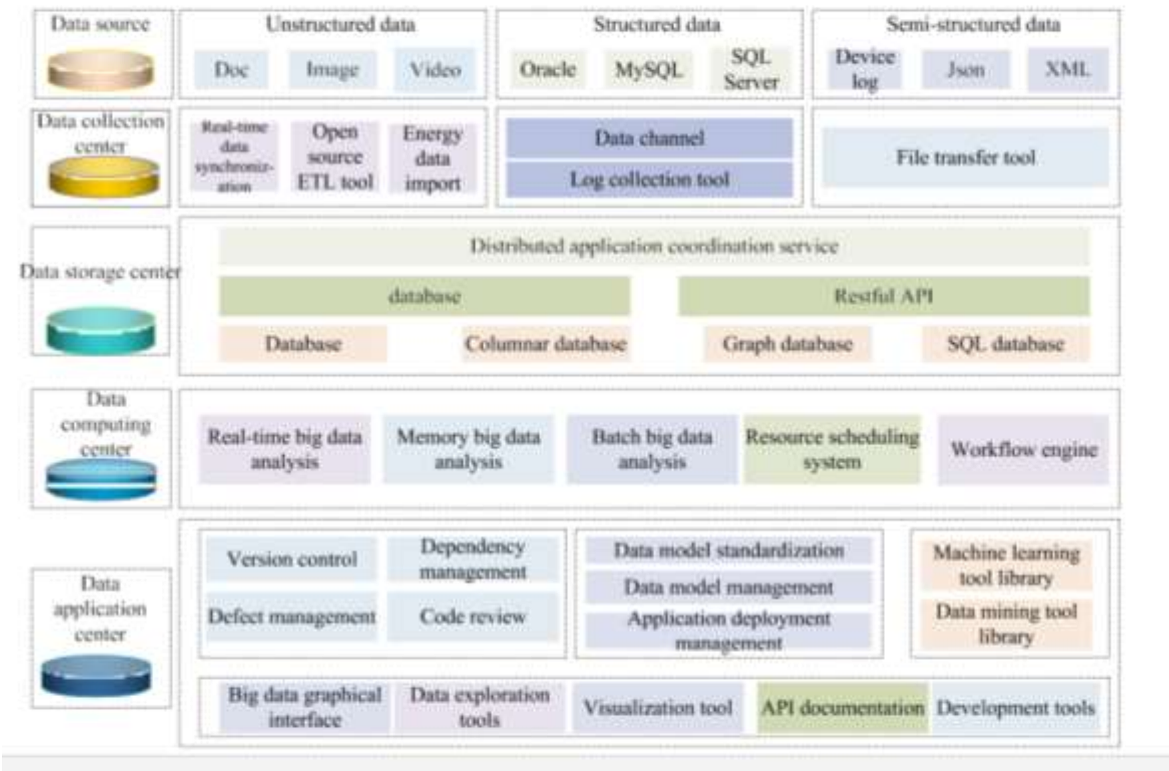

FIGURE3.DistributedHBaseSystemStorageArchitecture.

Industrial cloud platform application is a management system developed for smart factories, providing real-time robot interaction, status analysis, data analysis, manufacturing task scheduling, and other platform application services, providing Manufacturing Execution System(MES), Public Health Management(PHM), Product Lifecycle Management(PLM), and other management systems [43].

The industrial cloud platform can also issue operation and analysis instructions to the lower decision-making layer, call the corresponding Spark component module, from the storage system to obtain the corresponding data for analysis and processing, Spark will feedback the results to the cloud platform, to complete data analysis and decision-making and other actions.

B. MODEL OF A LARGE DATABASE STORAGE SYSTEM FOR INDUSTRIAL ROBOTS CPS

In the production process of a smart factory, a large number of robots and environmental sensors upload huge amounts of information such as acquisition and operation logs daily.

The contents of these logs are stored in a distributed storage system and constitute a larger data set [44], [45]. However, the heterogeneous nature of robot types and operations makes it unsuitable for storage and computational processing using traditional relational databases.

The base is a type of No SQL that is based on the HDFS file system and is stored as a binary string, allowing for real-time reading and writing.

It is based on the HDFS file system and is stored as a binary string. It also saves a lot of system space due to its column-based data storage and sparse table design, which does not adopt up storage space for null (NULL) columns [46]. At the same time, column store-based design can read the corresponding column clusters instead of the entire row of data for query processing requirements, increasing the efficiency of query processing. It takes two separate workshops an and B in the smart factory, which has CNC machines and SCARA assembly robots respectively and represents the equipment with a number such as the X the number in workshop A by number. Figure 3 shows the allocated HBase storage data model and storage architecture of the smart factory. HBase is divided into terms of data tables, which are deposited into the HBase database. Among other things, data tables are split into regions. A region is the smallest unit in HBase where data tables are stored in a distributed manner.

In the industrialized management database, device identifiers based on naming rules are arranged according to the rules so that they are assigned to the same region [47].

