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IoT edge computing-enabled collaborative tracking system for manufacturing resources in industrial park

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ABSTRACT

In manufacturing industry, the movement of manufacturing resources in production logistics often affects the overall efficiency. This research is motivated by a world-leading air-conditioner manufacturer. In order to provide the right manufacturing resources for subsequent production steps, excessive time and human effort has been consumed in locating the manufacturing resources in a huge industrial park. The development of Internet of Things (IoT) has made a profound impact on establish smart manufacturing workshop and tracking applications, however a growing trend of data quantity that generated from massive, heterogeneous and bottomed manufacturing resources objects pose challenge to centralized decision. In this study, the concept of edge-computing deeply integrated in collaborative tracking purpose in virtue of IoT technology. An IoT edge computing enabled collaborative tracking architecture is developed to offload the computation pressure and realize distributed decision making. A supervised learning of genetic tracking method is innovatively presented to ensure tracking accuracy and effectiveness. Finally, the research output is developed and implemented in a real-life industrial park for verification. The results show that the proposed tracking method not only performs constant improving accuracy up to 96.14% after learning compared to other tracking method, but also ensure quick responsiveness and scalability.

1. Introduction

Manufacturing is the cornerstone of sustainable social development and a direct source of wealth creation. Today's rapidly growing manufacturing industry presents a clear feature of a wide range of products, high customization requirements, and rapid changes in demand. Manufacturing workshop includes the production and logistics operations. In Industry 4.0 era, numerous scientific research has focused on the production stage especially in thriving of Internet of Things (IoT) technology. Once the manufacturing resource are on the production line, considering the operation plan, process technology and control parameters are basically fixed, the improvement of the manufacturing efficiency is therefore limited. Synchronization in the manufacturing industry refers to providing the right resources for subsequent production steps in a timely manner at the right time [1]. Irrespective of the ownership, transportation is likely to become an integral part of smart manufacturing due to greater reliance on the movement of materials, components, products and service personnel driven by personalized needs [2]. The logistics operations in manufacturing workshop is responsible to the material transfer between production stages, which will occupy nearly 95% execution time of the whole production process under normal circumstances [3]. Therefore, the synchronization between production and logistics is of great importance.

This research is motivated by a world-leading air conditioner manufacturer located in the Pearl River Delta of China. It owns an industrial park which agglomerates various upstream and downstream firms for better resource sharing and collaboration. There is one key manufacturing resources called material trolley since it conducts the major transportation tasks among different parties throughout the industrial park. However the recycle of the vacant material trolley becomes serious challenge for the industrial park. Excessive time and human efforts are consumed in searching and picking the material trolley. The shortage of real-time location information of the manufacturing resources results in the chaos in the logistics operation and become a bottleneck affecting overall manufacturing efficiency.

In recent years, the upper-level management system represented by Manufacturing Execution System (MES), Enterprise Resource Planning (ERP) and the promotion and application of Radio-frequency Identification (RFID) based information acquisition for manufacturing resources have achieved certain performance in the manufacturing

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industry. Accurate manufacturing resource information provides reliable real-time data for synchronization, realizing dynamic decision-making in production and logistics operations. Qiu, et al. [4] suggest that IoT can be an effective approach to fully realize industrial parks benefits and mitigate the problems by enabling the real-time tracing and tracking of physical assets, and bringing real-time visibility and communication to each individual partner. The rapid development of IoT provides solutions for tackling the location tracking problems. There are recent attempts to automate location tracking on manufacturing resources using IoT technologies, encompassing Global Positioning System(GPS) [5], RFID [6], Bluetooth [7,8] and combination of various technologies [9,10].

Despite the technologies and their applicability tests in identifying the manufacturing resources location, there are still several concerns when directly adopt these technologies in an industrial park. Firstly, in an industrial park, massive, bottomed heterogeneous manufacturing resources as the tracking object are involved, the simultaneous location estimation with high concurrency should be ensured. Smart phone-oriented tracking solutions using cloud computing capacity gains popularity recently, however the tracking focus should be shifted from people to objects. Secondly, GPS do performs outstandingly in outdoor environments and widely used in daily life. But GPS does not work well in indoor environments since the signal penetration and block issues. However, in the industrial park, apart from paths or open storage area, many plants or production lines are indoor constructed, some even multistoried. A universal solution for collaborative tracking in multi-storied indoor and outdoor environment is still a major concern. Thirdly, traditional indoor tracking requires large amount of signal data collection and calibration work and may obsolete after a period of use. How to alleviate the preparation work and ensure the effectiveness and accuracy of indoor tracking is open for investigation. Moreover, there is scarce research related to manufacturing resources tracking solutions has been proposed and implemented in an industrial park among different parties.

To well address the above issues, this research proposed a collaborative tracking framework for manufacturing resources through adopting IoT and edge computing technology. The location can be automatically tracked and traced based on Bluetooth signals and edge gateways. The whole system is implemented in a real-life world-leading air conditioner manufacturer located in an industrial park to verify the feasibility and effectiveness.

The rest of this paper is organized as follows. Section 2 presents a review of the IoT practice in tracking resources and state-of-art edge computing applications. The collaborative tracking framework is proposed and introduced in section 3. In section 4, the collaborative tracking procedure and supervised learning genetic tracking method is developed and presented. A real-life case study is conducted to verify the feasibility and effectiveness in Section 5. The last section concludes the research and discusses contributions, limitations and potential for future research studies.

2. Literature review

This section will review the relevant research and applications about IoT and edge computing, and discuss the tracking solutions in manufacturing scenarios in academic and industrial practices. The research gap is summarized in the end of this section.

The IoT refers to an inter-networking world in which various objects are embedded with electronic sensors, actuators, or other digital devices so that they can be networked and connected for the purpose of collecting and exchanging data [11]. The IoT permeates our daily lives such as smart home [12,13], smart city, and smart transportation [14]. With development of IoT, physical assets are able to sense, interconnect and communicate automatically and adaptively [15]. In manufacturing area, Yang, et al. [16] comprehensively explained the applications and potential of IoT. Cloud manufacturing as a new service-oriented manufacturing mode has been paid wide attention around the world [17]. Tao, et al. [18] carried out intelligent perception and access of manufacturing resources and capabilities based on IoT and advanced information technologies. The classifications of manufacturing resource, services and relationships are presented. Lu and Cecil [19] outlined an IoT-based framework to facilitate cyber physical interactions and collaborations for micro devices assembly. RFID technology is widely leveraged to realize the real-time information capture of the materials or equipment. Qu, et al. [20] proposed production logistics synchronization system combining the RFID and cloud manufacturing technology. In order to manage work-in-progress inventories, Huang, et al. [21] explained how RFID contributes to reengineer manufacturing shop-floors with functional layouts. Zhao, et al. [22] developed cloud forklift warehouse management system by attaching RFID tag on physical forklifts to realize the location information collection via smart phone. For other IoT technologies, Tei, et al. [23] introduced how the Bluetooth Low Energy (BLE) works and applications in manufacturing equipment and devices maintenance. Engineers and operators are able to read and write data via tablet PCs or smart phone with BLE module. Wan, et al. [24] implemented a manufacturing big data solution for active preventive maintenance in manufacturing environments via Zigbee and Wi-Fi. The online and offline industrial data collected through IoT is processed in the cloud. However, Mourtzis, et al. [25] believed the industrial big data tended to be increased the next years and new way of filtering and processing the data should be considered to reduce the produced and transmitted data.

