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iRobot-Factory: An intelligent robot factory based on cognitive manufacturing and edge computing

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HIGHLIGHTS

- This paper sets forth a new iRobot Factory system architecture from six points of view: intelligent terminal, system management, edge-computing node, cloud / cognitive engine, intelligent device unit, and the iRobot-Factory production line layer.
- This paper discusses efficient information interaction, multimodal data fusion, and automatic production and puts forward two solutions for modeling and active operation and maintenance based on cognitive manufacturing, communication, and interaction based on edge computing.
- This paper carries out the system-performance experiments between the iRobot-Factory and the traditional factory. The experimental results showed that iRobot-Factory significantly improved both chip assembly and production efficiency. The number of system instructions also decreased significantly.

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ABSTRACT

The Internet of Things (IoT) and Artificial Intelligence (AI) have been driving forces in propelling the technical innovation of intelligent manufacturing, promoting economic growth, and improving the quality of people's lives. In an intelligent factory, introducing edge computing is conducive to expanding the computing resources, the network bandwidth, and the storage capacity of the cloud platform to the IoT edge, as well as realizing the resource scheduling and data uplink and downlink processing during the manufacturing and production processes. Moreover, the emotion recognition and interaction of the Affective Interaction Intelligence Robot (iRobot), with the IoT cloud platform as the infrastructure and AI technology as the core competitiveness, can better solve the psychological problems of the user. Accordingly, this has become a hot research topic in the field of intelligent manufacturing. In this paper, we describe an intelligent robot factory (iRobot-Factory), adopt a highly interconnected and deeply integrated intelligent production line, and introduce the overall structure, composition, characteristics, and advantages of such a factory in details from the two aspects of cognitive manufacturing and edge computing. Then, we describe the implementation of the volume production of iRobot using iRobot-Factory and look at the system performance experimental results and analysis of the iRobot-Factory and a traditional factory. The experimental results show that our scheme significantly improved both the chip assembly and the production efficiency, while the number of system instructions also decreased significantly. In addition, we discuss some open issues relating to cloud-end fusion, load balancing, and personalized robots to make reference to promoting the emotion recognition and interaction experience of users.

1. Introduction

The booming development of technologies involving cloud computing, big data, mobile internet [1], augmented reality (AR), virtual reality (VR), and artificial intelligence (AI) has forced both academic and industrial researchers to carry out a lot of work in these areas [2]. Moreover, the fusion of these emerging information

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technologies and manufacturing industry has induced the current hot topic of intelligent manufacturing (IM).

In recent years, major manufacturing countries (Germany, the United States of America, and China) have rapidly achieved commanding heights in the field of manufacturing through powerful research, development, and social productive force. German Industry 4.0 digitizes and realizes the intelligence of the supply, manufacturing, and sales information in production using a Cyber–Physical System (CPS) [3], in order to realize a rapid, effective, and personalized product supply. The General Electric (GE) company first came up with the concept of an industrial internet, and the core idea was to combine the internet and machinery equipment, utilize the big-data analyses generated from the running machine, promote the running efficiency of the machine, and reduce downtime and unplanned faults. There is a significant strategic deployment planned for China in 2025 to promote Chinese manufacturing developments and quality, based on the general trend of international industrial transformation [4–6].

Thus, when various countries in the world are committed to realizing a high level of development in manufacturing industry, the entry of computer science, IoT [7–10], and AI technology enables further development towards intelligent manufacturing. This intelligent manufacturing is characterized by vertical integration, horizontal integration, and end-to-end integration to realize end-to-end interconnection, i.e., the integration of IT systems in different horizontal levels of the overall CPS network, focusing on the entire life cycle of the product (such as actuator and sensor, control system, production management, manufacturing and execution, enterprise plan, and other different levels) [11].

In this paper we focus on a detailed description and discussion of the vertical integration of intelligent manufacturing. The vertical integration-oriented intelligent manufacturing concentrated industry is called an intelligent factory and has four main characteristics: (1) High interconnection. The IoT [12], edge computing [13], data resources, and network resources are interconnected. (2) Dynamic reconfiguration. The orientation of the dynamic control and management are realized towards the actual network and system architecture. (3) Mass data. The efficient collection and deep mining of mass multimodal data are realized by IoT technology. (4) Deep integration. The deep integration of AI technology such as cloud computing, big data, mobile internet, machine learning (ML), and deep learning are realized.

In combination with our previous work in the field of emotion-aware social robot, the research of an intelligent robot factory (iRobot-Factory) will further enhance the intelligence and efficiency of robots in research and development, design, and production. In the field of the intelligence robot (iRobot) manufacturing assembly line, we should realize an efficient multimodal information exchange and multilevel industrial big-data processing [14,15] using an intelligent factory, and combine them with the demands of heterogeneous network communication and dynamic information interaction to achieve robot research and development in batch or customized production [16]. To achieve efficient and reliable heterogeneous communication, current advanced heterogeneous network selection strategies such as [17] can be employed, and some distributed information fusion mechanisms [18] can also be adopted to enhance the performance of the dynamic information interaction.

