

Retraction

Retracted: Optimizing Multitask Assignment of Internet of Things Devices by Reinforcement Learning in Mobile Crowdsensing Scenes

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] M. Wang, "Optimizing Multitask Assignment of Internet of Things Devices by Reinforcement Learning in Mobile Crowdsensing Scenes," *Security and Communication Networks*, vol. 2022, Article ID 6202237, 10 pages, 2022.

Research Article

Optimizing Multitask Assignment of Internet of Things Devices by Reinforcement Learning in Mobile Crowdsensing Scenes

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The objective is to optimize the multitask assignment (MTA) in mobile crowdsensing (MCS) scenarios. From the perspective of reinforcement learning (RL), an Internet of Things (IoT) devices-oriented MTA model is established using MCS, IoT technology, and other related theories. Then, the data collected by the University of Cambridge and the University of St. Andrews are chosen to verify the three MTA algorithms on IoT devices. They are multistage online task assignment (MOTA), average makespan-sensitive online task assignment (AOTA), and water filling (WF). Experiments are designed by considering different algorithms' MTA time consumption and accuracy in simple and complex task scenarios. The research results manifest that with a constant load or task quantity, the MOTA algorithm takes the shortest time to assign tasks. In simple task scenarios, MOTA is compared with the WF. The MOTA algorithm's total moving distance is relatively short, and the task completion degree is the highest. AOTA algorithm lends best to complex tasks, with the highest MTA accuracy and the shortest time consumption. Therefore, the research on IoT devices' MTA optimization based on RL in the MCS scenario provides a certain theoretical basis for subsequent MTA studies.

1. Introduction

Multitask assignment (MTA) is key to mobile crowdsensing (MCS) paradigm. The MTA strategy must consider optimal resource allocation while ensuring system response time and data quality. As environmental data grow exponentially, MTA is sure to replace the conventional single-task assignment methods in large-scale complex scenarios [1, 2]. Hence, an efficient and reasonable MTA method has certain research value and practical significance [3].

Fu et al. [4] designed an MTA framework active crowd to allocate perceived tasks to future users based on users' historical trajectories, thus ensuring real-time performance [4]. Agarwal and Bharti [5] proposed a new cost-effective swarm intelligence (SI) perception paradigm, considering perception performance, cost, and data quality. The proposed method reduced nodes to cut costs while ensuring perception quality [5]. Lv [6] optimized the IoT-native devices' MTA by factoring in privacy and security. A hybrid privacy protection mechanism was constructed for task allocation, reducing the perceived energy consumption of

mobile intelligence and protecting user privacy [6]. Liu et al. [7] put forward an MTA framework, TaskMe, by consulting game theory literature to balance user and task numbers. The reported framework could maximize user satisfaction but consume enormous energy and has low algorithm efficiency [7]. Ghavvat et al. [8] introduced an online pricing mechanism by eliminating the need for the task requester to set a price for each task in advance. Requesters only need to provide the overall budget of the task or the task quantity. For instance, workers applying to answer a task could give the expected task price or the task quantity [8]. Lv et al. [9], from the perspective of security performance, believed that the trust value of mobile workers depended on their service capability and the environment. As a result, many factors affected honest perception in the mobile workers' trust value, such as link reliability, service quality, and regional heat [9]. The above scholars have discussed IoT-native devices' MTA optimization from perceived performance, cost, privacy, and security perspectives. It provides new research methods, the theoretical basis for relevant research, and a writing direction for this work.

In this context, this work introduces reinforcement learning and uses the data from Cambridge University and St. Andrews University. It also expounds on multistage online task assignment (MOTA), average makespan-sensitive online task assignment (AOTA), and water filling (WF) algorithms to analyze the time and accuracy of MTA in simple and complex task scenarios. The innovation is that three different algorithms are applied to optimize the IoT-native devices' MTA. The optimal algorithm is selected through comparative analysis, ensuring certain reliability. Meanwhile, the contributions enrich the relevant research and provide a method reference for the IoT-native devices' MTA.

2. Research Theory and Method

2.1. Establishment of MTA Model under Mobile SI Perception. MCS means that ordinary large-scale users collect sensing data through their smart mobile devices and upload them to the server. The service provider records and processes the sensing data to provide targeted user services [10, 11]. Unlike traditional sensors, MCS uses a single sensing unit on the user end to collect data. Thus, it reduces cost and extends coverage based on the ubiquity of user-end mobile devices [12]. MCS has been applied in mapping environmental noise, monitoring environmental pollution and urban traffic conditions, social networking, and medical care. Foreseeably, it will be applied to more business scenarios [13]. The structure division of the MSC system is shown in Figure 1.

MCS uses ubiquitous mobile devices to support various novel IoT applications. It features low networking cost, easy maintenance, and strong service flexibility, greatly improving the efficiency of IoT applications [14]. Its architecture is illustrated in Figure 2.

In Figure 2, the MCS architecture comprises data requesters, perception platforms, and participants. Data requesters are generally organizations, such as governments, small businesses, and research institutions [15]. They send their requests to the perception platform. The perception platform, a virtual cloud server with powerful computing power and rich hardware resources, can assign tasks and collect and analyze data. [16]. Participants are the basic perception modules in the MCS system. They include user-end smart mobile devices that handle the assigned perception tasks and upload the collected perception data in time [17]. The workflow of MCS is displayed in Figure 3.

