A willingness-aware user recruitment strategy based on the task attributes in mobile crowdsensing

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Abstract
With the powerful sensing, computing capabilities of mobile devices, large-scale users with smart devices throughout the city would be the perfect carrier for the people-centric scheme, namely, mobile crowdsensing. Mobile crowdsensing has become a versatile platform for many Internet of things applications in urban scenarios. So how to select the appropriate users to complete the tasks and ensure the quality of the tasks has been a huge challenge for mobile crowdsensing. In this article, we propose a willingness-aware user recruitment strategy based on the task attributes to solve this problem. First, we divide the whole sensing region based on task attributes by a weighted Voronoi diagram and conduct the assessment about the sub-regions according to several parameters, and then categorize sub-regions as hot regions and blank regions. Moreover, we analyze the influence of user willingness on user recruitment and the task completion rate and assess the coverage ability of the users. Finally, we use the greedy method to optimize the user recruitment for each task to select the most suitable users for the tasks. Simulation results show that the willingness-aware user recruitment approach can significantly improve the task completion rate and achieve higher task coverage quality compared with other algorithms.

Keywords
Mobile crowdsensing, region partition, willingness-aware, task attribute, user recruitment strategy

Date received: 2 March 2022; accepted: 7 August 2022
Handling Editor: Yanjiao Chen

Introduction
Nowadays, because of the growing advancement of mobile communication (5G/6G) and ubiquitous sensing and computing technologies, the Internet of things (IoT) applications and services have been widely used in people’s life, for example, smart cities,1,2 remote healthcare,3 traffic and environment monitoring,4,5 and wireless indoor localization.6 These applications analyze and utilize the data sensed and collected by sensors deployed in the urban scenario to provide ubiquitous and intelligent services.7 But with the rapid development of intelligent mobile terminals, such as mobile phones, iPads, and wearable devices, these powerful mobile devices equipped with sensing, collecting, computing, and communicating capabilities can perfectly take place of the traditional static sensors. And the people’s random mobility who carry smart mobile devices provides the possibility of pervasive sensing.

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The prevalence of the increasing number of intelligent mobile terminals builds the solid physical foundation for a new sensing paradigm, known as mobile crowd-sensing (MCS).\(^8\) MCS takes full use of the smart devices with their myriad built-in sensors and has become the versatile platforms for many IoT applications, which can be found in Wi-Fi performance measurements,\(^9\) air quality sensing,\(^10\) noise mapping,\(^11\,12\) and urban traffic monitoring.\(^13\,14\)

Compared with traditional sensing technology, one of the most significant changes is that MCS applications no longer require to deploy a large number of static sensors previously to sense the data. The large-scale users with smartphones throughout the city would be the perfect carrier for the MCS applications. Therefore, acquiring data by MCS is no longer limited to the location. While people roam in the urban areas, MCS applications can easily obtain the data by users’ sensor-rich smartphones. For example, people can detect the noise level through analyzing environmental sound collected by sound sensors. Travelers can record their travel logs and share their travel tips through camera and Global Positioning System (GPS) sensors in the applications. Drivers or passengers can collect road congestion conditions through acceleration and cameras sensors, and then upload the data to the city administration. This human-driven sensing paradigm enhances the capabilities of IoT applications by effectively reducing the installation cost and ensuring sufficient space coverage.\(^15\) Consequently, a broad range of MCS applications has been applied in various IoT services, including public safety, traffic planning, and environmental monitoring.

In a typical MCS application, it is usually composed of large-scale mobile users with their smart devices, customers, and a cloud platform. The cloud platform can receive the tasks from the customers and release the sensing tasks. Mobile users will be recruited by the platform to collect the required data through using their smart devices. Then, mobile users transmit the corresponding data, for example, locations, local knowledge, air conditions, and congested traffic information in 5G/6G or Wi-Fi networks to the platform. By making the most of the technology of data fusion, the platform can get more effective and useful information for the customers.\(^16\) This enables MCS to be an efficient and appealing sensing paradigm.