The efficient interconnection between the system and the data has become the key to interactive experience improvements during the design and implementation process of an iRobot-Factory. Edge computing provides the possibility for such an interconnection [19]. The development of edge computing transfers the computation to the perimeter network by the joint optimization with caching and communications on edge clouds [20]. The steep

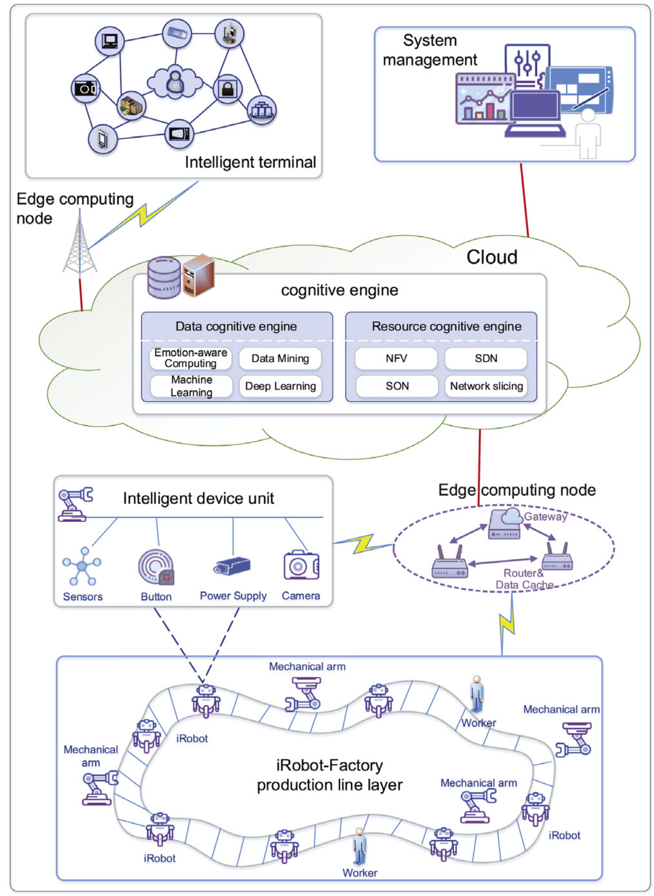

Fig. 1. iRobot-Factory system architecture.

rise in the edge device of the iRobot-Factory presents new challenges involving maintenance, operation, reliability, and extension to a data-centered and cloud-centered service mode. Introducing edge computing in an iRobot-Factory is designed to set up an intelligent system that integrates computation, storage, network, and application to realize the decentralization and efficient dynamic management of computing tasks [21]. In addition, edge computing plays a role in promoting the development of emotion recognition [22,23] and interactive applications, provides the intelligent services for such applications, and accordingly meets key demands such as real-time service processing, intelligent scheduling, and security privacy protection. The personalized demands on emotion recognition and interaction are increasingly obvious with the upgrade of the service. Therefore, the system needs to possess intelligence and high flexibility to establish personalized emotion recognition and an interactive model in accordance with the user characteristics [24]. Edge computing can make the best of the computing and storage capacity of a device on site, and realize personalized model deployment and application based on distributed information processing.

Edge computing implemented in the assembly line of an iRobot-Factory can meet the requirements of mobility and location independence, and provide the personalized and highly flexible demands for configuring the emotion recognition and interactive robot and its relevant application. At present, the range of the edge-computing node extends to a high-performance intelligent terminal (Arm core chip and Arduino core chip) from the IoT-embedded device only with a limited storage and computing capacity, in order to provide stronger capacity. Meanwhile, the edge-computing node will enable the cloud-based emotion-recognition service to be transferred to the terminal closer to the user, to develop the recognition business on the side of the terminal device. The contributions of this paper can be summarized as follows:

- According to the application of cognitive intelligence and edge computing in manufacturing industry, this paper sets forth a new iRobot-Factory system architecture from six points of view: intelligent terminal, system management, edge-computing node, cloud/cognitive engine, intelligent device unit, and the iRobot-Factory production line layer.
- This paper focuses on the characteristics of the iRobot-Factory; discusses how to realize efficient information interaction, multimodal data fusion, and automatic production; and puts forward two solutions for modeling and active operation and maintenance based on cognitive manufacturing, communication, and interaction based on edge computing.
- According to the main characteristics and advantages of an iRobot-Factory, we carry out the system-performance experimental results and analysis between the iRobot-Factory and the traditional factory. The experimental results showed that our method significantly improved both chip assembly and production efficiency. The number of system instructions also decreased significantly.

The remainder of this paper is arranged as follows. Section 2 provides an architecture chart of the iRobot-Factory and introduces the composition and functions of each part in detail. Section 3 introduces the application of cognitive manufacturing and edge computing in an iRobot-Factory. Section 4 shows the iRobot prototype produced by the iRobot-Factory, and carries out the system-performance experimental results and analysis between the iRobot-Factory and the traditional factory. Section 5 discusses some open issues about cloud-end fusion, load balancing, and personalized robots. Finally, Section 6 summarizes our work.

2. iRobot-Factory System Architecture

To realize the humanization, intelligence, and automation of the iRobot, the iRobot-Factory should possess a full set of assembly lines that can design, manufacture, assemble, and produce such an intelligent robot efficiently. In addition, the real-time feedback of the user is also crucial during the manufacturing process of the robot. We can adjust the production configuration of the robot dynamically by introducing edge computing to realize the real-time data collection of the factory and the user, the real-time efficient processing of user emotion data and robot production information, and the real-time intelligent operation of the robot manufacturing production line. Thus, this section puts forward the iRobot-Factory system structure, as shown in Fig. 1, which mainly consists of the following 6 parts:

(1) Intelligent Terminal

The users are the group that is contacting the iRobot most directly. They can feed back the Quality of Experience (QoE) correctly in accordance with the actual using effect. The iRobot designed by us has several different operating environments, e.g., an vehicle-mounted robot, emotion recognition and interaction Apps, an baby robot, an domestic robot, etc. The most important function of the intelligent terminal is to collect the user-emotion data. For example, a mobile phone (equipped with intelligent Apps) can collect the user's voice, image, facial video, action video, etc., while the iRobot, equipped with the tactile sensor, can collect the tactile information. The user can make the emotion interaction with the iRobot, and request the computing resources to the local, edge-computing node, or the cloud data center by the relevant operation [25,26]. The server can gain the audio-visual, physiological, and emotion data resources of the user, carry out the data mining and data processing with the cognitive engine [27], obtain the emotion-recognition results of the user, and then push the follow-up information and interoperability to the intelligent terminal on this basis.