2.2. Optimizing MTA by Reinforcement Learning (RL) Theory. RL, also known as evaluation learning, is a machine learning (ML) paradigm. In RL, agents learn strategies to maximize rewards or achieve specific goals through environmental interaction [18]. The applications of RL are vast and can be found in autonomous driving, robot intelligence, and investment quantification, with satisfactory practical achievements [19]. The basic idea of RL is explained in Figure 4.

A common model for RL is the standard Markov Decision Process (MDP) [20]. Its state transition probability

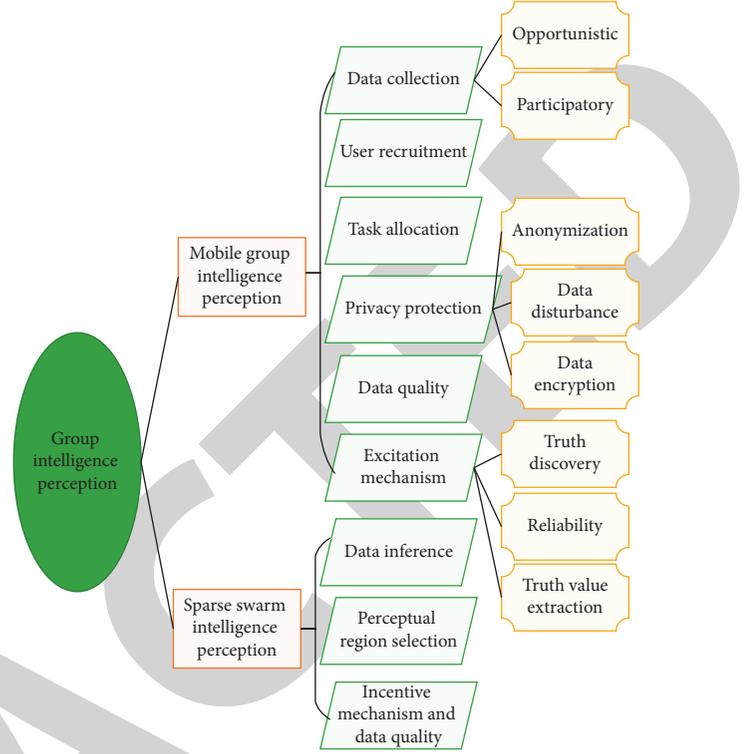


FIGURE 1: The structure division of the MCS system.

and reward are related to the agent's actions in the current state, and the specific calculation is as follows:

$$\begin{aligned} p_{ss'}^a &= p(s_{t+1} = s' | s_t = s, A_t = a), \\ R_s^a &= E[R_{t+1} | s_t = s, A_t = a]. \end{aligned} \quad (1)$$

Here, $p_{ss'}^a$ represents the state transition probability, and R_s^a expresses the environmental feedback to the agent's behavior. S means the state space in RL, A is the action space of the agent, a refers to the action, and s indicates status. An agent's action strategy in a certain state is a probability distribution. The probability is calculated by equation (2).

$$\pi(a|s) = p[A_t = a | s_t = s]. \quad (2)$$

Letters in equation (2) share the same definitions as those of the above equations.

RL can maximize long-term cumulative reward, which can be formalized as equation (3) based on MDP.

$$\pi^* = \operatorname{argmax}_{\pi} E_{\pi} \left\{ \sum_{k=0}^{\infty} \gamma^k r_{t+k} | s_t = s, \forall s \in S, \forall t \geq 0 \right\}. \quad (3)$$

In equation (3), γ stands for the reward discount factor $\in [0, 1]$. Decimals are used to describe the uncertainty of future rewards. It is also in line with the time discounting characteristics in real scenarios.

The original problem can be transformed into a solution to the Bellman equation to get the optimal strategy. Its calculation is as follows:

$$Q_{\pi}(s, a) = E_{\pi} (R_{t+1} + \gamma Q_{\pi}(s_{t+1}, A_{t+1}) | S_t = s, A_t = a). \quad (4)$$

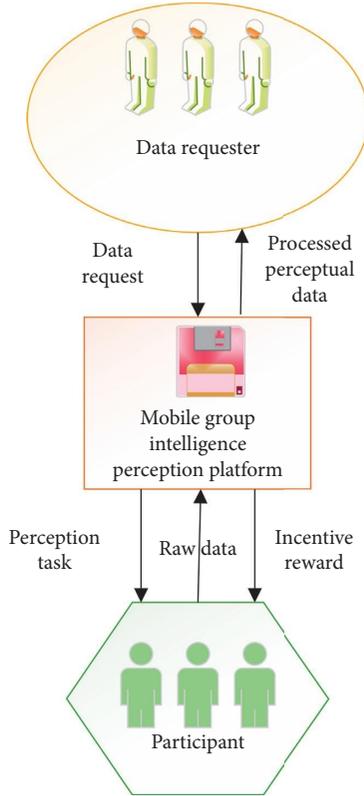


FIGURE 2: Architecture of MCS.