During the MCS application process, it is most vital for the platform to ensure the completion of the tasks. The user recruitment strategy\(^17\) for MCS applications in IoT has become one of the most crucial challenges. The purpose of user recruitment strategies is to select the appropriate mobile users who can make the greatest contribution to accomplish the sensing tasks.\(^18\) So how to recruit the most appropriate users to finish the tasks has drawn lots of researchers’ attention. More and more studies have focused on finding the optimal user recruitment strategy in certain scenarios. The researchers have attempted to address user recruitment strategies by considering different variables. For example, Fiandrino et al.\(^19\) designed a user recruitment in which the platform considered the users’ social characteristics and their willingness to select the suitable users to complete the sensing tasks. Pouryazdan et al.\(^20\) pointed out that the user reputation was also an important factor influencing the user recruitment strategies. High reputation users would be more reliable to participate in the tasks, but also be easier to get recruited, which would reduce the enthusiasm of low reputation users. Furthermore, An et al.\(^21\) found that the user’s activity capacity had a significant impact on the task execution performance. However, the studies above ignored the importance of the task attributes which had a great influence on the users’ selection. Meanwhile, there is another problem that the coverage quality of task completion cannot be guaranteed. Therefore, the MCS user recruitment strategy should fully consider the attributes of the task and other vital parameters of users.

Aiming at addressing the problems discussed above in the urban scenario, in this article, we are concentrated on dealing with the problem that how to improve the whole task completion rate and meanwhile achieve the optimal coverage. We design a willingness-aware user recruitment (WAUR) strategy based on the task attributes to provide a guarantee for a higher task completion rate and maximize the coverage for the sensing region. The main contributions of this article are three-fold as follows:

1. We introduce a weighted Voronoi diagram to divide the whole sensing region into several sub-regions based on the task attributes to make the tasks easier to find stable and reliable users to finish tasks. Then due to the uneven distribution and mobility of users, we conduct the assessment about the sub-regions according to the density of users in the region, importance of the task, and the area of the region and categorize the sensing sub-regions as hot regions and blank regions.

2. We analyze the influence of the user willingness on the user recruitment and the task completion rate, and then integrally consider the distance between the user and the task, remaining energy, and the task importance to evaluate the user willingness. Furthermore, we assess the coverage ability for the candidate users which may achieve the optimal coverage for the tasks.

3. We propose a novel WAUR strategy based on task attributes for MCS applications. In the hot regions and blank regions, we focus on different needs for the tasks. In the hot regions, we aim
to guarantee maximum coverage and improve the task completion rate. In the blank regions, we try to ensure that the tasks have the optimal coverage, meanwhile, guaranteeing the completion rate of tasks. In addition, we use the greedy method to optimize the user recruitment for each task. Simulation results show that the WAUR approach presents good performance compared with other methods.

The remainder of this article is organized as follows. Section “Related work” reviews and summarizes the related work about MCS systems and user recruitment strategies. Then, we introduce our system model in section “System model.” Section “WAUR strategy” analyzes user willingness and assesses the coverage ability of the user. Then, we propose a novel WAUR strategy based on task attributes. The performance comparison with other methods is shown in section “Simulation and numerical results.” In section “Conclusion,” we conclude our work.

Related work

Recently, extensive researchers have devoted themselves to the issues related to MCS applications and paradigms. In MCS applications, there are two approaches to sense the data from the users. One is participatory sensing, and the other is opportunistic sensing. In opportunistic sensing, the applications constantly collect the information by sensors such as location, weather conditions, and noise conditions while the users may not be aware of such operations. But in participatory sensing, the users will have the choice of whether to participate in the MCS applications. The applications publish the tasks and recruit users who have the willingness to take part in the applications. Furthermore, the users will decide which kind of data sensed by their phones can be shared so that there is no potential leak of personal information. The difference between participatory sensing and opportunistic sensing lies in whether the user actively participates in the applications. Therefore, they are all widely used in IoT applications, such as smart living, smart location, and privacy protection.