(2) System Management

The cloud data center of the iRobot-Factory is connected to the edge-computing node and super-computing node with a strong computing capacity where it carries out the real-time analysis and monitoring for the user emotion data, user experience data, and the intelligent factory manufacturing data that was collected. It can also conduct the intelligent management of potential industrial manufacturing problems, user interactive behavior and preference, network resource control, and other problems through artificial intelligence.

(3) Edge-Computing Node

The edge-computing node is an important component of edge computing. It transfers the computing capacity of the cloud to the IoT edge, caches big data generated by the IoT and intelligent factory and relieves the congestion and delay in the process of network transmission. To provide the optimal computing service for the user, with the help of the edge-computing node, cloud computing pays more attention to putting the computing resources into the high-precision computations, rather than bearing all the computing tasks.

(4) Cloud/Cognitive engine

The Cloud equipped with a cognitive engine is the brain of the iRobot-Factory. The subject of cloud computing is the data center, which deploys a high-performance artificial intelligence algorithm and stores much of the user's long-term analysis data and information, so as to provide a high-precision computation. We can realize the deployment of the cognitive engine in a three-layer network architecture by Software Defined Network (SDN) technology and AI technology. The cognitive engine includes two types of engines: a data cognitive engine and a resource cognitive engine. (1) The data cognitive engine processes the real-time multimodal emotion data flow in the network environment, possesses the capacity for data analysis and automatic business processing, executes the business logic in an intelligent manner, realizes the cognition of the business data and the resource data in various cognitive computing methods (involving data mining, machine learning, deep learning, and artificial intelligence), guides the resource distribution dynamically, and offers the cognitive service [28]. (2) The resource cognitive engine can perceive the computing resources, communication resources, and network resources (such as network type, business data flow, communication quality, and other dynamic environmental parameters) of the iRobot-Factory, feeds the integrated resource data back to the data cognitive engine in real time, while receiving the analysis results of the data cognitive engine, and guides the real-time dynamic optimization and distribution of resources.

(5) The Intelligent Device Unit

The intelligent device unit is the hardware basis of the iRobot. The intelligent factory develops the hardware facilities by itself, involving the motor-rotation interface, Wi-Fi antenna, camera, micro-USB charge port, knob switch, Li battery, film-type pressure sensor, LED indicator light, A33-Vstar2 board, MIC, horn, etc. These devices and components are assembled into different personalized robots in the intelligent production line for selling according to the user preference and experience data that was collected.

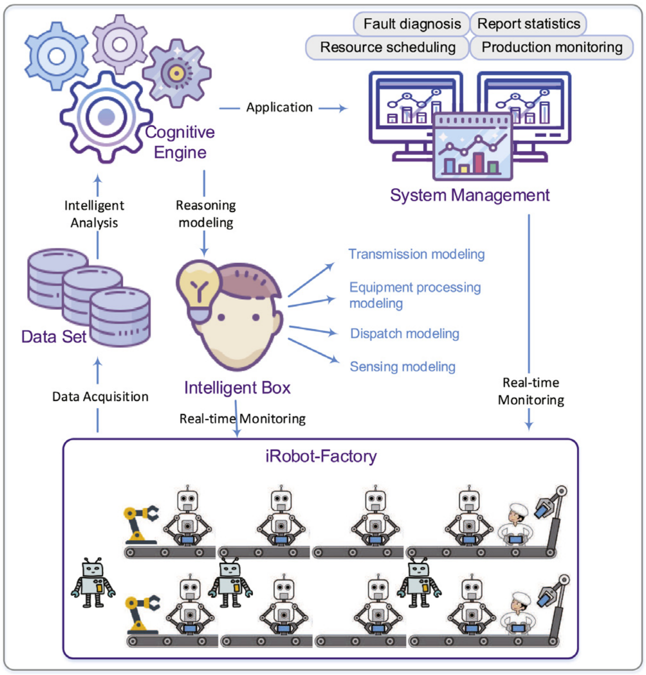

Fig. 2. Modeling, active operation and maintenance based on cognitive manufacturing.

(6) The iRobot-Factory Production Line Layer

After manufacturing the required devices and parts for the robot, the iRobot-Factory production line conducts the automatic assembly by means of a mechanical arm as the focus, a workshop worker as the supplement, and the cloud-system management as the guidance. With the help of an intelligent conveying unit and cognitive engine (analyzing the user preference, computing resources, network resources, and factory production status in real time), the production line can carry out the active operation, maintenance, and self-organizing dynamic reconfiguration, and realize efficient production, manufacturing, and assembly.