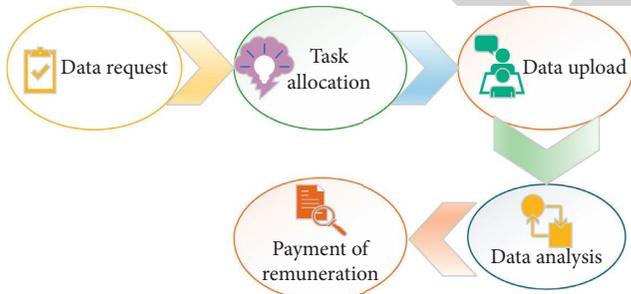


FIGURE 3: The workflow of MCS.

In equation (4), $Q_\pi(s, a)$ signifies the long-term reward expectation of action a in state s based on a certain strategy π . The remaining letters share the same meaning as the above equations. Equation (4) can be divided into two parts. One is the immediate reward expectation brought by action a in state s . The other is the product of the discount factor and the reward expectation at the next moment.

Many learning methods exist in RL, such as Q-Learning, Sarsa, and Soft Q-learning. The iterative update of Q-Learning is shown in equation (5).

$$Q(s, u) = Q(s, u) + u \left[r + \frac{\gamma \max_{a'} Q}{a'}(s', u') - Q(s, u) \right]. \quad (5)$$

In equation (5), u means the learning rate $\in [0, 1]$. Q shows the long-term cumulative reward expectation of action under a certain state. Equation (6) comprises two parts.

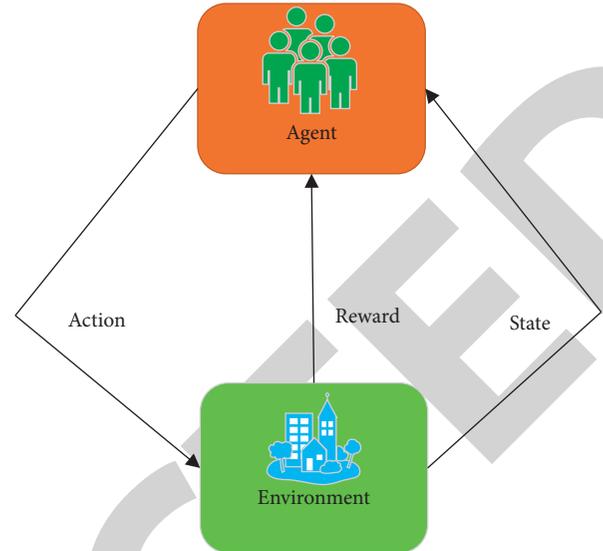


FIGURE 4: The basic idea of RL.

One is the real Q value that represents the sum of the immediate reward of the current state and the maximum Q value in the following status in the historical information. The other part is the error between the actual and the target Q values.

The core of Sarsa and Q-Learning is roughly the same, and its Q value is updated as follows:

$$Q(s, a) = Q(s, a) + a[r + \gamma Q(s', a') - Q(s, a)]. \quad (6)$$

The letters in equation (6) share the same meaning as the above equations.

Soft Q-learning is based on the maximum entropy theory, which adds entropy to the reward function in RL. The specific calculation is as follows:

$$\pi_{\max Ent}^* = \arg \max \sum_t E[r(s_t, a_t) + \alpha H(\pi(\cdot|s_t))]. \quad (7)$$

The comparison of equations (7) with (5) reveals that Soft Q-learning can maximize the sum of expected reward and state entropy.

2.3. Application of IoT Technology in MTA. IoT connects everything and is an extension of the internet as it combines various information sensors with the network. Besides, IoT realizes the interconnection of people, machines, and things anytime, anywhere [21, 22]. IoT has found applications in various fields. For example, IoT has promoted the intelligent development of the infrastructure fields, such as industry, agriculture, environment, transportation, logistics, and security. It helps managers allocate limited resources rationally, improving efficiency and effectiveness. The progress of modern IoT is inseparable from the wireless network, such as the Fourth (4G) and Fifth-generation (5G) mobile communication networks. Wireless network technologies make real-time positioning, uploading, and information sharing possible [23, 24]. In addition, the IoT background system is often supported by cloud technology. The virtual

public infrastructure based on cloud computing integrates monitoring, storage, analysis, visualization, and client-side delivery into end-to-end services for enterprises and users [25, 26]. The architecture of IoT is depicted in Figure 5.

Radio frequency identification (RFID) is a common technology in IoT applications. A corresponding tag is associated with the reader sending a query and is identified through the noncontact RFID method [27–29]. Multiple associated time slots (TSs) are combined into a frame, and the tag can respond to any TS in each frame. The specific calculation is as follows:

$$Q(Y = a) = M_A^a \left(\frac{1}{c}\right)^a \cdot \left(1 - \frac{1}{c}\right)^{A-a}, \quad (8)$$

Q refers to the probability, and C stands for the number of TS in the frame. M demonstrates an arbitrary reader value. A signifies the number of tags waiting to be identified. a means that the a tag selects TS at the same time.

The probability of recognizing an only tag in a TS is as follows:

$$Q(Y = 1) = M_A^1 \left(\frac{1}{c}\right)^1 \cdot \left(1 - \frac{1}{c}\right)^{A-1}. \quad (9)$$

According to equations (8) and (9), the system throughput rate D can be obtained by equation (10).

$$D = \frac{F(Y = 1)}{c} = \frac{A}{c} \left(1 - \frac{1}{c}\right)^{A-1}. \quad (10)$$

According to equation (10), when $A = C$, the system throughput rate reaches the maximum.