Cloud computing, which provides on-demand computing services (e.g., networks, servers, storage, applications and services) with minimal management effort or service provider interaction, gains popularity recently [26]. However, with the challenges imposed by the rapidly growing IoT ecosystem, the burden of processing massive industrial IoT data faced by cloud server, rendering inefficient bandwidth, high energy consumption and high latency [27]. Cheng, et al. [28] considered the communication latency and reliability issues are key issues of industrial IoT work in smart manufacturing. Data are often produced at the edge of the network (e.g., sensors, actuators or gateways). Edge computing refers to computing and process the data at the edge of the network. Shi, et al. [29] defined "edge" as any computing and network resources along the path between data sources and cloud server. Chen, et al. [30] proposed an architecture of edge computing for IoT-based manufacturing. In their research, agility and security can be dramatically enhanced by implementing edge computing in IoT applications. Wu, et al. [31] considered edge computing is the extension of cloud-based manufacturing, low network latency and ubiquitous remote access to near real-time data without spatial constraints are special benefits. They proposed an edge computing-based framework to collect real-time condition data of pumps and machines for process monitoring and prognosis, vibrations and energy consumption is monitored with accelerometers and transducers. Hu, et al. [32] designed and developed an intelligent robot factory where routers and gateways are regarded as edge computing node to relieve the congestion and delay in the process of network transmission. According to Ahmed and Rehmani [33], rapid and cost effective service development, optimized resources utilization and user transparent migration of application are still challenges for deploying edge computing in practice. In terms of resources management, the manufacturing tasks are carried out by autonomous agents to realize the responsive control of manufacturing resources [34]. Li, et al. [35] proposed logistics resource expression and service encapsulation's method to solve the logistics resources virtualization and service selection in cloud logistics scenario.

As early as 20 years ago, Brewer, et al. [36] presented that intelligent tracking has the potential to contribute to improvements in manufacturing and to the entire supply chain since real-time location information is the key to dynamic scheduling. They believed the real innovation in RFID is not in the technology itself, but in its application in real-world situation. Afterwards, numerous tracking studies were focused on the using the RFID technology. Brusey and McFarlane [37] proposed RFID-based object tracking approach and evaluated in a laboratory manufacturing system that produces customized gift boxes. Oner, et al. [38] proposed an RFID-based tracking system of work-in-process (WIP) resources including denim product, pallet and wheeled cage in denim manufacturing. Passive RFID tag is attached on the resources so that it can be tracked and traced in check points where fixed or mobile readers deployed. Result shows that the loss of products, inaccuracies of records has been decreased. Cao, et al. [39] proposed collaborative material and production tracking in a toy manufacturer. The accurate and reliable real time data is collected with the help of RFID and barcode technology. Combining with Ultra-wide bandwidth (UWB), Huang, et al. [9] introduced a real-time location platform in digital manufacturing workshop. Resources which need precise control are attached with UWB tag but comes with more cost. Woo, et al. [40] investigated the feasibility of Wi-Fi based indoor positioning of labor tracking at Guangzhou subway station construction sites. The Wi-Fi based positioning system requires training and tracking. They believed the system could be used for monitoring vehicles and materials as well. Nowadays, Samir, et al. [41] outlined the digital twin implementation in manufacturing, they considered real-time asset tracking is the starting point and seemingly crucial for the fulfillment of the task. Zhao, et al. [42] proposed distributed and collaborative location tracking method to locate the finished product in a forklift manufacturer. Bluetooth Low Energy, as the cutting-edge supporting technology of IoT, was adopted to realize the location estimation.

Regarding collaborative tracking in multi-storied indoor and outdoor environments such as industrial park, however, applications are mostly emphasised theoretical approaches rather than being practical studies or implemented in laboratory or limited scenario such as assembly line or shop floor. They take little account of the complex environmental characteristics with different areas, parties and processes involved. How to realize the real-time data collection, process and transmission in collaborative environment by means of IoT deserves more attention. Few existing research have gone deep in the study of the architecture and computing effectiveness of massive and heterogeneous manufacturing objects which need to be real-time tracked and traced simultaneously with high concurrency. Edge computing is widely discussed but rarely applied in the real-life tracking practice. Moreover, signal strength based tracking method usually requires plenty of calibration and signal collection work which is impracticable in large-scale deployment and not to mention the expansion of tracking area in the future. How to constantly improve location accuracy is rarely considered. Therefore, a collaborative tracking solution of massive manufacturing resources in industrial park with ability of continuous accuracy improvement is urgently needed.

3. IOT edge computing-enabled collaborative tracking architecture

With the goal of proposing a novel, useful and usable tracking architecture, there are several necessary considerations. In terms of project requirements, manufacturing resources are requested and travelled from plant to plant inside the industrial park. Indoor and outdoor environments are switched from time to time. In addition, manufacturing resources may move from assembly line to assembly line among various shop floors, which makes the problem more complicated. Therefore, the tracking solution is supposed to satisfy the requirement of collaborative tracking in multi-storied indoor and outdoor environment. From the perspective of technology, centralized cloud computing has proved to be an efficient way for data processing since it has powerful computing power than any edge devices. However, massive manufacturing resources with IoT devices produce enormous data at edge including sensing and signal processing data. The data need to be collected, filtered, analysed and transmitted to cloud which will give rise to huge unnecessary bandwidth and computing resources usage. Moreover, low latency guarantees the tracking effectiveness in that spatiotemporal information servers as key components location estimation. Lastly, most of the wireless sensors are energy hungry especially when they are conducting communication tasks. Minimizing the data volume at edge for transmission contributes to alleviate computation pressure. From the view of implementation scenario, industrial parks serve various parties which have different network connectivity, technology standards and infrastructure accessibility. Accordingly, the tracking architecture possesses independent operation ability.

Based on the considerations mentioned above, we propose IoT edge computing-enabled collaborative tracking architecture. The architecture is divided into three parts: the front-end, near-end and far-end in Fig. 1.

1) Front-end (Smart Manufacturing Resources)

Auto-ID, sensors and actuators are deployed at the front-end of the technology structure. They pair with physical manufacturing resources (e.g., man, machine, material and vehicles) to enable them to be identified, sensed and communicated. Enormous field data are thus generated. The basic components of one smart manufacturing resource is micro-computer, customized sensor, communication module, energy supplier and physical manufacturing asset itself. The micro-processor provides essential capacity to manage power, supply voltage, memory. Customized sensors are selected and assembled to provide sensing function such as temperature, humidity or vibration indicators. All sensed information is transmitted through communication module such as Bluetooth or Zigbee so it can be monitored and controlled in a remote manner. In order to maintain the basic function of the smart manufacturing resource, power supplier is necessary. Energy supplier such as batteries provides power to operate in front-end environment. Nevertheless, the capacity of power and computation is limited, the task of computation and communication should be reduced to maximize the service time. For tracking purpose, the received signal strength indicator (RSSI), as the input for propagation model, is considered as the most direct reference for location estimation. In this case, the sensed data that transmitted to upper level also includes the broadcasting strength from source node.