3. Application of cognitive manufacturing and edge computing in an irobot-factory

We introduce cognitive manufacturing (manufacturing industry with cognitive intelligence) and edge computing (an exactly three-layer smart-computing system consisting of the edge device, the edge computing, and the cloud computing) to realize the efficient data collection, automatic production, intelligent recognition and analysis, and active operation and maintenance of the iRobot-Factory. We introduce the application of modeling; the active operation and maintenance based on cognitive manufacturing; and the communication and interaction based on edge computing in the iRobot-Factory, as described below.

3.1. Modeling, active operation and maintenance based on cognitive manufacturing

In the cognitive manufacturing schematic diagram, as shown in Fig. 2, the key parts are the iRobot-Factory production line, the cloud data center, the cognitive engine (see Fig. 1 for its component), system management, and the intelligent box (the most crucial cognitive knowledge base).

- The iRobot-Factory production line is responsible for parts manufacturing as well as robot assembly and production. To realize the automatic production and efficient robot manufacturing based on a mechanical arm and an intelligent industrial robot the iRobot-Factory only needs a small number of workshop workers as supplements.
- The data set is a safe and reliable mass-storage unit deployed in the Cloud, in charge of storing the production and manufacturing data collected by the IoT intelligent device (production line and various sensors of the workshop) for real-time analysis and accurate monitoring. The efficient multimodal data-collection mode also performs the data detection and storage.
- The functions of the cognitive engine are introduced in detail in Section 2. During the process of cognitive manufacturing, it is mainly responsible for conducting the intelligent analysis of the production data stored in a data set (adopting the AI technologies of ML/DL), and enhancing the recognition accuracy as much as possible, for the purposes of a follow-up application.
- The system management has four main functions in an iRobot-Factory, i.e. fault diagnosis, report statistics, resource scheduling and production monitoring. It is the intuitive embodiment and application of the cognitive engine, and helps monitor the production status of the intelligent factory in real time.
- The intelligent Box is an important component of cognitive manufacturing, and is the knowledge base. It consists of the cognitive engine reasoning and analysis, in a sense. It can do the all-around modeling in accordance with the real-time analysis results of the production line, assist in real-time monitoring of the iRobot-Factory, adjust the production scheme dynamically, and realize the active operation and maintenance.

3.2. Communication and interaction based on edge computing

In this section, we first introduce the overall architecture of the iRobot-Factory based on edge computing, and then interpret the necessity and innovation of introducing edge computing from the perspectives of data fusion and interaction, and intelligent communication. As shown in Fig. 3, the iRobot-Factory integrated edge computing is mainly consisted from device domain, data domain, network domain, and application domain. (1) The device domain includes the devices embedded in or close to the iRobot-Factory, such as the image sensor, interactive mechanical arm, audio sensor, robot, intelligent terminal, etc. (2) The data domain obtains the data storage, the data preprocessing, the feature extraction, and other services from the data source of the IoT edge, and enhances the availability of the mass multimodal data. (3) The network domain connects the IoT terminal device to the cloud platform, and realizes the intelligent network transmission and control by the SDN [29]. (4) The application-service domain enables edge computing to provide a universal, flexible, and interoperable intelligent application service.

Because the iRobot mainly offers the emotion recognition and interaction service, we proposed an intelligent communication scheme based on edge computing to realize real-time transmission, as shown in Fig. 4. The cloud computing in the upper layer relies on data centers and a cognitive engine. It adopts the virtualized mode to enable a larger number of edge users and devices to use it simultaneously. The cloud computing realizes the data analytics and the data modeling with the support of powerful hardware facilities and AI technology. The edge computing in the intermediate layer is a good supplement to the cloud computing and the edge device, and is aimed at offering a computing service with high performance, low latency, and a high bandwidth for the devices of the iRobot-Factory. The edge-computing nodes (involving the wireless access point, base station, router, etc.) form a connecting

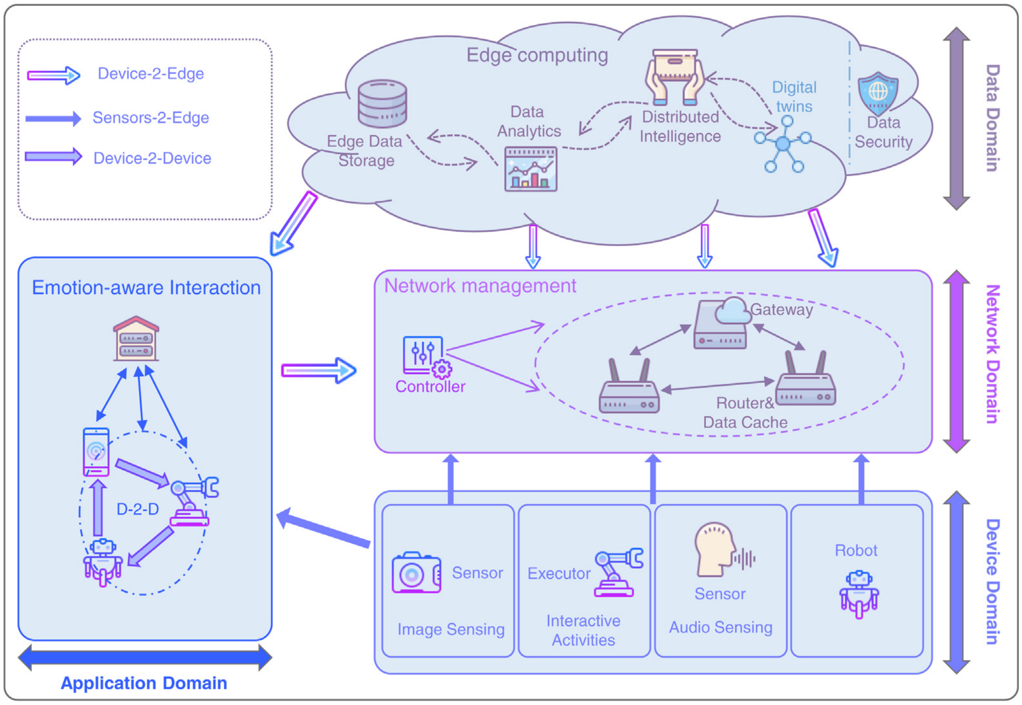

Fig. 3. The iRobot-Factory based on edge computing.