RFID divides each node into multiple subnodes and sends instructions “a” and “b” to Node 1 and Node 2, respectively. The subnodes continue to fork according to “a” and “b.” Its communication cycle is as follows:

$$P = (E = E_a) = E - 2^n \cdot E \cdot \frac{1}{2^n} \left(1 - \frac{1}{2^n}\right)^{E-1}. \quad (11)$$

In equation (11), $P(E)$ means the communication cycle. E_a denotes the tag, and 2^n expresses the number of TSs. E illustrates the total number of tags.

Its time complexity is calculated by equation (12).

$$F(E = E_a) = \frac{E - 2^n \cdot E \cdot (1/2^n)(1 - 1/2^n)^{E-1}}{E}. \quad (12)$$

In equation (12), $F(E)$ shows the time complexity, and the remaining letters share the same meaning as the above equations. The throughput of the RFID system is as follows:

$$T = \frac{E}{C(E)} = \frac{E}{E + (E/\ln 2) \cdot (1 - \ln 2/E)^{E-1}}. \quad (13)$$

In equation (13), T indicates the system throughput, and the remaining letters share the same meaning as the above equations.

MOTA, AOTA, and WF, which are the three task allocation algorithms, will be used here. MOTA follows the multilevel allocation strategy to allocate tasks to more users,

thereby improving the algorithm applicability. AOTA assigns tasks dynamically to users encountered in the mobile process through a greedy strategy. Ideally, the algorithm can almost get the optimal allocation results. The WF algorithm assigns tasks to the earliest idle users, following a specific sequence in the task set. In other words, the tasks assigned by the WF algorithm are in a random order.

2.4. Building IoT-Native Devices’ MTA Model. Currently, IoT devices in the MCS scenario have failed to consider MTA [30, 31]. Accordingly, this work introduces the RL theory to optimize IoT devices’ MTA strategies. The form of MTA in the MCS scenario is demonstrated in Figure 6.

In Figure 6, user A first assigns tasks to systems B and C that meet. After completing the perception task, B and C will feed back the data results to A. The task assignment and feedback process require a fast and reliable wireless network like the 5G network. The MTA scenario under the mobile SI perception can be abstracted into a mathematical model. The task allocator is ready to collect effective information in the perception area within a certain period of time, allocate this information into several subtasks, and then carry out SI perception activities [32, 33]. In this model, parameter β is the reciprocal of the expected meeting time between users and task assignors. The specific calculation method is as follows:

$$t_{ip} \int_0^{\infty} t \beta_i e^{-\beta_i t} dt = \frac{1}{\beta_i}. \quad (14)$$

In equation (14), t refers to time, and β refers to the parameters. (14) gives the rules of the encounter between the task assignors and users. The assignment strategy of perceptual tasks can be dynamically optimized according to the matrix information in parameter β .

3. Results and Analysis

3.1. Optimization of IoT-Native Devices’ MTA. The data from the University of Cambridge and the University of St. Andrews are used for the current research. The specific dataset is displayed in Figure 7. In addition, Intel, Cambridge, Infocom, and Andrew sassy datasets are shown in Table 1.

The three datasets, A, B, and C, are collected by the University of Cambridge. In Figure 7, the number of encounters and users of these three datasets is increasing. The timespan of dataset A is 99 hours. The timespan of dataset B is 145 hours and that of dataset C is 76 hours. The dataset D, organized by the University of St. Andrews, has the largest number of encounters and timespans but the smallest number of users. Regarding the number of encounters, the number of users, and the timespan, dataset B has a shorter encounter time and the most uniform encounter pattern. Dataset D has large irregularities because of the number of encounters, the number of users, and the timespan. Hence, the two data sets, B and C, will be mainly studied in the follow-up experiments.

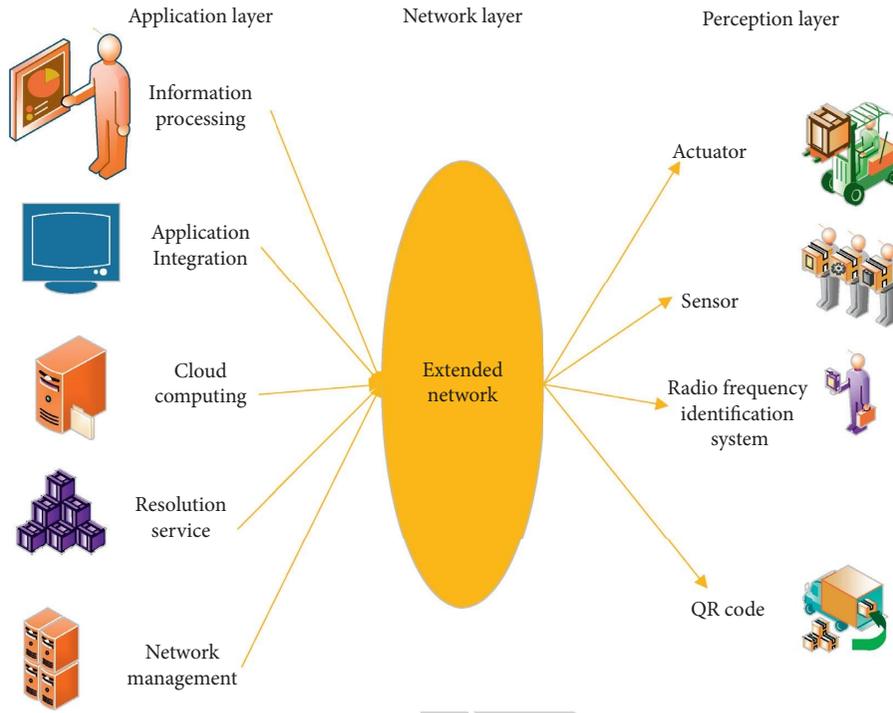


FIGURE 5: The architecture of IoT.