As can be viewed, the three main parts of the HBase table storage structure are row keys, time stamps, and column clusters. Column clusters are separated into as many columns as needed to represent different types of data. After the data have been collected and processed for aggregation, the data from different regions are allocated to different regional servers according to the design of the allocation attribute [48]. The data identified by Computer numerical Control (CNC) are distributed to the regional server and stored while the data identified by

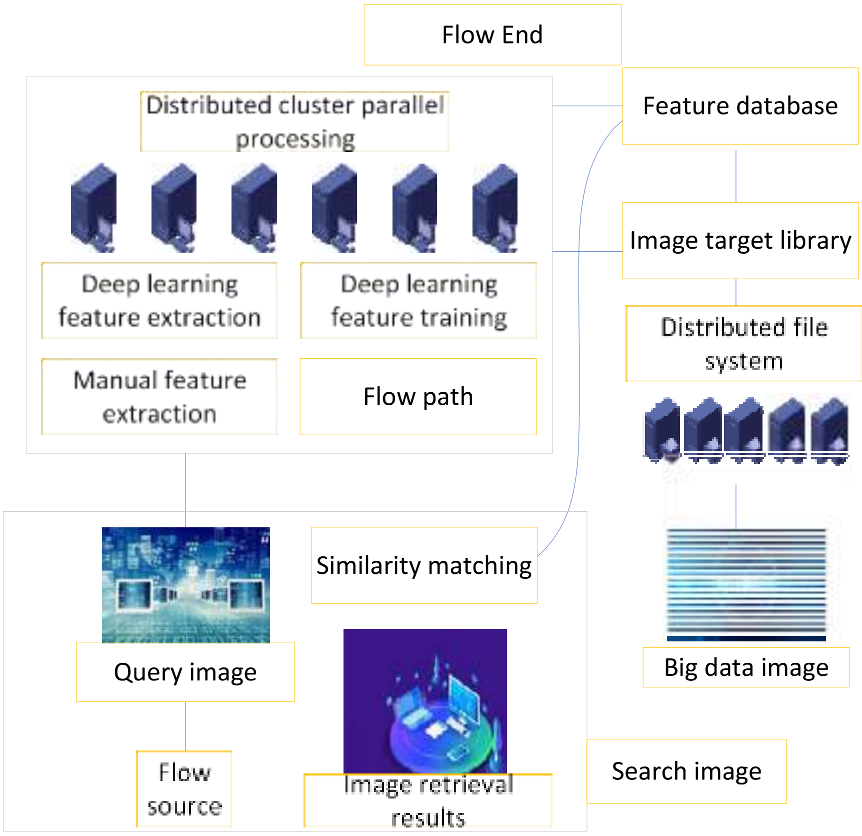

FIGURE4.FlowandarchitectureoftheCPSbasedindustrialrobotmotionmonitoring and control system.

Selective Compliance Assembly Robot Arm (SCARA) are stored in the regional server, completing the distribution of the data. In the lower part of the diagram, you can see that the data tables are not stored in rows. Instead, they are kept in a form known as a Cell, which includes a combination of keys that determine the primary key in the H Base database. As can be seen, the data table with CNC as the region is stored in two separate files in the underlying storage model, i.e. Two forms of storage key. Distributed table data based on the above column storage meta model data reduce the granularity of operations such as database additions, deletions, checks, and changes without the need for whole row data operations [49]. It can be well used in industrial substantial data processing actions such as querying and analyzing large amounts of data for a certain keyword.

C. MODELINGANDDESIGNOFACLOUD-BASED PLATFORM FOR THE PHYSICAL FUSION OF HUMAN INFORMATION FOR MACHINE BIG DATA DRIVERS

The majority of robots in the industry are robotic arms, and multi-joint robotic arms are the most widely used robots, offering the benefits of high efficiency, precision, and flexibility.

Robotic arms are generally made up of basic components such as motors, transmissions, shafts, and connecting rods. In general, the number of degrees of freedom represents the number of spindles and links, i.e. The number of links, degrees of freedom, and spindles are the same.

The six joints are driven by DC motors of singular power and torque, and the speed gain is made by a gearbox transmission. The Modelic a based arm is modeled based on the movement behavior of its joints, which are articulated mechanisms that connect the linkages and achieve relative rotation or oscillation, consisting of the actuators, rotary shafts, and bearings.

As shown in Figure 4, it is often necessary to add properties such as stream delay attributes and system processing cycles to process, system, and connection components based on actual system characteristics. Due to a large number of processing tasks in CPS systems such as command delivery, image monitoring, and other actions required to ensure real-time data, and the design of mobile robots makes the data commands involve the transmission of multiple systems such as local processing, network communication, and platform computing. Therefore, at the early stage of development, the components through which the data streams pass need to add stream delay attributes and processing times to ensure that the system's real-time requirements are met. The end-to end flow is a complete data flow design for a certain behavior, which includes three parts: flow source, flow path, and flow end. In the system design, it is necessary to set the flow delay properties for the components through which the end-to-end flow passes [50].

In this paper, we select the behavior of remote giving mobile commands by the user of the cloud platform robot as the object of end-to-end stream delay analysis. In the mobile robot CPS system designed in this paper, the behavior of flow information passing through multiple components until the body for current body position information calculation, starting from the external information received through sensors, involves the end-to-end flow design problem.