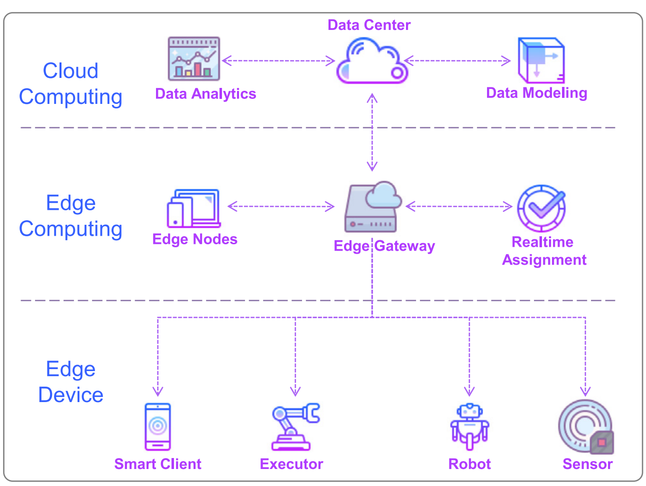

Fig. 4. Intelligent communication based on edge computing.

link between the preceding and the following, and realize the local environmental information collection, interaction, summary, computation, and the real-time regulation and control of many edge devices. Thus, edge computing can support the real-time processing of a local business better, so as to reduce the network pressure, and promote the data security and privacy protection. Due to the edge-computing node being nearer to the edge device (intelligent terminal, mechanical arm, intelligent robot, sensor, etc.), the devices can connect to the edge-computing node directly through the wireless channel, and the computing tasks do not need to reach the remote core network.

In addition to efficient and intelligent communication, we also need to provide the mass multimodal data fusion and an information-interaction scheme for the active operation and maintenance of the iRobot-Factory. Fig. 5 shows the schematic diagram of data fusion and interaction based on edge computing. Data fusion with different types and sources is a very important step for intelligent business processing and scheduling of an iRobot-Factory. In addition, edge computing can enhance the data-fusion ability of the network edge. Edge computing can maximize the iRobot-Factory, the user-carried intelligent terminal, and intelligent robot sensor resources to realize accurate and real-time production data and user-experience data collection. The edge computing nodes can carry out feature extraction from the sensor signal using technologies involving time-series analysis, frequency analysis, and wavelet analysis. Then, it operates the AI or ML modules, conducts the data-change prediction using the extracted feature, and carries out dynamic reasoning based on the predicted data and newly collected data. During this process, the edge-computing nodes can fuse the redundant information according to the predefined optimization standard and algorithm. This demonstrates that edge computing improves the intelligence of service scheduling and data source perception, enabling the peripheral equipment to execute the business logic analysis and autonomous computing. From the perspective of the server, edge computing mainly realizes the intelligent integration, scheduling, and management of edge-computing resources. Some monitoring tasks operating in the cloud can be unloaded into the edge-computing node, so as to reduce the delay of executing real-time monitoring and achieve autonomous monitoring and dynamic feedback. Edge computing, in favor of integrating the information model independent of the network facilities, realizes the seamless communication between different terminal devices and the efficient interaction between the terminal and the Cloud.

4. Testbed and experimental result

4.1. Introduction to testbed and experimental setting

The computing tasks that the iRobot-Factory needs to process mainly includes all kinds of sensor data, such as video, image, and digital signals. In the current environment, the automated mechanical arms and mobile industrial robots are taken as local devices, while the local server is deployed as the fog computing node [30]. At the same time, the Cloud also deploys the Big Data

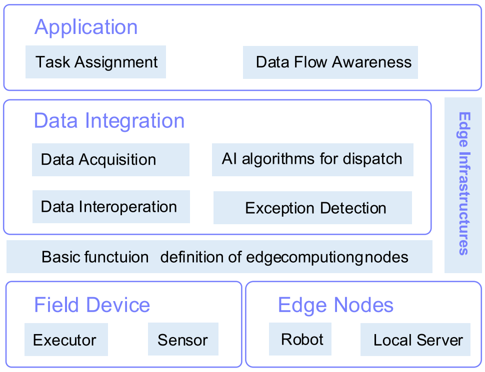

Fig. 5. Data fusion and interaction based on edge computing.

Center and Analytics Server as remote services backstage for local devices. The overall structure of the volume production for chips, robot assembly, and cloud computing nodes in an iRobot-Factory is shown in Fig. 6. The hardware-configuration parameters for each node are listed in Table 1. Its basic computing capacity is Robot(Local device)<Local Server(Fog Computing Node)<Big Data Center(Cloud), while the Analytics Server, as an independent algorithm server, carries out the algorithm model training.