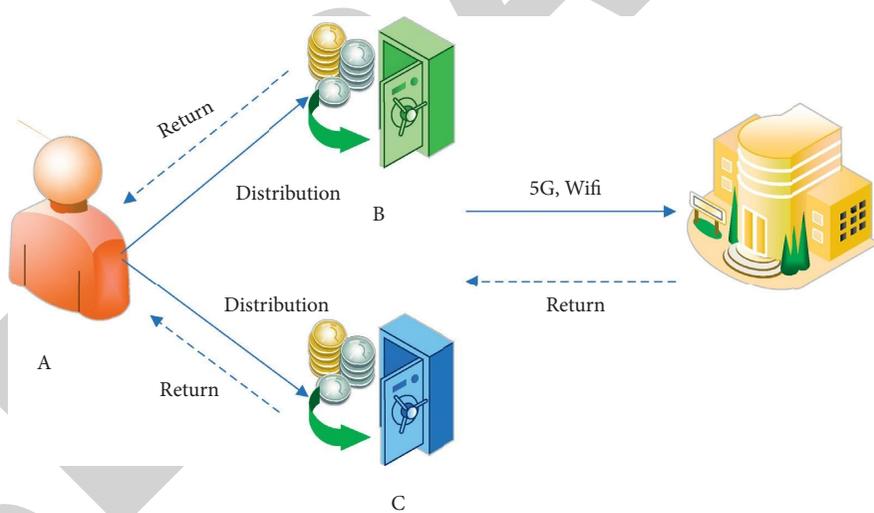


FIGURE 6: The form of MTA in the MCS scenario.

To optimize the IoT devices' MTA, the MOTA, AOTA, and WF algorithms are introduced. Firstly, with a constant task load, the time consumption by changing the task quantities is demonstrated in Figure 8.

Figure 8 shows that with the increase of the task quantity, the average time consumption on datasets B and C increases. Comparing the average time consumption knows that the algorithm performance is $MOTA > AOTA > WF$.

Next, with a constant task quantity, the time consumption for different task loads is plotted in Figure 9.

Comparing Figures 8 and 9 reveals that with the increase in task quantity, the average time consumption on the two datasets, B and C, increases. Comparing the average time

consumption shows that the algorithm performance is $MOTA > AOTA > WF$. With a dynamic task quantity, the consumption time of the AOTA algorithm on dataset C is about 28.5% less than that on dataset B. With a task load, the time consumption of the AOTA algorithm on dataset C is about 30% less than that on dataset B.

3.2. Results of MTA in Simple and Complex Scenarios. The MTA method in the MCS scenario is divided into simple and complex scenes according to the task complexity. The IoT assignment results of the MOTA and WF algorithms in a simple task scenario are compared in Figure 10.

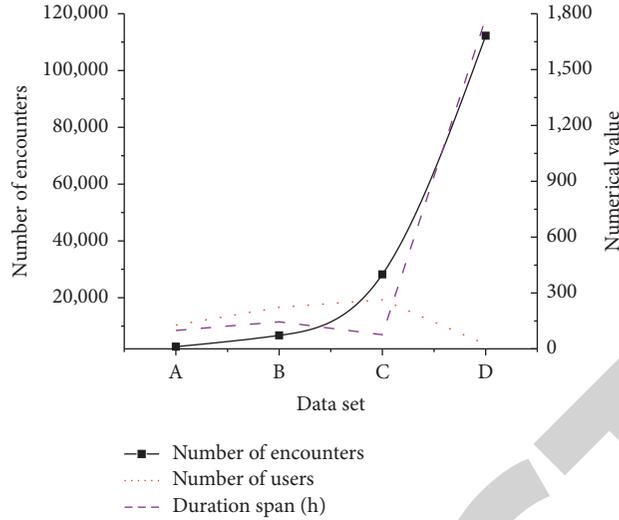


FIGURE 7: Dataset information (A. Intel dataset, B. Cambridge dataset, C. Infocom dataset, and D. Andrew sassy dataset).

TABLE 1: Four different datasets.

Data set	Abbreviation	Number of encounters	Number of users	Duration span (h)
Intel	A	2,766	128	99
Cambridge	B	6,732	223	145
Infocom	C	28,216	264	76
Andrew sassy	D	112,264	25	1,776