The motion control system of a robotic arm has multiple motion control axes, but from a control point of view, multiple motion control axes in the same motion control system usually use the same underlying control algorithm, below we analyze the mathematical model of a single motion control axis.

An electromechanical equivalent circuit is first established, which leads to the introduction of the voltage balance equation:

$$u_a(t) = \sum E_a + \sum R_a i_a(t) + \sum L_a(t) \quad (1)$$

Where the induced potential is:

$$E_a = 30uK_a\phi\blacktriangle \quad (2)$$

The inductive potential is proportional to the motor speed when it must not be constant, and the mo speed n can be obtained as:

$$n = K_e\phi\left(\frac{u_a(t) - R_a i_a}{L_a(t)}\right) \quad (3)$$

In the above expressions, qua, ie, Ra shows denote voltage, current, and resistance, respectively. La, Ke, and φ must denote the total inductance, induced electromotive force, and flux per pole of the circuit respectively.

We let the J be the amount of rotational inertia applied to the motor shaft, and B be the damping factor on the motor shaft, through the electromagnetic torque of the motor with the equation of torque balance derived from the above equation:

$$T_m(t) = T_d(t) + Jdo(t)' \, Bo(t) \quad (4)$$

where Tm is the electromagnetic torque of the motor, Td is the sum of the no-load torque and the load torque on the motor shaft. The position coordinates of the optical encoder can be calculated as follows:

$$\Phi(s) = \frac{G_p(s)}{G_c(s) + F(s)R(s) + T_d(s)} \quad (5)$$

$$F(s) = \frac{\sum K_e + 1}{\tau_m s} \quad (6)$$

III. CLOUD-BASEDPLATFORMFORBIGDATADRIVEN ROBOTCPSMULTI-POSEIMAGERECOGNITION ANALYSIS

A. REAL-TIMEEQUIPMENTCONDITIONMONITORING ANALYSISINCPSFORINDUSTRIALROBOTS

This paper first analyses the importance of automated monitoring of equipment status in CPS, and proposes a two-stage indicator detection algorithm based on SSD, taking a finger device with multiple status indicators as the research target, and compares it with a Hough-transformed circle detection algorithm based on shape features. The field environment has a large impact on the color of the collected indicators, a color recognition algorithm based on HSV color. The algorithm is compared with a Hoff transform circle detection algorithm based on shape features only. All of the above algorithms will be tested on captured video of the device in operation and deployment validation will be implemented. Before the complete computerization of industrial equipment, the site contained a large number of devices that could not be networked to report their status and to monitor the status of these devices in real-time, this was often done utilizing manually manned cameras or manual inspections. The basic requirement of CPS for field equipment is internalization, i.e. It used the status of the equipment as a data source for subsequent real-time analysis through automated environmental awareness [51]. The facial recognition technology in the previous chapter is the application of target recognition technology in CPS, and industrial equipment is also a target that can be identified. The use of target detection recognition technology can improve the real-time and ease of equipment status detection [52].

The status of equipment is often presented utilizing digital tubes, pointer gauges, indi- cators, displays ,etc. This chapter investigates the application

This test directly on the original map based on circular shape features detection. Rate is low, and the false detection rate is high. If the manual calibration method is used and the calibration is confirmed to be correct there is no problem of missed and false detection, this method is also the mainstream method of automatic status identification for current engineering applications, but it will increase the workload of the staff. The work is to automate the detection of indicator lamp position, will slightly improve the detection rate and reduce the no-decrease rate through technical means, and eventually achieves the requirements of engineering applications. As shown in Figure 5, the device contains 1200 indicators, the average number of detections is 400 and the average number of false detections is 1600. Reducing the value of the Hough transform Min can reduce the number of false detections, but will also decrease the number of detections.

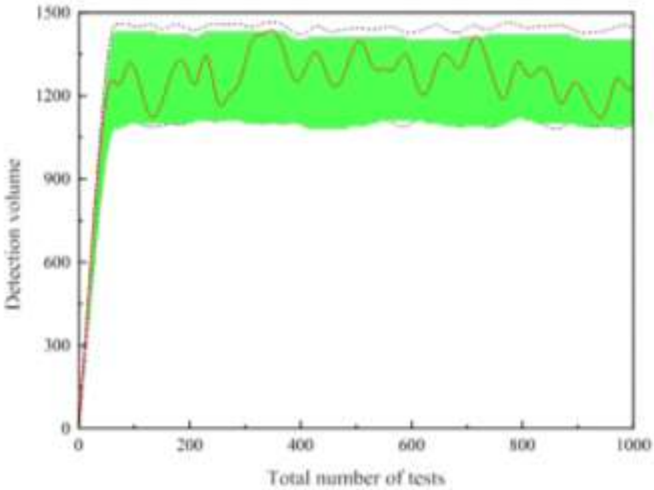

FIGURE5.TestresultsoftheHoughtransformontheoriginalfigure.