4.2. Experiment results and analysis

Based on the above configuration we carried out an experiment on the volume production of iRobots in an iRobot-Factory. Then, we compared it with the production results from traditional manufacturing factories. A comparison of the assembling efficiency of robot chips is shown in Fig. 7. We analyzed the computing time delay of the iRobot-Factories and the traditional factories. Supposing that the recognition algorithm on the cloud server was the same (in fact, our algorithm is more intelligent and personalized), the computing time delay of the iRobot-Factories is shown in Formula (3), and that of the traditional factories is shown in Formula (2), where T_{local_total}, T_{fog_total} and T_{cloud_total}, respectively, represent the total computing-time delay of the local devices, the fog computing nodes, and the remote cloud data center; the total delay in local device is calculate by $T_{local\_total} = T_{up} + T_{robot} + T_{down}$; T_{up} and T_{down} represent the data upload and download time delays; T_{robot}, T_{fog} and T_{cloud} represent the computing time of the local devices, the fog computing nodes, and the cloud servers; $T_{robot\to fog}$ represents the time for the data to be transferred from the local devices to the fog computing nodes; and $T_{fog\to cloud}$ represents the time for the data to be transferred from the fog computing nodes to the cloud server; α, β and γ represent the probability of taking an integer in [0,1], i.e., the iRobot-Factory dynamically selects computing nodes and adjusts the computing and unloading scheme according to the particular network situation and the size of the computing tasks. While traditional factories are directly calculated in accordance with the Formula (2), which greatly increases the computing pressure on the cloud server and the congestion probability of the network, which is not favorable for balancing the network load and optimizing the production efficiency.

The experimental results shown in Fig. 7(a) also confirm the above analysis. The total assembly amount and the average assembly quantity per minute of the iRobot-Factory increased with the time, but the assembly growth rate of traditional manufacturing factories decreased with the time. When the recognition computing task was unloaded in the production and assembling process, each computing node uses the machine-learning algorithm deployed in the cognitive engine to analyze the data of the sensor. The longer the time, the more data was collected, and therefore the higher the recognition accuracy of the algorithm. Considering the characteristics of the edge computing in the iRobot-Factory, its communication and computing time delay is more dynamic and controllable than that of traditional manufacturing factories. Therefore, its efficiency of production scheduling is higher, and the assembly speed is faster. We adopted the least-squares method to process the data fitting for the average assembly number of chips per minute in two kinds of factories to better reflect the production efficiency under the two modes. Fig. 7(b) shows a graph after fitting, and the comparison result is consistent with our previous analysis of whether AI and edge-computing technology should be adopted.

In addition, we statistically calculated the number of instructions issued by the system within 720 min, and compared the average number of instructions per minute by the iRobot-Factory and the traditional factories, as shown in Fig. 8. Since the system has cognitive intelligence, as time increases and the sensor data collection increases, the iRobot-Factory will have a better understanding of the production conditions in the workshop. Thus, the number of instructions issued per minute is obviously smaller than that in traditional factories, and it shows a stable trend after 360 min. In research the fields faced with intelligent manufacturing, computing science (cloud computing, fog computing, edge computing, etc.), IoT, AI, and other technologies have effective ways to realize the intelligence of the manufacturing industry, as well as to increase the automation and the efficiency.

$$T_{fog\_total} = T_{up} + T_{robot\to fog} + T_{fog} + T_{down} \tag{1}$$

$$T_{cloud\_total} = T_{up} + T_{robot\to fog} + T_{fog\to cloud} + T_{cloud} + T_{down} \tag{2}$$

$$\begin{cases} T_{iRobot} = \alpha T_{local\_total} + \beta T_{fog\_total} + \gamma T_{cloud\_total} \\ \alpha + \beta + \gamma = 1 \end{cases} \tag{3}$$

5. Open issues

When researching intelligent manufacturing, the technology of Computing Science (cloud computing, fog computing, and edge computing), IoT, and AI are effective ways to realize intellectualization, and increase the automation and efficiency of the manufacturing industry. However, although we have proposed the architecture of the iRobot-Factory and discussed the active operation and maintenance/communication interaction scheme based on cognitive manufacturing and edge computing, there are still a lot of scientific and research difficulties to be solved in the production and manufacturing of iRobots. For example, the intelligent scheduling and network communication of an iRobot-Factory in terms of large-scale mechanical arms or industrial robots, the problem of computing the offloading [31] and network load-balancing algorithm, and cloud fusion technology based on edge computing. A detailed discussion of these specific issues follows.

5.1. Intelligent scheduling based on cloud fusion

Intelligent scheduling is also known as knowledge-based scheduling. It is one of the research areas that AI and intelligent control are interested in. In reality, many combinatorial problems are very complex. A large search space is required to find the optimal scheduling scheme from possible combinations or sequences. This can lead to a problem known as combinatorial explosion. When applied to iRobot-Factory scenarios, intelligent scheduling can provide us with more convenient and efficient solutions in the mass production and manufacturing of iRobots. As our intelligent factory provides cognitive manufacturing and edge-computing functions, the mechanical arm of the workshop