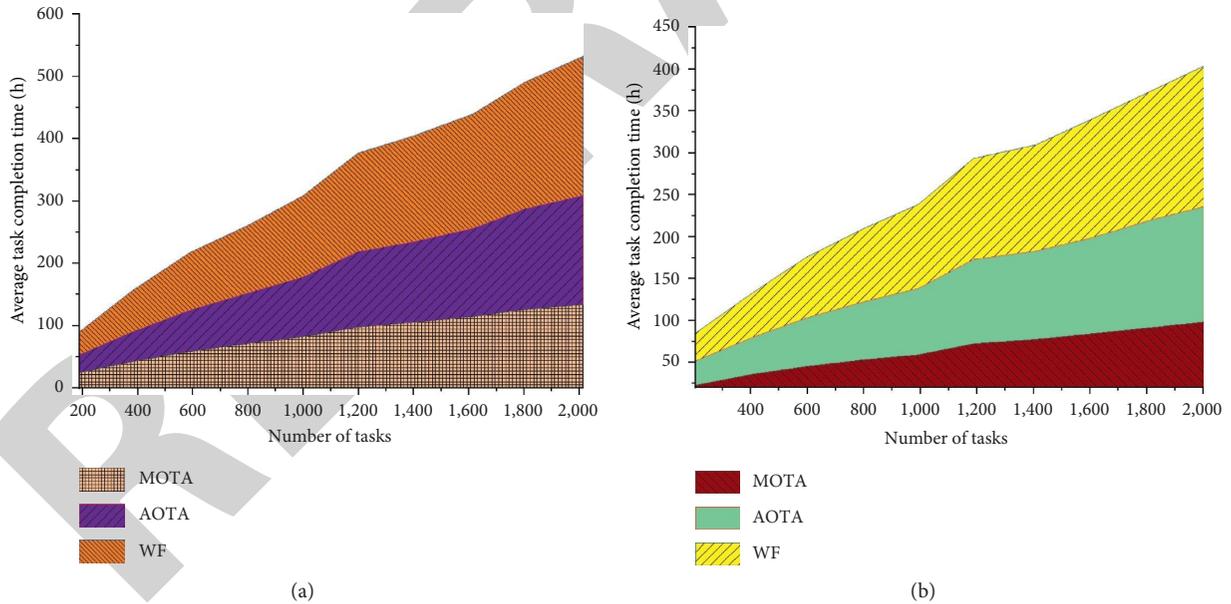


FIGURE 8: Changes in the MTA consumption time with a constant load and a dynamic task quantity ((a) means the dataset B, and (b) means the dataset C).

Figure 10 shows that in a simple scene, the MOTA and WF algorithms' relationship curve between the task quantity and the user moving distance rises. Nevertheless, the total moving distance of MOTA is shorter than the WF algorithm. It is because Q-learning is added to the MOTA algorithm to optimize its path. With a dynamic task quantity, the task completion of the two algorithms is exhibited in Figure 11.

Figure 11 shows that as user quantity increases, the curve of both algorithms rises. However, the task completion degree of the MOTA algorithm has always been higher than that of the WF algorithm. With 8,000 tasks, the task completion degree of the two algorithms gets close. The MOTA algorithm can maintain a high task completion even with a small user quantity and works well in MTA.

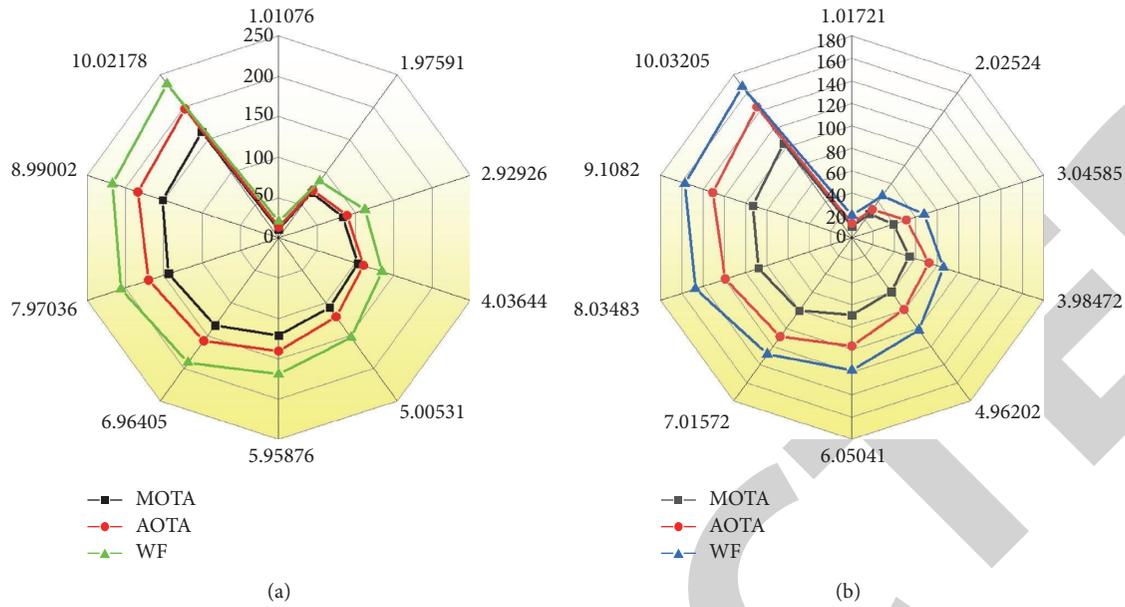


FIGURE 9: The MTA consumption time with a constant task quantity and a dynamic load ((a) the dataset B and (b) the data set C).