More and more studies about participatory sensing which relies on the active participation of the users in MCS applications are emerging. They concentrate the attention on some promising challenges in MCS, such as user recruitment strategy (or called participant selection), incentive mechanism, and task allocation algorithm. In this article, we make a great many efforts to focus on a variety of user recruitment strategies. A good user recruitment strategy is to help the platform find the most suitable users who can make the greatest contribution and perfectly complete the tasks in the different requirements and environments. Most of the MCS applications depend on the users who volunteer to participate in the tasks, so the willingness of users may have a great influence on the completion, accuracy, and quality of the tasks. Moreover, meeting the requirements of the tasks and considering many parameters, these have motivated extensive researchers to engage in MCS user recruitment strategy for more than a decade.

Reddy et al. first developed a participant recruitment framework that allowed the platform to select the most-suited participants to complete the tasks. They built a user reputation system based on the users’ locations, availability, and past participation records to evaluate the users who met the requirements of the task. To et al. investigated the problem that how to complete as many tasks as possible under budget constraints. They only selected the participants who were in the task’s spatiotemporal vicinity as candidates and then found an optimal subset of candidates under a certain budget to accomplish the tasks. Zhang et al. mainly focused on how to find the most appropriate users to achieve maximum spatial and temporal coverage for the tasks under a limited budget. Compared with traditional algorithms, they just chose a subset of mobile participants to achieve the purpose. However, they ignored the task’s characteristic—durations which may result in the user completing the tasks after they had ended.

Fiandrino et al. integrally considered three criteria—distance, sociability, and energy, and then designed an MCS user recruitment framework over fog computing platforms to improve the task completion rate and the efficiency and accuracy of the task completion. While this solution could guarantee the task completion rate, there was uncertainty in the quality of the coverage for the tasks. Zhang et al. indicated that quality control was a vital problem in MCS, and they formulated the user recruitment problem as an optimization problem in terms of the quality control. Alagha et al. proposed a novel stable data-based recruitment system (SDRS) which included a two-step recruitment strategy to integrally consider users localization, mobility traces, and reputation. Then they designed a stable coverage assessment method based on the distance between the tasks and users and the spatiotemporal characteristics of users. However, this approach did not consider the user willingness which decided whether the users volunteer to participate in the tasks. This means that more users can be the candidates for the tasks, the size of the user-pool will be bigger which affects the task completion rate.

The above studies have proposed reliable algorithms to achieve the goals from different perspectives. They always consider a variety of parameters like distance,
time, and sensing ability because the MCS system is driven by users. But none of them start from the perspective of the task attributes which has a significant impact on the execution of the tasks\textsuperscript{38} and on the user recruitment strategy. Hence, we propose a novel WAUR strategy based on task attributes for MCS applications aiming at improving the task completion rate and achieving a higher coverage quality.

**System model**

In order to select the proper users to make contributions and accomplish the tasks, and help the MCS applications get high-quality and sufficient data from the users, our MCS system includes four phases: “Task Assignment,” “Information Acquisition,” “User Recruitment,” and “Evaluation,” where the “Task Assignment” phase is responsible for the publication of the tasks information which comprises of locations, time, real-time status, and requirements. The duty of the “Information Acquisition” phase is to collect the user personal information, including the registration, willingness, spatiotemporal characteristics, and so on. In the “User Recruitment” phase, we use the proposed user recruitment strategy based on the various considerations to select the most suitable users to perform the tasks. In the final phase, the platform will get the acquired data from the selected users and then conduct the data processing and evaluation.