2) Near-end (Edge computing)

Fixed edge gateways deployed in near-end environment regarded as “ladders” for bridging the connectivity between cyber and physical world. It deployed in the near-end environment will support most of the traffic flow. It is composed of computation board, add-on sensing kit and communication kit. In this architecture, ARM-based Raspberry Pi is used as the computation board which provides not only the computing capacity but also a friendly eco-system for developers to customize. Add-on sensing kit contributes to identifying and sensing compensation and supports high data volume and energy-hungry application. Communication kit forwards the secured data to cloud through Narrow Band IoT or 4G/5G service provided by local internet service provider. Fixed edge gateways passively receive the signals from smart manufacturing resources during a certain time window while mobile edge gateway proactively sense the nearby signals. Mobile edge gateway is made up of smart devices such as smartphone or tablets which has essential computation power and communication module. It is usually carried by operator to trigger location based service based on the

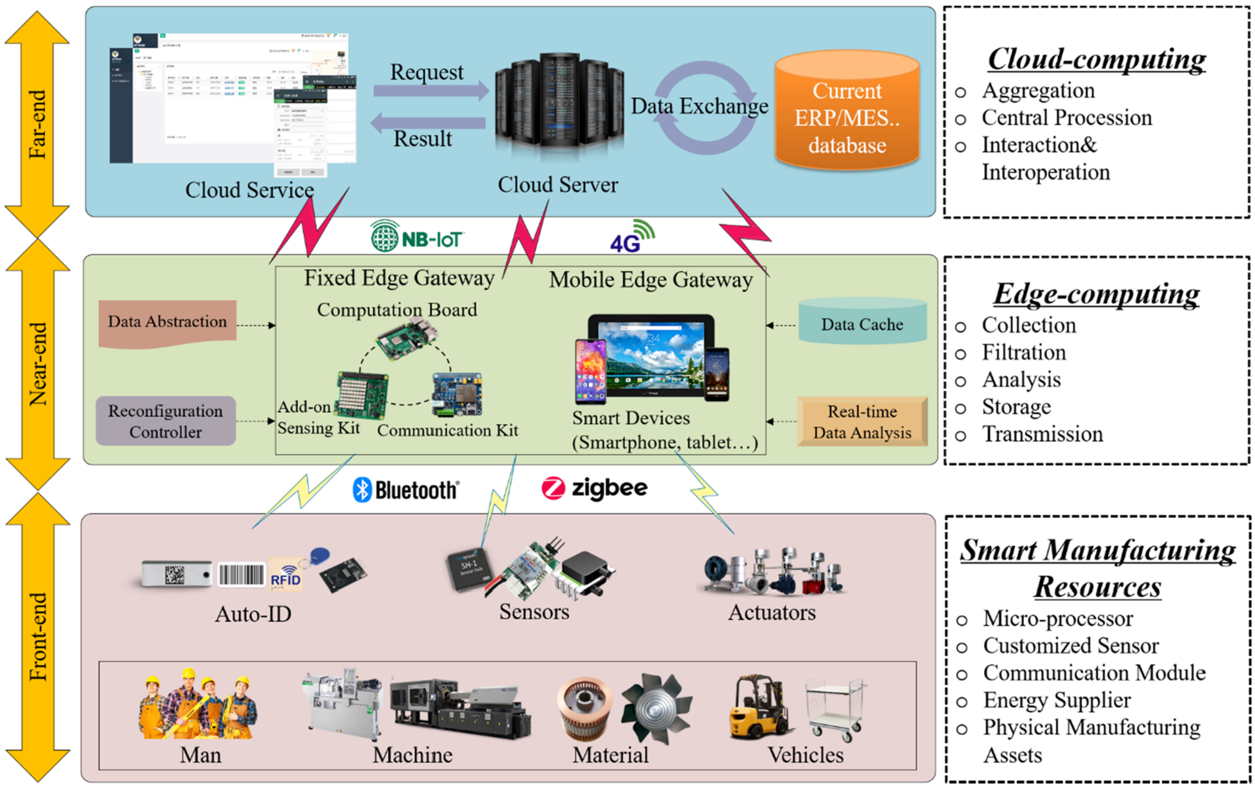


Fig. 1. IoT edge computing enabled collaborative tracking architecture.

nearby measurements of smart manufacturing resources. The distributed decision can be made by the mobile gateway since it can sense nearby signals for further matching with task pool. Moreover, data caching and computation offloading performed at edge gateways help to mitigate the pressure of cloud server. Abstract data forwarded from edge gateway to cloud server are refined with minimum data volume.

3) Far-end (Cloud computing)

Cloud server deployed at far-end side. It receives the processed data from all edge gateways in the certain time window for centralized processing. Data storage such as signal radio map for location estimation is therefore prepared and synchronized updated in cloud server. The cloud server can provide collaborative tracking based on full-scale data reference because of more computing power and data storage. As the back-end server, the cloud services are established for response user's request and provide results for better interoperation and interaction based on Client/Server structure. All involved parties have authorized token to exchange location and sensed data through authorized application programming interfaces. Cloud computing also provide massive parallel data processing to ensure the high concurrency. The web applications are deployed at the cloud server. Different roles with different authorities are able to access the contents.

In this architecture, the smart manufacturing resources at front-end transmits field sensed data to the edge-computing part at the near-end side. Then the edge gateway receives, filters, process and transmit the data to cache and upper level. The cloud computing in far-end side conducts centralized computation and also interaction with systems in other parties. The cloud computing is able to send commands to the near-end edge gateways such as configuration and registration request. The smart manufacturing resources may not always under the coverage of the edge gateways. The sensed data may store in its cache which has limited storage. In this case, the near-end gateways are able to send paring request with the smart manufacturing resource for data exchange.

4. Mechanism of collaborative tracking

With the help of the collaborative tracking architecture, the deployment of IoT hardware is therefore have rules to follow considering the massive and heterogeneous object distributed in collaborative environments. This section mainly discuss the tracking procedure and mechanism to realize precise location estimation and location based services. The method is built and embedded inside the IoT hardware such as fixed edge gateways or cloud server to realize coarse and fine location estimation.

4.1. Supporting technology

For realizing the resources tracking in the industrial park, proper tracking technologies and techniques are required through the collaborative tracking architecture. In this subsection, we mainly discuss the supporting technology.

GPS works well in outdoor applications however it cannot track precisely in indoor environment as the signal penetration issues. Moreover, the power consumption poses challenges to large-scale and long-term use. The RFID characteristics of low cost and easy deployment push forward academic research and practical case study. The passive RFID solution often leverages massive reference tags to assist collaborative tracking [43]. It is acceptable when implementing in a test area or one particular assembly line. Nevertheless, deployment all around an industrial park seems unpractical considering limited effort. Active RFID and Zigbee can contribute to asset tracking with successful applications in hospital and warehouse. However the smart phones, act as edge gateways, do not support active RFID and Zigbee functions. Recently, many research take advantage of existing Wi-Fi infrastructure to lower the deployment cost [44,45]. However, with many parties involved in industrial park, the different standards of technology and security level complicate the Wi-Fi based tracking solution. Besides, the energy-hungry Wi-Fi tag can only be applied in short-term project or testing purpose. UWB solution provides precise location estimation with error in centimeters. However the high cost of UWB stalls entrepreneurs [46]. In this research, we adopt BLE as basic tracking technology for the following reasons. 1) The low power consumption of Bluetooth 4.0 enables 3-year use of BLE tag (broadcasting power: −4 dBm, advertising interval: 1000 ms) 2) Smart phones are widely equipped with Bluetooth module which contributes to better user interaction and location estimation assistance. 3) BLE tag are able to transmit signals up to 150 m which can alleviate the deployment density.