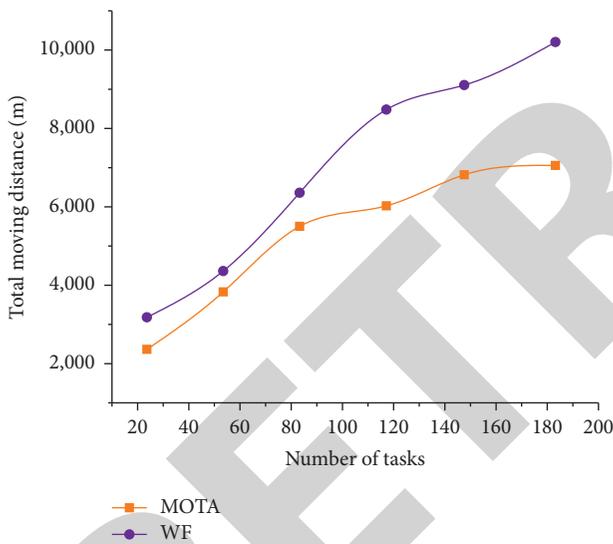


FIGURE 10: The total distance the user moves in a simple scene.

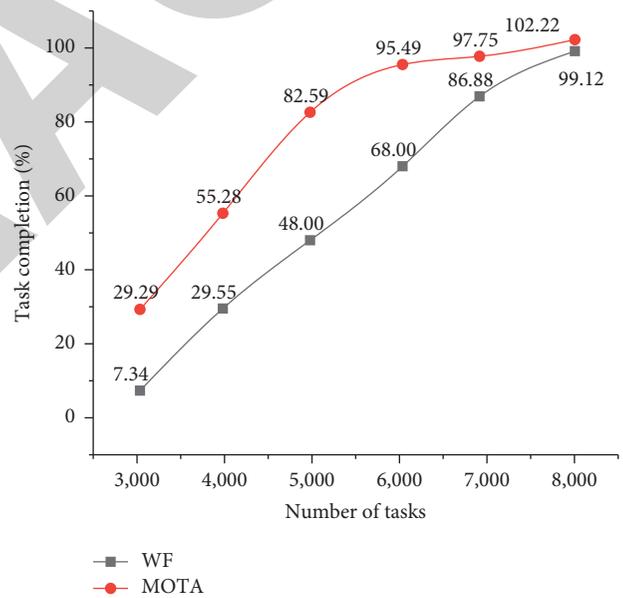


FIGURE 11: Completion of task assignment in a simple scene.

In practice, unexpected situations also bring difficulties to IoT devices' MTA. Subsequently, MOTA, AOTA, and WF are applied to the complex perception scene. The specific situation is shown in Figure 12.

Apparently, with the increase in complex tasks, MOTA, AOTA, and WF algorithms' perception time is prolonged. In particular, the perception time fluctuation is $WF > AOTA > MOTA$. The perception time of the MOTA algorithm is the shortest, and the perception sensitivity is relatively low. The WF algorithm fluctuates the most because different complex tasks limit the action space of the agent. The comparison shows that the AOTA algorithm lends best to complex events.

Figure 13 shows the relationship between the task quantity and the MTA accuracy.

Obviously, the MTA accuracy of MOTA, AOTA, and WF fluctuates gently with task quantity. When task quantity = 200, the accuracy of MOTA, AOTA, and WF algorithms is 73.1%, 84.6%, and 33.6%, respectively. With a constant task quantity, AOTA is the most accurate, followed by the MOTA and WF in turn. Thus, AOTA lends best to MTA.

The relationship between the time consumption of different algorithms and the task quantity is compared in Figure 14.

Evidently, as task quantity increases, the time consumption of MOTA, AOTA, and WF prolongs, with tiny differences. The MOTA and AOTA algorithms' curves

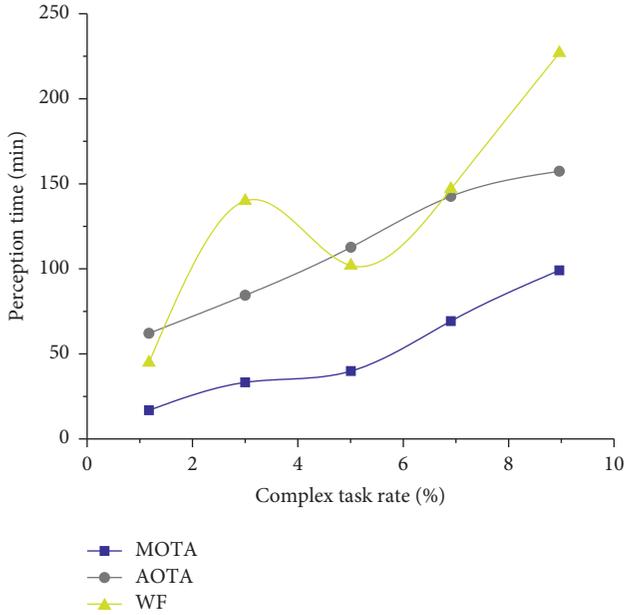


FIGURE 12: Multitask perception time in complex scenes.