To exclude the influence of areas other than the device in the image, the device location is intercepted and magni- fied 2 times for the indicator detection test. After manually intercepting the area of the device i.e. manually excluding other areas of the image, the parameters can be adjusted appropriately to lower the threshold. The test was carried out on the same video and the number of detections per frameis shown in Figure6.Theaveragenumberofdetectionswas 100, with no false detection, which is much better than the direct detection of the original image .Intercepting the device area in the above operation requires a manual operation, i.e. Manual calibration of the device position, which would be greatly facilitated if the device position could be detected automatically.

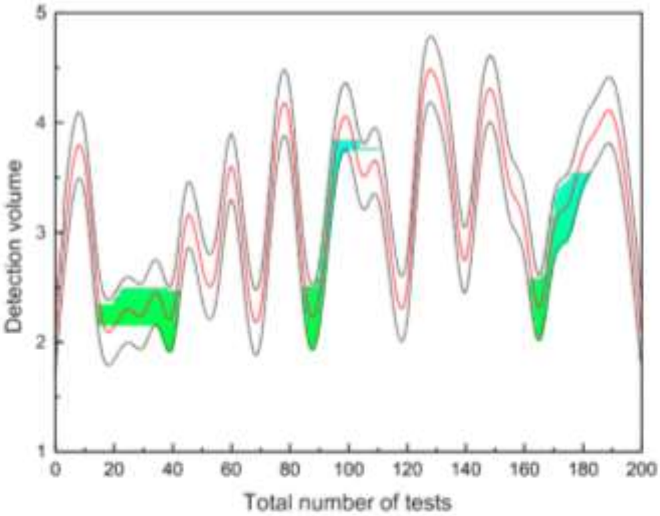

FIGURE6.Numberofdetectionafterinterceptingthedevicearea.

B. EVALUATIONOFCPSMULTI-FRAMEFUSION DETECTIONALGORITHMSFOR INDUSTRIALROBOTS

For system schedulability analysis, it is necessary to perform an execution system execution platform in Architecture Analysis and Design language (AADL) which is mainly used to simulate computer hardware and physical system components, i.e. abstraction of the computing platform. After setting up and adding the execution platform, it is necessary to bind the running threads and processes, processing systems, and other processing components to the execution platform. AADL has a large number of deployment attributes that can be associated with the bound platform and used to describe the computer performance and statistical scheduling feasibility after the bound platform. For example, the amount of time required for the execution of a thread is defined within the cycle time of the thread or process execution. These properties need to be defined during the modeling of the component. The conventional detection algorithms detect indicators based on their geometric characteristics and carry out comparison tests, showing from the results that detecting indicators only within a device area improves the detection rate, and if the camera monitoring area is manually adjusted to the indicator panel of a single device, dense devices require a large number of cameras to monitor them [53]. The indicator light detection algorithm first trains the model to detect the device location and detects the indicator light located within the device region of the output of the first stage. In this, the first stage uses the convolutional neural network model SSD to detect the device location, and the second stage uses the Hough transforms to detect the circular indicator light location within the output region of the first stage. Meaningful learning-based target detection algorithms can be divided into two categories, one-stage, and two-stage [54]. The basic idea of two-stage is to first generate a series of candidate frames according to some algorithm, and then classify them through convolutional neural networks, with representative algorithms such as R-CNN, Fast-CNN, and CNN, etc. The one-stage does not have to generate candidate frames, and directly converts the problem of target frame location into a regression problem, with representative algorithms such as POLO series and SSD. Comparing these two types of algorithms, the one-stage algorithm has obvious advantages in speed, and the two-stage has strengths in detection accuracy and localization precision. In this paper, SSD, one of the one-stage algorithms, was chosen for the ensuing study. In addition to the network model, the dataset is also an important factor in the effectiveness of the profound learning model. It is much simpler to just label the device location than to label the indicator locations on the captured images. An AADL system model describes the architecture of the software and execution platform components that make up the application system and the interaction between these components in the system runtime environment. When modeling with AADL, the system requirements should first be analyzed, and the system should be divided into multiple subsystems according to their functions, and the subsystems should be modeled separately. If you encounter a property relationship that is not supported by AADL, you can extend the modeling by using AADL custom properties or attachment functions, such as Spatio-temporal properties, behavioral properties, and physical hardware devices in the system. After defining the components of each subsystem, the subcomponents are connected by the port interface component through the semantics of data exchange and control in the AADL standard, and then the non-functional attributes of the system are modeled in a rationalized manner. Moreover, in AADL, the components are affirmed with object-oriented ideas, i.e., encapsulation, inheritance, and polymorphism, and the established subcomponents can be extended in the later analysis and verification process. Finally, all the components are bound in the corresponding execution platform, such as memory bound to the processor, process bound to the processor, and thread bound to the processor. After the model is built, the system architecture, semantic checking, binding and scheduling of threads, and error system can be