As shown in Figure 1, our MCS system model is mainly used in the urban environment. A platform \( P \) and a large number of mobile users \( U \) with smart devices are the most important components of the MCS system. The mobile users \( U = \{u_1, u_2, \ldots, u_U\} \) who are active in the sensing region can be the participants or requesters. And every user \( u_i \) has its own file which is represented as a multi-element tuple, \( F_u = (l_u, v_u, W_u, s_u, RE_u) \), which contains the user real-time location, speed, willingness, sensing radius, and the remaining energy of user mobile devices. The platform \( P \) is responsible for the task acquisitions from the users and the publication of the sensing tasks \( u = (u_1, u_2, \ldots, u_n) \) about certain regions. The relevant details of the task are described by another multi-element tuple, \( F_\theta = (\theta_{typ}, l_j, t_j, R_j, I_j) \), which, respectively, represents the tasks type, location, duration, coverage radius, and importance. The locations of users \( l_u \) and tasks \( l_j \) are described by latitude and longitude. The duration of the task \( t_j \) is usually divided into some timeslots to be performed in order to acquire more comprehensive data in different periods. \( \theta_{typ} \) and \( R_j \) usually indicate the task attributes. \( I_j \) denotes the

![Figure 1. MCS system model.](image-url)
task importance. The higher the value is, the more important the tasks are. Upon receiving the sensing requests from the requesters, the platform $P$ releases the sensing tasks $\theta$. The mobile users $U$ will choose whether to participate in the tasks based on the relevant information $F_{\theta}$. Then, the platform $P$ evaluates the user real-time status information to select users as the candidates $C_{\mu}$. Finally, trying to reduce the cost, the platform $P$ finds the most suitable user to accomplish the task based on the proposed user recruitment strategy.

### WAUR strategy

In this section, we investigate the issues of the coverage for sensing tasks of MCS in urban environments. When users consider whether to participate in the tasks, the attributes of the tasks play an important role. And these have brought new challenges to MCS applications, especially for the user recruitment strategy. We first introduce a Grid Division method to divide the sensing region into several sub-regions based on the task attributes, and evaluate the heat of the sub-regions because of the distribution and mobility of users. Then, we analyze the recruitment parameters and describe the whole process in detail. Finally, we design a WAUR strategy based on task attributes which aims at improving the task completing rate and meanwhile tackling the problem of maximum coverage of sensing tasks for MCS applications. The main symbols and their definitions in our proposed user recruitment strategy are listed in Table 1.

**Table 1. Symbols list and description.**

| Symbols | Description |
|---------|-------------|
| $A$     | Whole sensing area |
| $P$     | Platform |
| $U$     | Users |
| $\theta$ | Tasks |
| $t_{\theta}$ | Duration of a task |
| $l_{\theta}$ | Location of a task |
| $w_{\theta}$ | User willingness |
| $R_{\theta}$ | Sensing radius of task |
| $R_{\theta}$ | Remaining energy |
| $I_{\theta}$ | Task importance |
| $w_{\theta}$ | Weight of a task |
| $D_{\theta}$ | Density of users in region |
| $V_{\theta}$ | Assessment for a region |
| $V_{\theta}^{Assess}$ | Threshold of the region assessment |
| $V_{\theta}^{I}$ | Weighted Voronoi cell |
| $C_{\theta}^{cov}$ | Coverage for a task |
| $C_{\theta}^{cov}$ | Coverage sensed by a user for a task |
| $C_{\theta_{i}, \theta_{j}}^{cov}$ | Coverage ability for a user |
| $f$ | Recruitment factor |
| $\alpha, \beta, \lambda, \mu$ | Balancing coefficient |

**Region partition and assessment**

Intuitively, a large number of users taking part in the MCS tasks will provide a guarantee of a high task completion rate. However, it cannot ensure that there is a good coverage rate for some sensing tasks, such as some real-time environmental monitoring tasks. In real environment and life, due to the uneven distribution and random mobility of users, there will be a vast number of users gathered in some regions waiting for participating in sensing tasks at some moments. On the contrary, there will be a blank region where there are even no active users in this area. This uneven distribution of users in the sensing region will significantly reduce the tasks completion rate in some blank regions. Therefore, how to improve the task completion rate and provide optimal coverage quality for sensing tasks becomes a tough challenge.