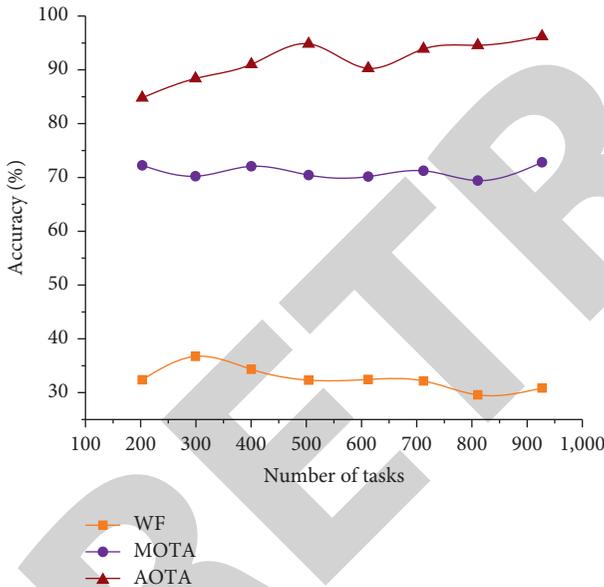


FIGURE 13: The relationship between the task quantity and MTA accuracy.

fluctuate less than the WF algorithm. Meanwhile, the time consumption of the WF algorithm is the longest, followed by the MOTA and AOTA in turn.

To sum up, the factors, such as the time consumption and task quantity of MOTA, AOTA, and WF, are comparatively analyzed. Then, the IoT devices' MTA methods in simple and complex task scenarios are discussed. Consequently, the AOTA algorithm shows the optimal MTA accuracy and time consumption. Ultimately, this work chooses the AOTA for IoT devices' MTA to improve the time consumption and accuracy.

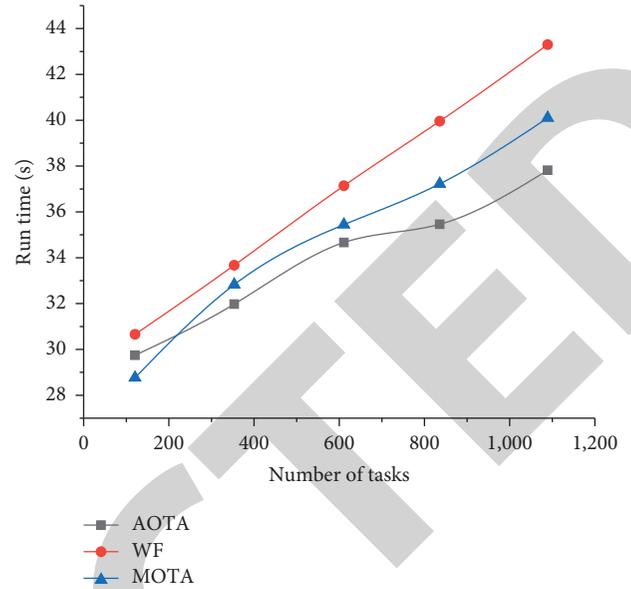


FIGURE 14: The relationship between the time consumption of different algorithms and the task quantity.

4. Discussion

5G and mobile internet have given rise to intelligent devices. To optimize the IoT devices' MTA, this work chooses the data collected by Cambridge University and St. Andrews University to verify MOTA, AOTA, and WF algorithms. Specifically, it analyzes the three algorithms' MTA accuracy and time consumption in simple and complex task scenarios. Tang et al. [34] used the mobile SI perception and error elimination decision theory for quality assessment to identify low-quality and abnormal data. The research contributed to quality assessment from the error reduction perspective [34]. Malik et al. [35] defined the trading market and achieved unified pricing and task allocation in mobile crowdsourcing by reaching the Walras equilibrium. The incentive mechanism has always been an important research area in mobile SI perception, and the integration with interdisciplinary has always been an effective means. The future research trend might shift from traditional classical economics to relevant disciplines that reflect human behavior characteristics and psychologies, such as behavioral economics and consumer psychology [35]. The above two works optimized MTA from the perspective of mobile SI perception. By comparison, this work employs comparative analysis and finds that the AOTA algorithm's MTA accuracy is the highest with a constant task quantity. The finding provides solutions for the follow-up MTA optimization research. However, the disadvantage lies in relatively few factors considered. The future work will fully consider the task's time, content description, and data type and reasonably combine the online or offline perceptual tasks.

5. Conclusion

5G technology and wireless network advancement provide opportunities for MCS development. This work studies the IoT devices' MTA optimization by introducing RL in MCS

scenarios. The main conclusions are as follows: (1) the data collected by the University of Cambridge and the University of St. Andrews are used to verify MOTA, AOTA, and WF. The three algorithms aim to optimize IoT devices' MTA. With a constant task load or the task quantity, the algorithm consumption time of MOTA is the least, followed by the AOTA and WF algorithms in turn. (2) The MOTA algorithm is compared with the WF algorithm in a simple task scenario. The result indicates that the MOTA algorithm's total moving distance is relatively short, and the task completion degree is the highest. (3) The AOTA algorithm lends best to complex task scenarios with the increase of complex tasks. Under a constant task quantity, the AOTA algorithm has the highest MTA accuracy. As the task quantity increases, the WF algorithm's consumption time is the longest, followed by the MOTA and AOTA, in turn.

Last but not least, this work has some limitations in data acquisition, resulting in some deviations in data analysis. The research on IoT devices' MTA optimization based on RF in the mobile SI perception scenario involves many or incomplete user constraints. In the follow-up, the role of task assignors can be completed by Unmanned Aerial Vehicles (UAVs), and software can be used to interact directly with users. This work does not consider user privacy, perceived data quality, and efficient user selection in MTA. Further research can be carried out on these aspects to make the MTA method more efficient and convenient.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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