analyzed by model instantiation, such as end-to-end flow delay verification analysis, system schedulability analysis verification, binding, and scheduling of threads, error tree, etc. By verifying the analysis model, the system is modeled with rationalization and modification until the system model meets all requirements. After the system modeling is completed using AADL, the execution platform of the system's software platform binding can be used for subsequent system verification and analysis only after the binding of the system's software platform is done. The execution platform refers to the processor, memory, and bus. Since the process is the allocation unit of system resources, and the thread is the smallest scheduling and execution unit of the system, we need to bind the system resource allocation to the process, such as processor resources and memory, and then bind all threads to the processor when we do the binding. After completing the binding of the system software platform, we can examine and analyze the system to verify whether the system design meets the requirements analysis, such as the real-time use of processor and memory resources, and whether there is a deadlock problem in the critical resources between processes. As shown in Figure 7, this paper achieves the automatic extraction of device locations from the video stream, thus providing input for the Hough transform. However, with an average detection rate of 53.7% and a maximum detection rate of 78.9% for the indicators on the equipment area picture, there are a large number of missed detections and the loss of status has a huge impact on the comprehensive status monitoring of the equipment. Considering that the relative position of the cameras used to monitor status in a CPS site to the equipment is constant most of the time. In the actual scene, the camera captures the color of the device indicator is greatly influenced by the environment, such as light, the device's conditions, and other factors, it is difficult to set a uniform threshold for all the device indicator color recognition and needs to be adjusted one by one. Based on a convolutional neural network to learn the actual image of the field equipment indicator, it can replace the manual process of adjusting the reference one by one. As the image colors do not contain complex features, this paper utilizes a LeNet-based network structure for training. Due to the small size of the data set and the fact that color recognition does not require complex features compared to handwritten digit recognition, a LightLeNet structure is designed based on the LeNet structure, which reduces the number of channels compared to LeNet. The modified network structure is shown in the following table with a total number of epochs of 240. The number of network parameters for LightLeNet is close to 1/3 of that of Le Net.

C. CPSMULTI-POSEFACERECOGNITIONANALYSISFOR INDUSTRIALROBOTS

Facialrecognitioncanbedividedinto1:1verificationand1: N recognition. The face verification technology is currently commonly used, for example, to verify whether the face

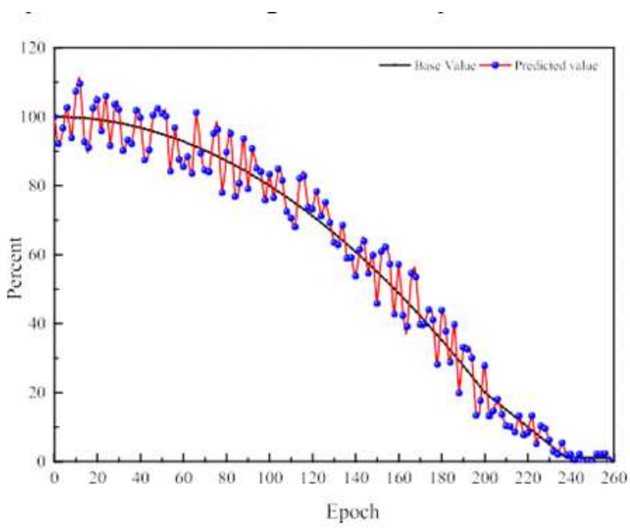

FIGURE7.Training convergence of CPS detection models for industrial robots.

information corresponding to the ID card matches the person holding the card in swiping the ID card into the station, to verify whether the face information of the Alipay registration matches the current operator, and to unlock the door with a face. Face verification technology can be used for 1: N identification. Both need to exist in CPS, for example, identifying people directly in surveillance is 1: N identification while verifying faces when swiping cards is 1:1 verification. The deployment of face recognition systems can be divided into centralized and distributed deployments, where the centralized deployment uses a high-performance server at the back end to process the video streams from all the cameras, and the distributed deployment only needs to process a small amount of camera data at the edge nodes and send the processing results to the back end server. The centralized deployment will also bring huge network pressure. Therefore, this paper chooses to adopt a distributed deployment scheme. The aim of the pose estimation algorithm proposed in this paper is to be able to exclude the influence of samples in the sample pool that differ significantly from the pose of the face to be measured, rather than just choosing the closest pose sample pool for recognition, so the metrics of rank 2 and rank 3 are more important compared to rank 1. Except for PD-67, the rank 2 neighborhood pose recognition accuracy of both models is above %, and the rank 3 recognition accuracy is close to 100%. The accuracy of model B is close to that of model A, while the accuracy of rank 2 and rank 3 on PD-67 is both much higher than that of model A. Therefore, model B will be used in this paper in succeeding studies. As shown in Figure 9, the current mainstream faces recognition techniques are based on metric learning, i.e. Learning the similarity between different samples and using a loss function to constrain the metric relationship between classes of the same category and different categories. The model encodes features on faces and uses the Euclidean distance or cosine distance of the altered facial features encoded to measure similarity; the smaller the distance, the higher the similarity, and when the distance is less than a set value of the same class.