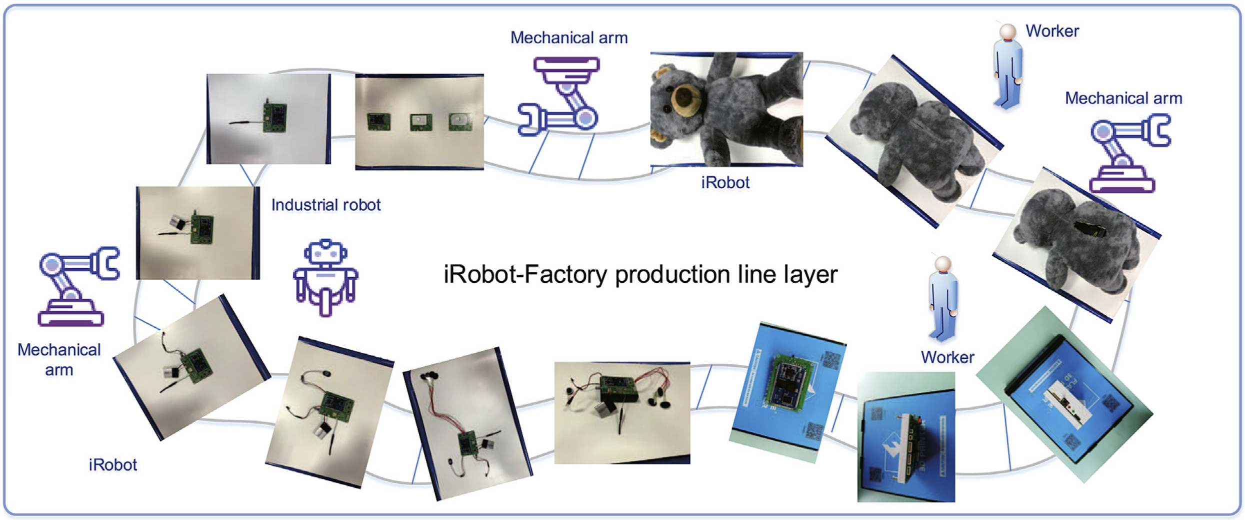

Fig. 6. iRobot-Factory production line.

Table 1
System parameter.

	Operate system	Hardware	Hardware parameters
Robot	Android 4.4	CPU DDR memory NAND Flash	4-core, 1.2 GHz frequency 1 GB DDR3 SDRAM 32 GB NAND Flash
Local server	CentOS 7	CPU DDR memory HardDisk	Quad-core, 3.4 GHz frequency 16 G DDR3 SDRAM 1050 G NAND Flash
GPU analytics server	Ubuntu 16.04	CPU DDR memory NAND Flash	NVIDIA GTX1080ti*2 32 G DDR3 SDRAM 6-core, 3.5 GHz frequencyh
Big data center	Android 4.4	CPU DDR memory HardDisk	(16-core 4 GHz)+(42-core 4 GHz) (256 G)+(336 G) (3.6 T)+(252 T)

and industrial robot scheduling, or the system administrator's monitoring of the remote Cloud and other aspects are not the only things to be taken into consideration. The introduction of Cloud Fusion Technology not only satisfies the above needs, but also brings new challenges to the designers of intelligent factories, which are specifically embodied in sensor-data acquisition, data fusion and security assurance, intelligent identification and detection algorithms, and other aspects. However, due to the fact that the computing and capacity of local devices (various sensors, mechanical arms, industrial robots, etc.) are limited, while workshop recognition and scheduling require large amounts of computing capacity (especially when an AI algorithm is used to identify and detect), the multidimensional data collected by local devices often needs to be sent to edge nodes or Clouds with better computing performance for further processing. Therefore, how do we ensure the efficient and reliable information sharing between devices, as well as fog nodes and remote Clouds, and how do we ensure that the data is safely stored in smart Clouds and can be fed back to the cognitive engine so as to guide the production and intelligent scheduling of workshop devices? These are difficult problems that will require future consideration.

5.2. Network communication and load balancing

In the iRobot-Factory, a large number of local devices (especially automated mechanical arms and mobile industrial robots, etc.) are distributed across different physical locations of the network. To satisfy the intelligent assembly-line production mode with high strength, it is necessary to consider an ultra-low time delay and ultra-high reliability for the calculation and processing capacity. Therefore, consideration is needed as to how to coordinate and manage the different types of computing resources effectively and automatically. Specifically, this includes the effective connection and data inter-transmission between local devices and fog networks, resource scheduling and task migration between fog networks, master nodes needed inside the fog network to integrate the processed subtasks, and the balance of communication and computing resources needed for remote Clouds, fog networks, and other problems. Among them, the unloading of computing tasks can lead to a long delay or unloading failure for unstable network connections and constant switching between network access points. Therefore, additional intelligent protocols are needed to satisfy the resource allocation based on unloading priority, to ensure the smooth unloading of the tasks by means of balanced computing resource allocation, to reduce the computing result feedback delay and the computing unloading energy consumption, perform proper backup, and so on according to the condition of the network [32].

5.3. Personalized intelligent robots

Nowadays, customers of emotion robots have increasingly tough requirements for service quality and cost performance. While meeting these needs, service providers present themselves with new challenges, which are shown in the aspects of emotion-data acquisition, the privacy and security of emotion data, the intelligence of the emotion-recognition algorithm, personalized