4.2. Collaborative tracking procedure

The basic collaborative tracking procedure is shown in Fig. 2, fixed edge gateways deployed all over the industrial park passively receives the signals sent from the various BLE tags which attached on the manufacturing resources. Smart phone, with distributed computation capacity, act as mobile gateway carried by operator proactively senses surrounding BLE tags as well. The existence of certain BLE tags triggers related location based services. Then edge gateways start filtering and analysing the received packets to offload pressure from cloud end. The shrunken and refined data which occupy limited network bandwidth then transferred to cloud side through 4G or NB-IoT by fixed edge gateways for coarse location estimation using Cell of Origin (CoO) method. In this research, outdoor location estimation is mainly acquired by the CoO method to reach "room-level" accuracy. However, the indoor environment often requires more precise location estimation. Cloud server starts supervised learning of genetic tracking method for fine location estimation.

4.2.1. Fixed edge gateway

Fixed edge gateways received all sensed BLE signals with sequences of RSSIs. Sending all the data for cloud computing is unwise given limited network bandwidth and cloud computation capacity. Latency is intolerable as tracking is spatiotemporal decision. Therefore, necessary filtering and analysis conducted in near-end edge computing alleviates far-end pressure. The RSSI dramatically fluctuates during transmission considering the signal disturbance and fast fading issue. Noise generated during measurements significantly affect the location estimation accuracy. Kalman Filter is regarded as one of the most widely used methods for signal processing. It estimates some unobserved variable based on noisy measurements. The Kalman filter function is therefore embedded in the edge gateway for smoothing the measurement signals.

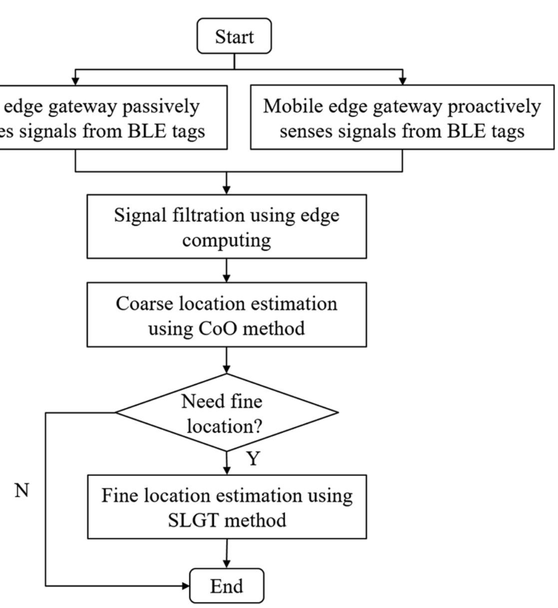


Fig. 2. Basic collaborative tracking procedure.

4.2.2. Mobile edge gateway

Mobile edge gateway provides edge computing capacity in-near end as well. Smart phone with characteristics of portable, pervasive and platform-supportive, is a good candidate for mobile edge gateway. Unlike fixed edge gateway, mobile edge gateway is location service oriented. Carried by operators, mobile edge gateway proactively senses nearby signals from BLE tag. After conducting Kalman Filter function in mobile edge gateway locally, the filters results are then send to cloud server. Application user interface then shows the answer of "which are the target objects need to take action from my sensed nearby manufacturing resources?" In this case, operators conduct adjacent delivery tasks based their current locations to eliminate unnecessary travelling and searching efforts. Scheduling efficiency is ingeniously boosted based on mobile edge computation rather than complicated cloud and global calculation.

4.3. Cell of origin

In industrial park, the requirement of tracking accuracy is different. For instance, in open-air single functional area with limited manufacturing resources in outdoor environment, providing "room-level" location estimation results can be sufficient for operators since the operators are able to identify target object within eye's reach given narrowed location tracking results. It is out of question to search one particular object inside the whole industrial park, but it turns to be feasible given specific hints of area information. Cell of origin method is based on cellular networks where the position of the smart phone is determined by knowing which base station the smart phone is utilising at a given time. The coordinates of the base station is therefore the location of the smart phone. The smart phone usually connects to the closest base station. It is one of the simplest positioning methods to implement given limited computation power. In this research, the location of fixed edge gateways with maximum value of RSSI is marked as the resource coarse location.

4.4. Supervised learning of genetic tracking

However, in multi-storied indoor centralised manufacturing plants with various assembly lines, equipment and constantly changing processes and plants, unlike outdoor environment, "room-level" location information cannot satisfy daily operations. More accurate location estimation is urgently needed. RSSI-based fingerprinting has been proved to be the most accurate indoor positioning techniques over triangulation and lateration method. A radio map is first established by collecting and storing the RSSI vectors at divided area during the offline phase of fingerprinting. Then various matching algorithms are used to compare currently obtained readings with those in radio map during the online phase.

Nevertheless, there are several challenges when adopting the fingerprinting method. Firstly, collecting RSSI vectors at each reference points from edge gateways is time-consuming and labour-intensive, not to mention deployment in large-scale site. Secondly, shop floors and assembly lines with massive manufacturing resources around may severely affect the quality of the radio map since existence of obstacles, materials and even weather conditions [47]. Thirdly, few research considers the accuracy after using a period of time. The environment change may obsolete the radio map which cause the failure of location