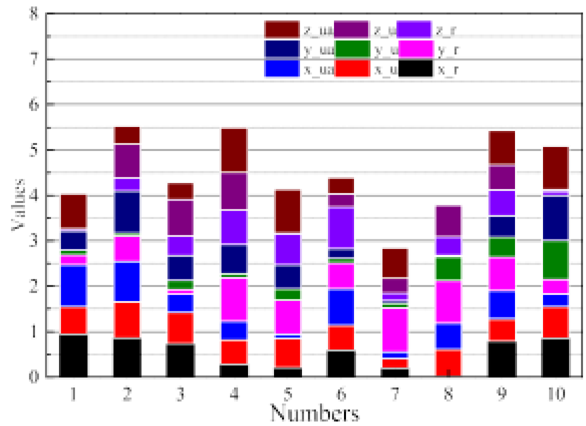

FIGURE8.Comparison of data training for CPS modeling algorithms for industrialrobots.

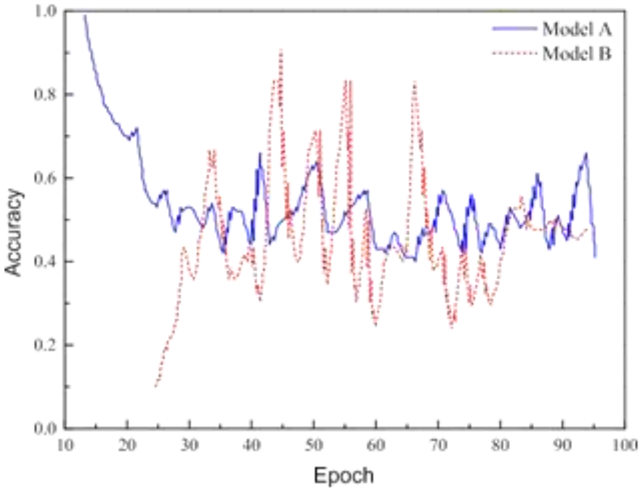

FIGURE9.Comparisonoftrainingresultsoffacerecognitionalgorithms for industrial robots.

IV. CLOUD-BASEDPLATFORMFOREVALUATINGBIG DATA-DRIVENROBOTICCPSINFORMATION ENTROPY DATA

A. INFORMATIONENTROPYDATACOMPLEMENTATION BASED ON IMM ALGORITHM UNDER CPS FOR INDUSTRIALROBOTS

In a CPS system environment, pre-processing of data is a step that cannot be ignored and completing missing data in a data series or data set is a fundamental task in data preprocessing. There are two principal methods of processing missing data: deleting and completing the missing data. The deletion of missing data is relatively simple and brutal, but the deletion operation destroys the data integrity of the system, and often some data is still valuable, especially when the data set itself is small, and the deletion of records may directly affect the objectivity and accuracy of the system's analysis results. To improve the response rate of the CPS system to real-world emergencies, data with superior information entropy that reflect the presence or absence of emergencies are sent, while data with low-information-entropy are not sent. The IMM algorithm is an association of a Kalman filtering approach and a Bayesian estimation approach. The IMM algorithm is a blend of Kalman filtering thinking and Bayesian estimation, so it is relatively simple to calculate. In check to see the method described for complementing the information entropy low data. This paper takes the monitoring of temperature sensor data in a CPS based furnace monitoring system in the industry as an example. The furnace monitoring system transmits the information entropy flow data collected by the temperature sensor every 10 s. Full factual information entropy low data collected in 100 min are shown in Figure 10. Based on all the information entropy low data within 100 m in the figure, the information entropy low data were selected at every 10 s interval and then this information entropy low data were used to obtain the predicted values by the method in this paper. Assuming the original node position coordinates of the data in the CPS system are 0, the sensor collects data at a period of 10 s, observations are made for X and Y respectively, and the standard deviation of the observations is set to 50. The model for the data at 150 s is predictable, the model at 270 s are unpredictable, and the model at 271-400 s is predictable. In filtering calculations with the IMM algorithm, the two model sets, the predictable and unpredictable models, are used, and we now assume that the impulsive model has a state offset rate of.

The video acquisition part is aimed at the control of camera devices, as well as the acquisition and encoding of video data. The video data acquisition is carried out based on the hardware of the webcam, and the operation process is designed through the multimedia audio and video processing framework. After setting and controlling the webcam, the raw video data of the camera will be acquired in real-time and cyclically, decoded and compressed by using relevant hardware, and the encoded data will be temporarily stored in local disk resources.