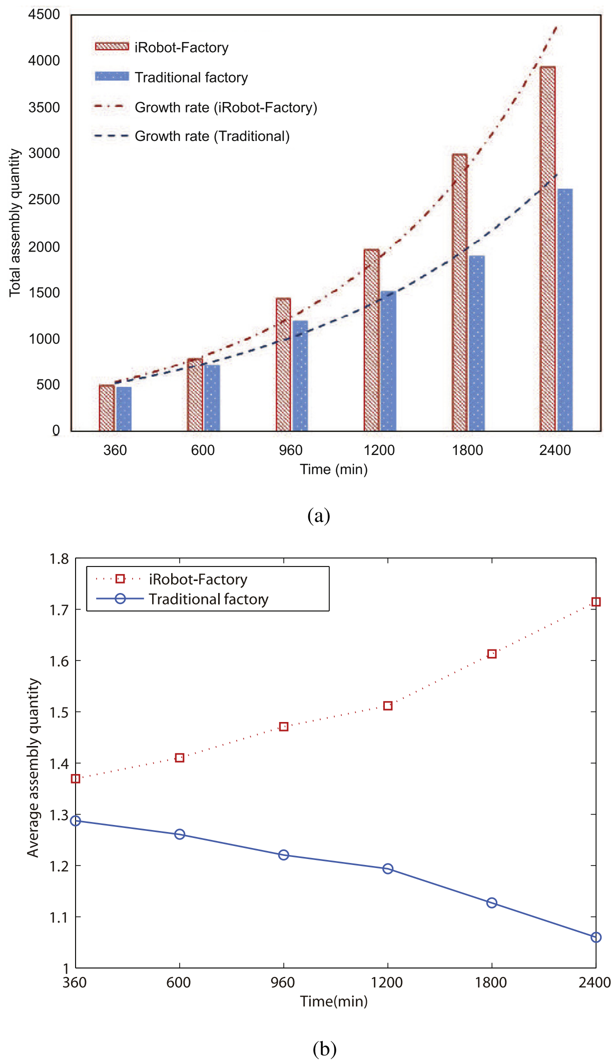

Fig. 7. Assembly quantity comparison between the iRobot-Factory and a traditional factory: (a) Total assembly quantity; (b) Average assembly quantity.

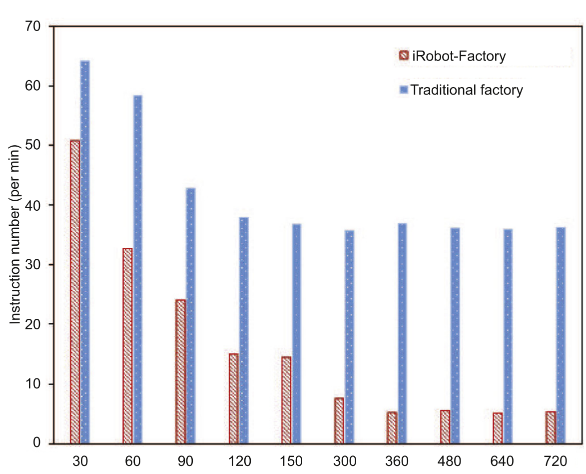

Fig. 8. Instruction number comparison between iRobot-Factory and traditional factory.

and intelligent robots, etc. There are a large number of heterogeneous access devices in the IoT composed of emotion-recognition applications, such as smart healthcare [33], smart clothes, mobile phones, computers, emotion robots, etc. In addition, most of them are mobile users. With respect to the problems mentioned above, if the iRobot-Factory wants to produce personalized emotion recognition and interactive robots that meet market demands, it needs to make a great effort with the cognitive engine (recognition algorithms, data and resource engines, etc.), and the robot's own hardware design. There are additional challenges in the evaluation of emotion recognition. This is because in traditional emotion recognition, training data and test data usually come from the same corpus or have the same data distribution. However, there is a big difference in the emotion data obtained from different objects, devices, and environments, which is usually reflected in languages, emotion expressions, emotion-labeling schemes, acoustic signal conditions, etc. This leads to a reduced performance of the trained model when it is applied to another data set. Therefore, future emotion recognition needs to pay more attention to individualized long-term emotion model construction. Emotion data is very private and sensitive. Disclosure of a user's private information can cause a serious problem for individuals. On the one hand, its original data contains private information, such as location, video, sound, etc., and on the other hand, the result of emotion data analysis is closely related to the mental world of individuals. A more intelligent protocol is necessary for mass users to access the IoT.

6. Conclusion

In this paper we focus on the research of intelligent manufacturing, and combined it with machine intelligence, cognitive science, and computing science. We attempted to optimize the production efficiency, and to realize the intelligentization and personalization of robot production. Based on the related background of intelligent manufacturing and the related research in the field of iRobots, the system architecture of the iRobot-Factory is proposed and elaborated in this paper. This paper introduces the planning of an intelligent factory that can efficiently manufacture and produce iRobots from six different aspects. In addition, based on cognitive manufacturing and edge computing, we put forward solutions for important functions such as active operation and maintenance, data fusion, efficient communication and interaction, etc. This paper provides comprehensive knowledge and an experimental basis for the iRobot intelligent factory. At the same time, it summarizes and looks into future research schemes. In addition, comparative experiments on batch production in the iRobot-Factory and traditional factories were carried out. Experimental results showed that the iRobot-Factory was superior in both the total amount of chip assembly and the average assembly number growth rate per minute. Furthermore, as the system has cognitive intelligence, the amount of instructions per minute in the iRobot-Factory decreased with the time. This indicates that compared with traditional factories, the network communication time delay of our scheme was shorter, and the recognition rate of our system was more accurate. Next, we discussed some open issues of intelligent factories based on three aspects of intelligent scheduling: cloud fusion, network communication, and load balancing. Finally, we concluded with a discussion about the production of a personalized and intelligent robot, and laid the foundations for future research.

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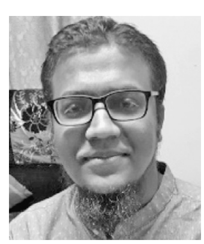

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