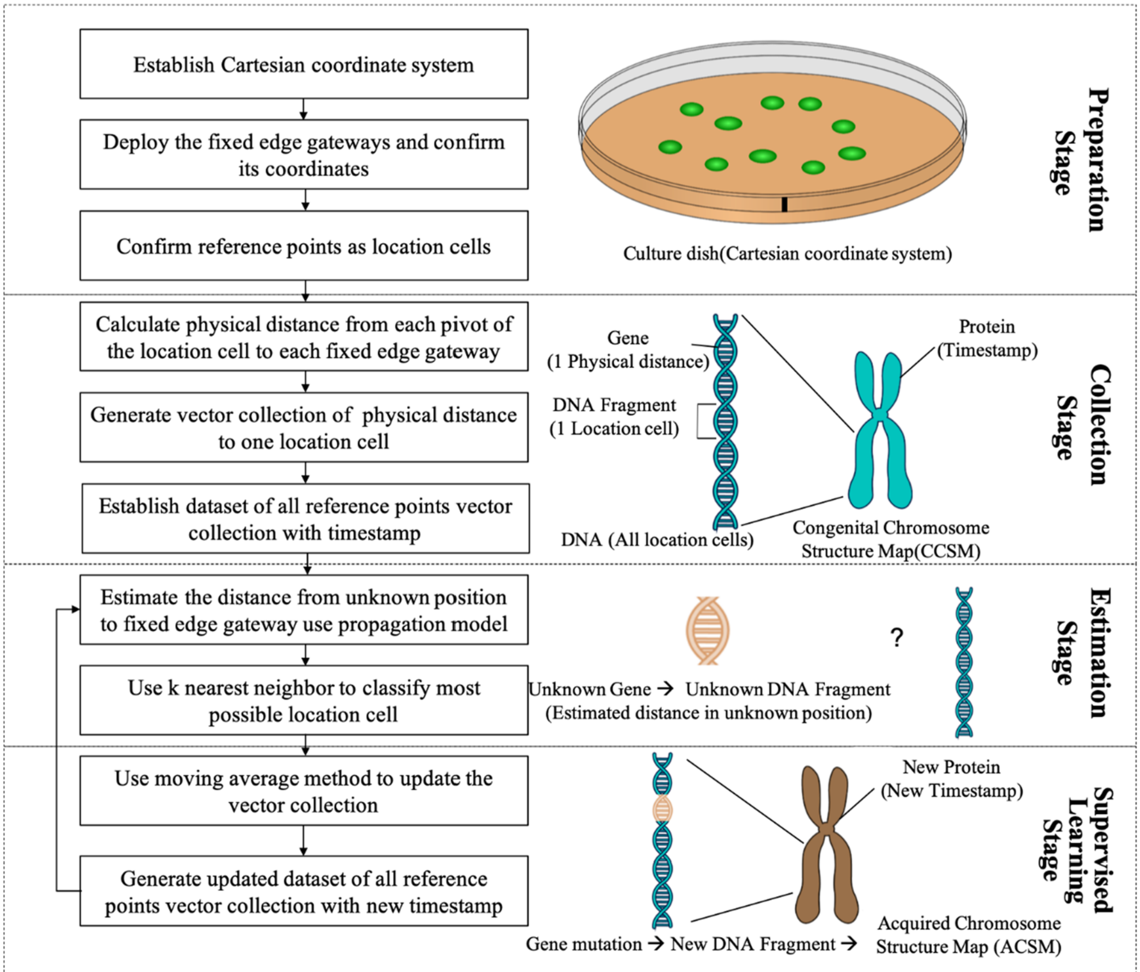


Fig. 3. Tracking procedure in SLGT method.

estimation. Therefore, supervised learning of genetic tracking (SLGT) method is proposed.

4.4.1. SLGT work process

The fine location estimation is conducted in SLGT method. SLGT can be regarded as one derivative of the fingerprinting method [48]. The basic concept is that the original gene and chromosome are automatically generated once the animal is born. A large amount of gene the forms up DNA fragment. Multiple DNA fragments then combine to DNA. Chromosome is finally established with DNA and protein. With personality, as with most human traits, it is nature and nurture. Acquired facts such as gene mutation, crossover according to biology environment change may significantly affect the chromosome. Unlike the well-known "Genetic Algorithm (GA)", the GA method is to solve non-linear programming problems, acquire near-optimal results and reduce a large amount of computation time. However, the SLGT concentrates more on the classification problem and acquire accurate results. The SLGT focuses on the real-life measurements of RSSI to estimate the right location and then trains the chromosome and gene to be more close to reality. It contains adaptive learning process to generate location results along with the constantly changing of the real environment.

There are total four stages in SLGT method in Fig. 3. In the preparation stage, the Cartesian coordinate system should be firstly established based on the tracking area which requires fine location estimation. Culture dish is regarded as Cartesian coordinate system which is firstly prepared for the next experiments. Fixed edge gateways are mounted for power supply ease with coordinates recorded. Then it divides the total area to various reference points based on location accuracy requirements. More precise location often requires more computation capacity. The reference points are regarded as location cells. In collection stage, according to known coordinates of fixed edge gateways, the physical distance from one location cell to one fixed edge gateway is regarded as one gene. DNA fragment is composed of a large amount of genes which means one location cell consists many physical distances vectors from all fixed edge gateways. Then the physical distances vectors from each location cells to all fixed edge gateways is established and regarded as DNA. In the end of collection stage, congenital chromosome structure map (CCSM) is generated with DNA and protein. The protein here represents the timestamp of the dataset. In the first two stages, it can be regarded as offline phase which only requires one-time effort. In the estimation stage, the distance from unknown position to fixed edge gateways can be estimated through Kalman filter and signal propagation model. The estimating DNA fragment of the unknown location cell is also generated but it comes with the actual measurements. The DNA of location cell from CCSM and estimating DNA are used as inputs in the k nearest neighbor algorithm to classify the most possible location cells. After the location estimation, it comes to learning stage where the new gene and DNA fragment is going to mutate into the CCSM using moving average method. The acquired chromosome structure map (ACSM) is then updated with new timestamp information.

4.4.2. Mathematical model

List of symbols

LC_i	ith location cell
FEG_j	jth fixed edge gateway
$PD_{(i,j)}$	physical distance between ith location cell and jth fixed edge gateway
x_{LC_i}	x coordinate of ith location cell
y_{LC_i}	y coordinate of ith location cell
x_{FEG_j}	x coordinate of jth gateway
y_{FEG_j}	y coordinate of jth gateway
CF_i	congenital DNA fragment vector of ith location cell
ulc	unknown location cell
$RSSI_{ulc}$	RSSI vector of unknown location cell
$R(ulc, j)$	RSSI value from unknown location cell ulc to jth fixed edge gateway
P	logarithmic function of the distance between the gateway and unknown location cell
P_0	P_0 is the mean power received at the reference distance
X_σ	zero-mean Gaussian random variable
$MD_{(i,j,k)}$	kth measuring distance between ith location cell and jth fixed edge gateway
EF_{ulc}	estimating DNA fragment vector of the measuring distance among fixed edge gateways to tag
$FD_{(ulc,i)}$	DNA fragment Euclidean distance between estimating DNA fragment vector and congenital DNA fragment vector
$AG_{(i,j,k)}$	new gene from ith location cell to jth fixed gateway in timestamp k

In mathematical model, we denote LC_i as the ith location cell ($i \in N^*$), FEG_j as the jth fixed edge gateway ($j \in N^*$). N^* denotes all positive integers. The physical distance between the LC_i and G_j is defined as $PD_{(i,j)} = |LC_i - FEG_j|$. The physical distance is the gene and can be easily calculated by as:

$$PD_{(i,j)} = |LC_i - FEG_j| = \sqrt{(x_{LC_i} - x_{FEG_j})^2 + (y_{LC_i} - y_{FEG_j})^2} \quad (1)$$

where x_{LC_i}, and y_{LC_i} is the $\times$, y coordinate of LC_i respectively. Therefore, the congenital DNA fragment of LC_i can be denoted as $CF_i = \{PD_{(i,1)}, PD_{(i,2)} \cdots PD_{(i,j)}\}$. The congenital DNA fragment of each location is established automatically without any signal collections since the physical distance (gene) generated objectively. The definition is then completed once all location cells have the DNA fragment vector. In the estimation phase, each fixed edge gateway first acquires the RSSI from the unknown location cell ulc within the broadcasting range. The RSSI collected in the time period t has been filtered by Kalman Filter which conducted in fixed edge gateways. RSSI vector can be established as $RSSI_{ulc} = \{R_{(ulc,1)}, R_{(ulc,2)} \cdots R_{(ulc,j)}\}$, where $R_{(ulc,j)}$ refers to the RSSI value from unknown location cell ulc to jth fixed edge gateway. The distance of the unknown location cell from fixed edge gateways can be calculated by the radio propagation model. We adopted log-normal shadowing path loss model, it is shown as:

$$P = P_0 - 10n\log_{10}(MD_{ut}/MD_0) + X_\sigma \quad (2)$$

where the received power P (expressed in *dBm*) is seen as a logarithmic function of the distance (MD_{ut} in meters) between the gateway and the tag from unknown location cell. P_0 is the mean power received at the reference distance MD_0, usually in 1 m, the n variable is the propagation constant which is environment dependent. X_σ is zero-mean Gaussian random variable. These parameters depend greatly on the environment and the operating frequency. So, before the calculation of the distance, we estimate these parameters first by testing among known location cells. Therefore, the unknown location cell has an estimating DNA fragment, which can be denoted as$EF_{ulc} = \{MD_{(ulc,1)}, MD_{(ulc,2)} \cdots MD_{(ulc,j)}\}$. Once the estimating chromosome of the unknown target has been calculated and generated. Pattern recognition algorithm such as k nearest neighbours can be used to classify which location cell can be classified to the location of the unknown location cell. K nearest neighbours algorithm calculates the Euclidean distance between the DNA and estimating DNA fragment from each location cell as:

$$FD_{(ulc,i)} = |EF_{ulc} - CF_i| = \sqrt{\sum_{j=1,\cdots,N} (MD_{(ulc,j)} - PD_{(i,j)})} \quad (3)$$

where $FD_{(ulc,i)}$ is the DNA fragment Euclidean distance between estimating DNA fragment EF_{ulc} and congenital DNA fragment vector CF_i. The location cells of the first k smallest distance errors are therefore chosen. With the support of initial location estimation results, operators contribute to supervise and recognize the correctness of the results and update the measurement into the CCSM. In this case, gene that inside congenital DNA fragments starts to mutate to acquired gene and DNA fragments which refers to the theoretical physical distance learned to become practical signal-distance according to real measurements. Every mutation (learning) may affect the chromosome structure with updated timestamp so as to improve tracking accuracy constantly. The learning method we adopt utilize weighted moving average method. A weighted average is an average that has multiplying factors to give different weights to data at different positions in the sample window. It can be simply defined as:

$$AG_{(i,j,k)} = \frac{kMD_{(i,j,k)} + (k-1)MD_{(i,j,k-1)} + \cdots + 2MD_{(i,j,2)} + PD_{(i,j)}}{k + (k-1) + \cdots + 2 + 1} \quad (4)$$

In the weighted moving average model, we denote $AG_{(i,j,k)}$ as new gene from ith location cell to jth fixed gateway in timestamp k, also defined as measuring times. $MD_{(i,j,k)}$ refers to the measuring distance from from ith location cell to jth fixed gateway in kth measuring. The DNA fragment and chromosome are also updated to acquired chromosome structure map(ACSM) simultaneously.

The main advantages of the SLGT model are summarized as follows: (1) The offline phase of signal collection in tradition fingerprinting method is extremely time-consuming and labour intensive. People are required to record signals at each reference points. In SLGT model, collection efforts can be lowered to the physical distance between location cells and gateways. Human actions can be avoided. The time and labour force can be saved in this stage. (2) Traditional indoor tracking concentrate on the present location estimation. The location accuracy seems to be a fixed index that many researchers trying to uplift through various models and algorithms. However, in SLGT model, after estimating the location result, the gene constantly mutates according to true measurements in order to keep the effectiveness of the overall chromosome structure map under the supervised learning. The location tracking result is not a fixed data but a continuously rising process. (3) Signals can be affected by many factors such as obstacles, multi-path effect and environmental changes. The training fingerprints with signal indicators in traditional fingerprinting method are restricted to the device model, environment, battery level or even human movement. The tracking effectiveness of the tracking system may obsolete and render not applicable after using a period of time. In the SLGT model, the change of physical world can be synchronous reflected in the acquired chromosome structure map. Location tracking effectiveness is therefore ensured.

5. Case study

In order to verify the feasibility and effectiveness of the proposed collaborative tracking architecture, the research team collaborated with one world-leading air-conditioner manufacturer located in Pearl River Delta area where a core region of modern manufacturing in China. Their main business covers residential air conditioners, central air conditioners, intelligent equipment and home appliance. An industrial park was established which covers an area of more than one million square meters. Upstream and downstream suppliers were also invited to enter the industrial park for better collaboration and delivery cost reduction. Plants such as central air-conditioning plant, evaporator and condenser plant are built multi-storied under indoor environment with assembly lines and equipment. Parking area and injection area are outdoor or semi-outdoor for better ventilation. The following Fig. 4 shows industrial park working conditions at different places. It can be seen that the material trolley with WIP or materials are distributed all around the industrial park.

5.1. Motivation scenario

It is noticeable that the material trolley plays a vital role in daily operations because it fulfils the delivery tasks of materials or WIP products. Raw materials, components such as axial propellers or shells and work-in-process products are carried by material trolley from production lines to production lines as well as plants to plants. Operators haul the material trolley from plants to plants to prepare raw materials or collect WIP product for next production stage. Once the material trolley is delivered to target position, operators will leave for conducting next task. The manual confirmation of material receiving and report of unexpected operations are time-consuming, subjective to judgements and prone to error as the logistics visibility cannot be achieved. The material trolley may move frequently and haphazardly for material replenishment purpose along with traveling down the production line. High mobility achieves fast and flexible responsiveness, however, the recycle of the material trolley then become the greatest challenge for the industrial park since the real-time location of the available material trolleys is unknown. Recycling is necessary since constantly increasing transportation mission are awaited. Excessive material trolleys accumulated in field not only impede the delivery scheduling but also increase the risk of asset lost and personal safety. The collaborating company encountered following two challenges which severely affect not only the logistics efficiency but also the whole manufacturing efficiency as the unpunctual arrival of material trolley delays the on-stream time. Firstly, as mentioned before, the real-time location of the material trolley in industrial park is unknown. How to assign the nearest operator to conduct recycling work of material trolley become the another challenge since the real-time location of the operator is also necessary.

5.2. System implementation

The demand from real-life industrial case drives this research move forward. According to the case company, they have proposed and implemented RFID solution before by attaching passive RFID tags on material trolley and deploying readers at some specific checkpoints due to low cost reason. However, limited reading distance and signal interference often confuses and fails the location estimation. Frequent reading and clicking work fatigue the operators. Moreover, outdoor location estimation became unreachable. The complaints from end-user lead to seeking other proper solutions.

In this section, we mainly discuss how to implement IoT edge computing enabled collaborative tracking solution. The Fig. 5 depicts the details of one floor of indoor multi-storied central air-conditioner plants which requires the fine location estimation.

ARM based Raspberry Pi 3B with 4G dongle is adopted to build the fixed edge gateways. Kalman Filter function is designed and developed in Python scripts which embedded inside the edge gateway [49–52]. As can be seen from the figure, fixed edge gateways are irregular deployed on pillar or wall for the ease of power supply and fixation. There are two types of BLE tag for different kinds of manufacturing resources. The necklace BLE tag, powered by button cell, is designed for operator where linked with his staff card. The waterproof asset BLE tag, powered by AA batteries, is attached on the material trolley. Humidity and temperature sensors are also included inside the tags. The information of MAC address as the identifier for both BLE tags is printed as QR code on the surface. The QR code provides entry of manufacturing resources and BLE tag paring work. According to the case company, we characterize 2 m side length location cell as reference points which meets the accuracy requirements and mark on the Cartesian coordinate system. The coordinates of fixed edge gateways is recorded during the preparation stage. In the collection stage, after acquiring the coordinates of fixed edge gateways, the physical distance (gene) is computed simply from the pivot of each location cell to the one fixed edge gateway. We wipe off the distance above 15 m since the signal propagation model cannot provide reference value thereafter. Each location cell, divided in 4 square meters, computes the DNA fragment. All the physical distance of all location cells compose one complete DNA. Timestamp, acts as protein, contributes to recording the time of the structure map and learning times. Therefore, the congenital

Fig. 4. Industrial park onsite condition.