acquisition part, the system's ability to perform high-quality video recording and efficient disk usage are fully considered and optimized to ensure the stable operation of the overall system. The video transmission part mainly focuses on the communication transmission from the data acquisition side to the server-side or the user side. The user side generates the communication request to the data acquisition part, and the request will contain the IP address, port number, channel number, code stream, and other information to obtain video data, and then confirm the required data stream from many data, and upload it to the server-side through the network according to the standard format, the server-side parses the information and data in the request and reads and writes the data continuously to start to obtain the relevant video data from the video acquisition part. The server side parses the information and data in the request and reads and writes the data continuously to start getting the relevant video data from the video capture part and then transmits the video data through the communication network. Webcam-based monitoring can better integrate the human factor into the interconnected human-machine-object environment, and the video data provided by the camera head guides the human to achieve feedback intervention, which complements the safety and reliability of the physical layer to the Cyber layer of the industrial robot. During the selection process of the web camera, the main consideration of this study is that the camera has the requirements of long monitoring time, high video stream quality, and stable monitoring data, etc. Also, we hope that the monitoring system can be played on the website but do not want to install plug-ins. To establish the industrial robot motion monitoring system, the selected webcam is to be configured and debugged. When the initial setup of the camera is completed, data such as account number, password, IP address, and other related data stream key information data are recorded. To make a directional analysis of the prediction results of the filtering, we took the node position deviation and root means the square error of the predictable model, unpredictable model, IMM filtering, and the actual value respectively, and then further compared them to derive the predictable model and unpredictable model probabilities at each time point accordingly, as shown in Figure 11. The IMM filtering is critically influenced by the changeable model, but at other time points, the unpredictable model is the key factor, as would normally be expected. The IMM algorithm automatically adjusts the probability of each model to predict data with low-information-entropy in the CPS system. The key to the IMM algorithm is that when filtering the low-information-entropy data, the IMM error values can calculate each model filter in parallel, then predict it through a mixture of probability and Bayesian prediction ideas, and finally weight it, which is a comprehensive calculation process during which it can automatically switch and adjust the model. Based on the low information entropy data selected at l0 ◦ intervals within 100m, the prediction can be made well for

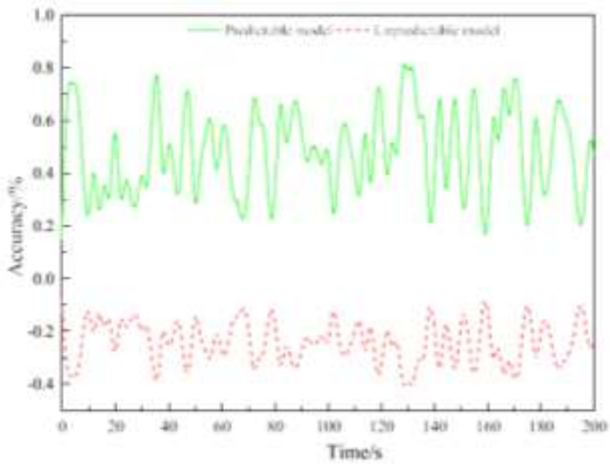

FIGURE11.Predictablemodelaccuracyateachtimepoint.

all the low information entropy data within 100m. Based on the low information entropy data within 100m, the low information entropy data is selected at every l0 ◦ interval, and then the Kalman filtering algorithm is used to predict these low information entropy data, and the prediction results are shown in Figure 12. By comparing the root-mean-square error of the predicted values with the actual values of the low information entropy data, the prediction of the low information entropy data by this method is more accurate than that of the Kalman filter.

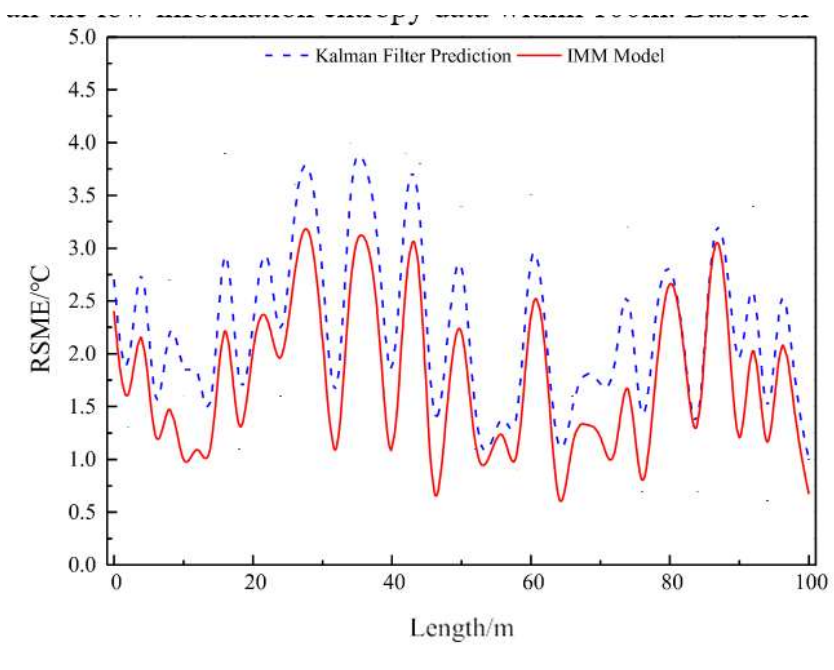

FIGURE12.ComparisonofpredictedandactualKalmanfiltererrorsfor industrial robot CPS models.