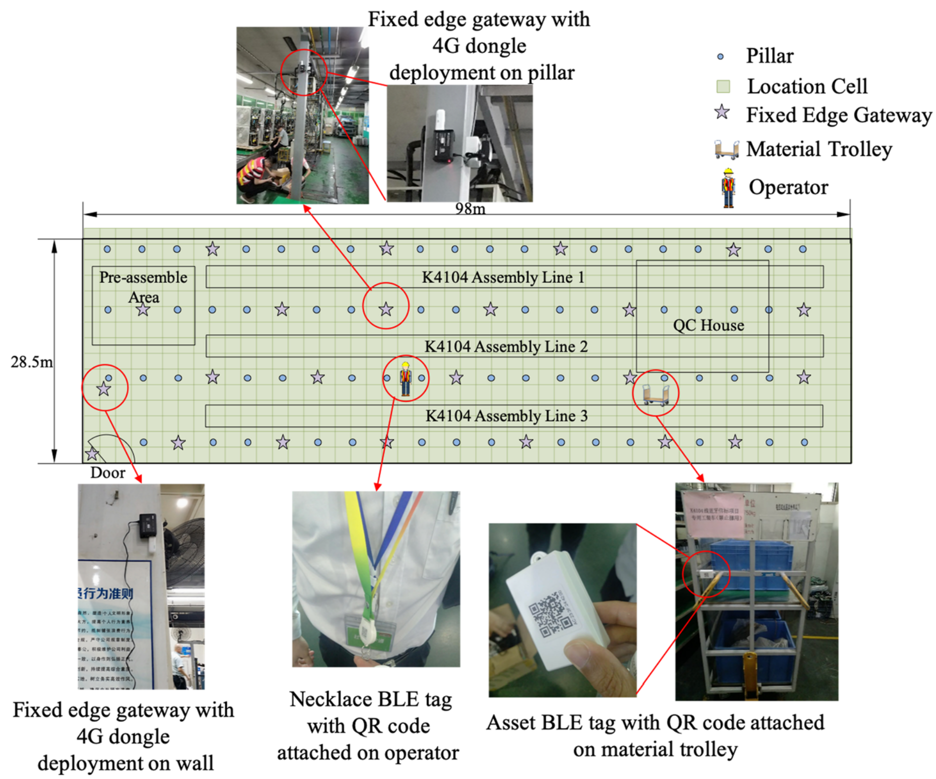


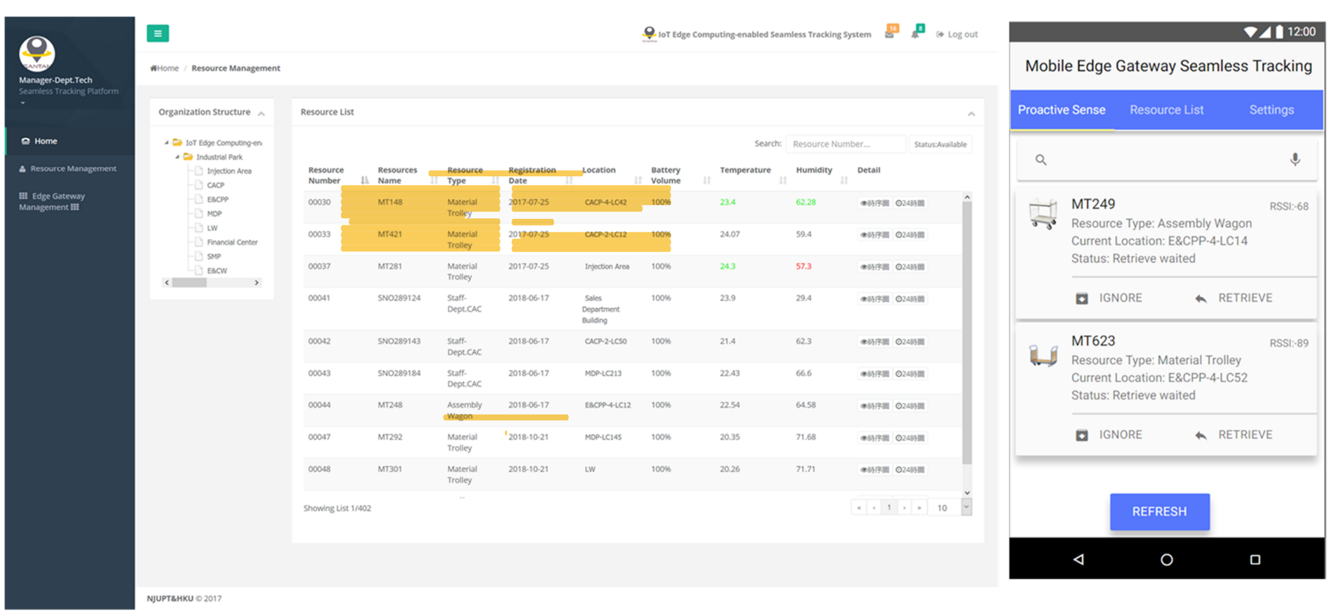
Fig. 5. One floor of the indoor plant layouts and hardware implementation.

chromosome structure map is established. For the outdoor location estimation, specific outdoor locations are each paired with fixed edge gateways. The CoO method is supposed to generate coarse location estimation by judging the strongest RSSI indicators. The following Fig. 6 presents the web and mobile application system.

The IoT edge computing-enabled collaborative tracking system is developed in web and mobile application. The web page in Fig. 6(a) is cloud server based solution for managers to view the real-time location and status of all manufacturing resources. The visibility of logistics can be realized. For the mobile edge gateway application in Fig. 6(b), operators open the application to proactively sense nearby manufacturing resources, real-time scanned and filtered results are pushed to cloud server for verification of identity and status. The manufacturing resources which need to take action will show on the list.

5.3. Result analysis

The case study lasts more than one year to verify the feasibility and effectiveness of collaborative tracking method. For fine location result estimation, the SLGT method requires continuous learning to improve



(a) (b)

Fig. 6. Screen capture of web and mobile application system.