B. BIGDATA-DRIVENINDUSTRIALROBOTMONITORING INFORMATIONENTROPYDATAAPPLICATIONS

In this paper, the state codes of different information sources are spliced into a one-dimensional vector as the CPS state at the current moment, while the events of different information sources in the scenario do not occur at the same moment, so the state vector of the historical moment is also spliced on this state of the past 60s, so the input data dimension of the final decision tree is 18600. due to the lack of real data in the actual scenario, it is necessary to generate data for simulation testing according to the scenario requirements. Other attributes to be encoded are in the range of 60 and are laterally stitched into the system state vector. To closely match the data in the actual scenario, it is also necessary to set different probabilities for the values of a different attribute. There will also be data inflow and outflow, and such events have a higher probability of occurrence, and the equipment may switch between different states during normal operation. In this study, the probability of such an event occurring is also set to 0.3. When the system is in stable operation, executable programs are generally not added frequently, so the probability is set to a smaller value of 0.02. The capture of an unrelated person by a camera inside the physical environment of the CPS is a live intrusion event, and the probability of such a situation occurring is smaller than the probability of an unrelated person being captured by a camera outside the physical environment, which are set to 0.01 and 0.03. According to the above rules 10,000 samples are randomly generated for scenario 1 and scenario 2 respectively, where the number of positive samples for scenario 1 is 3322, and for scenario 2 is 2894. the generated datasets are divided into training and test sets according to the ratio of 8:2, and finally, the recognition accuracy of the two scenarios on the test set reaches 100%, which shows to some extent that the decision tree algorithm is feasible in this use This shows to some extent that the decision tree algorithm is feasible for the scenarios described in this way. There are other more information sources and attributes in the actual scenes. Only the states related to the target scenes are considered in the system state coding, which is equivalent to an artificial feature compression, and only two scenes are considered in the classification without the interference of other factors, so the final test accuracy is higher. The progress of robotics and industrial robots has become an important part of industrial manufacturing and can take on more tasks and higher loads. Of course, all of this affects the robot’s performance, so it needs to be monitored and managed to provide real-time feedback on the robot’s operational status. In contrast to traditional sensor monitoring, digital twin technology is based on it, combining the collected data with the current state of motion of the industrial robot, making it easy to observe the unqualified motion process. This paper occurs when the motion data of the industrial robot are known to solve the torque of each joint and the velocity of the end-effector including time, angle of each axis, displacement, and acceleration. The ADAMS simulation software contains a large number of constraint libraries, force libraries, and the outputs displacement, velocity, acceleration, and torque data. ADAMS has combined a series of processes to calculate the simulation model within the software, and the user can import the model by Setting parameters that allow the entire robot motion to be simulated, reducing analysis time and increasing staff efficiency.

The ADAMS software allows external files to be imported into the software using the ADAMS/Exchange module to create solid models. In this paper, a simplified Solid Works model is created, then the model is solidified, the format of the model is changed to SLDASM format and the model is imported into ADAMS .Some of the collected data removed to retrace the real motion of the industrial robot. Through simulation, the speed and acceleration of the end-effect or and the torque of each axis can be obtained and various data curves are generated. Figure 13 shows the joint torque variation curves respectively.

As can be seen from the end-effector curves, the speed and acceleration curves are both continuous and smooth, with no ’spikes’ and no exceedances of the permitted maximum values, indicating that the robot is operating well, with smooth transitions and few shocks during movement. The torque curves show that the torque of the dual axes changes slowly over time and that the torque values do not change much, and are in normal use.

This indicates that the industrial robot is currently in normal working condition

V. CONCLUSION

Based on the demand development of industrial robots, this paper proposes an improved CPS system architecture based on the definition of CPS system architecture to solve the problem of massive data processing of industrial robots in smart factories using a cloud platform. And it uses OPC UA heterogeneous data standardization to solve the problems in heterogeneous integration of smart factory robots. This paper proposes a hierarchical modeling approach and process of AADL for large CPS robotic systems. The overall modeling of a smart robotic factory is carried out through three levels: cell-level CPS, system-level CPS, and SOS-level CPS. Among them, in the cell-level CPS system modeling, the mobile robot trolley is employed as an example. The component and part conversion of Simu link models to AADL models is investigated to extend the modeling application capabilities of AADL. To reduce congestion caused by limited network bandwidth in the CPS system, improve the ability to identify 34678 VOLUME 9, 2021 N. Zhang: Cloud-Based Platform for Big Data-Driven CPS Modeling of Robots abnormal data with great uncertainty, and fully guarantee the response rate of the CPS system to emergency events, the complexity of the CPS system is analyzed from the perspective of information theory, and the average dynamic complexity of the CPS system is set as a Min value to determine the first and second degree of sensor data information in a certain period, and the CPS system selects information The CPS system selects the data with high information priority and analyses its effectiveness through experiments. Based on the characteristics of smart factories and the analysis of modeling requirements, this paper proposes a modeling method for information-physical fusion systems based on AADL analysis and design. Using the feature that AADL can model system software and hardware simultaneously, the software components of the system are mapped to the implementation platform when modeling the system, and design factors specific to the implementation platform are added to achieve co-design and co-analysis of computer software and hardware. This study also designed a pose estimation algorithm based on the face pose feature map, using an improved Alex Net network model to train the face pose feature dataset, and compared to the original Alex Net model, the improved Alex Net improved the recognition accuracy on the validation set by 1.03%, reaching 94.42%. Rank 2 neighborhood pose recognition accuracy reached 100% on the test set. Rank 2 adjacency pose recognition accuracy for different pose categories on the pose sampling dataset reached over 96%.

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