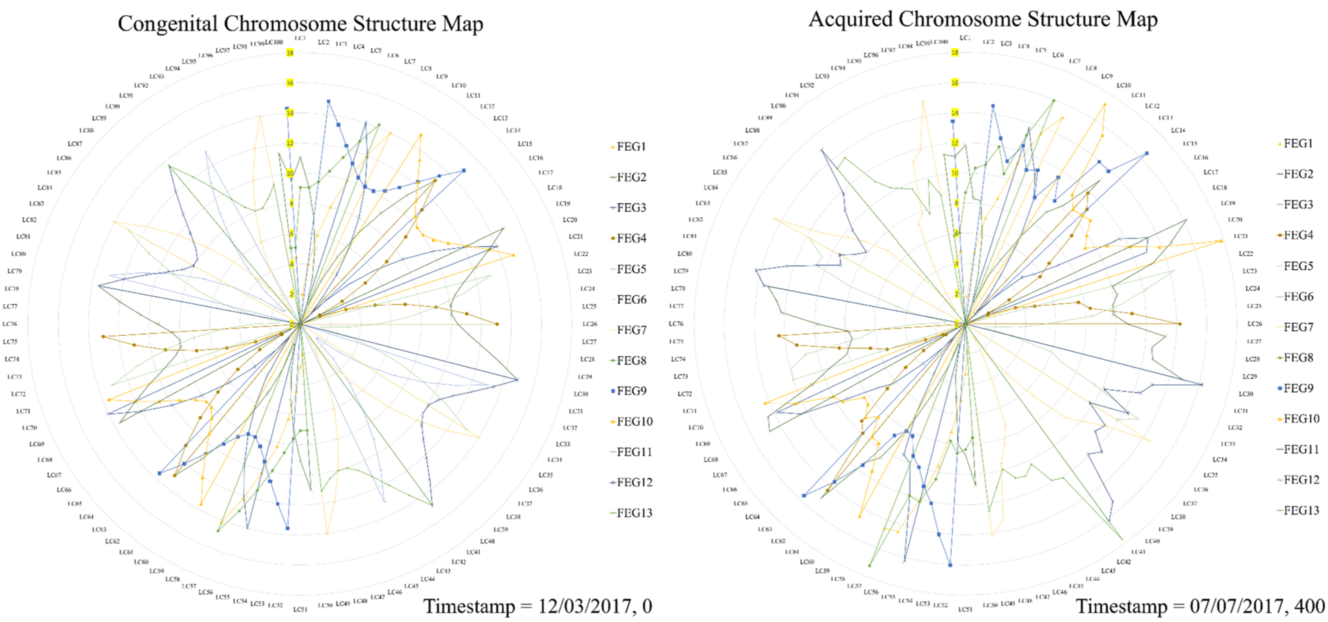


Fig. 7. Comparison of congenital chromosome structure map and acquired chromosome structure map.

Table 1
Performance comparison of three localization methods in indoor environment.

	Triangulation	Fingerprinting	SLGT
Duration of signal collection	–	67 min	–
Localization accuracy after implementation	85.42%	93.42%	80.56%
200 Times learning localization accuracy	–	–	90.35%
400 Times learning localization accuracy	–	–	96.14%
Localization accuracy after 12 months running	74.89%	< 50%	97.57%

accuracy and maintain effectiveness. Fig. 7 shows the comparison between congenital chromosome structure map and 400 time of supervised learning after the implementation.

The multi-path effect on signals may significantly affect the results of signal processing. Signal attenuation occurs during daily operation in industrial park also lead errors and inaccuracy. As can be seen from Fig. 7, after 400 times of learning, the gene is mutated mainly due to the surrounding factors such as battery level, obstacles and environment change.

Based on the accuracy requirement in indoor environment, a performance comparison study of three localization methods is conducted. Triangulation method, measuring the distance from three or four known anchors to formulate the coordinates of the unknown target, plays important role in outdoor GPS localization. The 3–4 strongest signals received from the fixed edge gateways are transferred to distance using log-normal shadowing path loss model. The location estimation of coordinates is also mapped with location cells for comparison. Fingerprinting, as classic indoor Wi-Fi localization method is also selected to verify the effectiveness of the tracking solution. Table 1 shows the performance comparison of three localization methods.

In Table 1, the result of localization accuracy in fine location estimation with three methods is illustrated. The size of reference point in three methods is 2 m square. Firstly, the fingerprinting needs time and efforts to conduct the signal collection work in order to classify the measurements to proper location cells. It shows that the initial localization accuracy of triangulation and fingerprinting is higher than SLGT method after implementation due to the reason that CCSM does not consider any signal interference and fluctuations at first. This result illustrates that the proposed method after 200 times of learning already performs better than triangulation method and 400 times better than fingerprinting method. The localization accuracy after 200 and 400 times learning reach 90.35% and 96.14% respectively. After one year use, the localization accuracy of triangulation method drops to 74.89% mainly due to the consumption of BLE tag affect broadcasting strength. The fingerprinting method is no longer reliable since the layout of the indoor environment has changed. The obsolete signal database is no longer informative. However, the SLGT performs even better under the circumstance of constantly learning. Consequently, it is suggested that the SLGP method provides constant satisfying result but also adaptable to long-term use.

The responsiveness of the tracking system is crucial especially when the tracking objects is increasing. In order to verify the effectiveness of data processing using edge computing, another comparison study is conducted. Task duration refers to the duration time of one time tracking of all smart manufacturing resources from initiating the tracking request to returning the request, which is regarded as the key performance indicator of computing pressure.

The task duration is mainly composed of four kinds of latency including transmission, propagation, handling and queuing. Propagation and queuing latency is negligible as the internet infrastructure and limited data package. As can be seen from the Fig. 8, cloud computing prevails edge computing when the number of tracking objects is under 200. The reason is that the tracking data is limited. The transmission latency is nearly same. However, the edge gateway requires computation of signal data filtration and packing instead. As the number of tracking objects increases, the edge computing shows an overwhelming advantage. The edge computing that shrinks and analyze and the data contributes to reduce the handling and transmission delay compared to cloud computing.

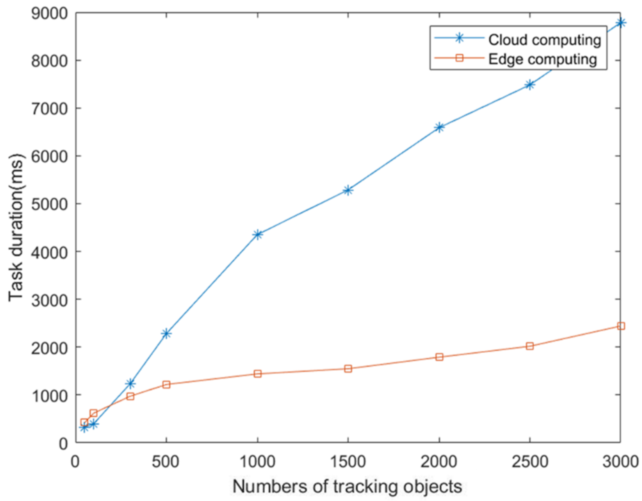


Fig. 8. Task duration comparison of cloud computing and edge computing.

6. Conclusion

In this research, we propose a collaborative tracking architecture using IoT and edge computing technology. Collaborative tracking procedure is introduced and supervised learning of genetic tracking method for fine location estimation is innovatively developed. Moreover, a case study of a real-life air-conditioner manufacturing industry park is conducted for verify the feasibility and effectiveness of proposed method. The contributions of this paper can be concluded as follows.

(1) This research leverages the concept of the edge computing and integrates with IoT technology to realize real-time data collection and process under heavy sensing and calculating pressure. An indoor-outdoor collaborative tracking architecture is therefore developed. The distributed computation power contributes to offloading cloud server pressure and realizing low latency for massive manufacturing resources tracking simultaneously.
(2) Inspired by biology science, we follow the gene mutation paradigm to propose supervised learning of genetic tracking method. Excessive work of signal collection and calibration in traditional fingerprinting method can be dramatically alleviated especially in large-scale deployment and the expansion of tracking area in the future. In addition, the SLGT method ensures the continuous improving of localization accuracy and lasting localization effectiveness.
(3) The proposed architecture and tracking method are successfully deployed and implemented in a real-life manufacturing industrial park where the inefficiency of material trolley logistics becomes the bottleneck of production. A comparison study is conducted to illustrate the SLGP method in practice. Web application, together with fixed edge gateways, provides access for manager to view overall real-time situation of manufacturing resources while mobile edge gateway application is developed to realize proactively sensing to match the nearby tasks.

In the future, this work could be further extended in the following directions. Firstly, edge computing can commit to more computation task to mitigate the calculation pressure from the cloud side in 3D space tracking. Secondly, the forthcoming 5G and other indoor positioning technologies can contributes to the improvement of accuracy and streamlining of architecture. Thirdly, knowing the exact location of the manufacturing resources is just a start. Production and logistics synchronization deserves more attention.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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