In our MCS system model, we assume that the platform $P$ releases the $n$ sensing tasks $\theta = (\theta_1, \theta_2, \ldots, \theta_n)$ about certain regions acquired from the users, and their relevant information of the tasks are denoted by $F_{\theta} = (\theta_{\theta_1}, l_{\theta_1}, t_{\theta_1}, R_{\theta_1}, I_{\theta_1})$, which, respectively, represents the tasks type, location, duration, coverage radius, and importance. Due to different tasks type $\theta_{\theta_1}$, coverage radius $R_{\theta_1}$, and importance $I_{\theta_1}$, these attributes not only affect the size of the sensing task region but also limit the user’s willingness to participate in the tasks. Therefore, we take the task locations $l_{\theta_1}$ as cluster heads, introduce a weighted Voronoi diagram in our previous work, and comprehensively consider the attributes of the tasks to make sure that the platform can easily find the most appropriate user to complete the tasks by dividing the sensing region into $n$ sub-regions.

As we know, the coverage radius $R_{\theta} = (R_{\theta_1}, R_{\theta_2}, \ldots, R_{\theta_n})$ and the importance $I_{\theta} = (I_{\theta_1}, I_{\theta_2}, \ldots, I_{\theta_n})$ vary in different tasks, so we can obtain the weight equation by comparing as follows, $w_{\theta_i} = R_{\theta_i}l_{\theta_i}/R_{\theta_{\min}}T_{\theta}$, where $R_{\theta_{\min}}$ denotes the maximum coverage of the tasks and $T_{\theta}$ represents the average value of the importance of the tasks, calculated by $T_{\theta} = \sum_{i=1}^{n} I_{\theta_i}/n$. Furthermore, we can get the weighted Voronoi diagram equation as follows

$$V_{\theta} = \left\{ u \in U : \frac{d(l_u, l_{\theta})}{w_{\theta_i}} \leq \frac{d(l_u, l_{\theta})}{w_{\theta_j}}, i, j = 12, \ldots, n ; i \neq j \right\}$$

(1)

where $V_{\theta}$ indicates $n$ sensing sub-regions, and $d(l_u, l_{\theta})$ denotes the distance between any user location $l_u$ in this region and the task location $l_{\theta_i}$. Through equation (1), we can get $n$ irregularly shaped sensing sub-regions where the distance from any user in this region $V_i$ to the task location $l_{\theta_i}$ is closer than any other task $l_{\theta_j}$. Although we divide the sensing region into sub-regions based on the locations,
coverage radius, and importance of the tasks, there is no guarantee for the task completion rate and coverage rate. In practice, the tasks which are published in a large number of active users can easily find a proper user to finish the tasks. However, when the platform releases the tasks in a region where there are few active users, this can lead to such a situation that there are no insufficient candidates to complete the tasks, and further affect the task completion rate of the whole region. Hence, we try to conduct an assessment about the sub-regions divided by the weighted Voronoi diagram according to the density of users in this region in their durations, the importance of the tasks, and the whole area of the sub-regions which are closely related to the region assessment in this article.

We assume that $D_i^0$ denotes the density of users in the region $V_i^0$ during their durations $t_i$, which is calculated by $D_i^0 = N_i^0 / N_u$, where $N_i^0$ is the number of the active users in region $V_i^0$ during their durations $t_i$, and $N_u$ is the total number of users during this time. $I_i$ represents the importance of the task $i$ and $A_i$ is the whole area of the region $V_i$. So, we can get the region assessment equation as follows

$$V_{i}^{\text{Assess}} &= \alpha \times D_i^0 + \beta \times \frac{I_i \times A_i}{I_i \times A} \quad (2)$$

where $V_{i}^{\text{Assess}}$ denotes the assessment for the region $V_i$, and $A$ denotes the whole sensing area. $\alpha$ and $\beta$ are the balancing coefficients, ranging from 0 to 1, where $\alpha + \beta = 1$.

In addition, we select $V_{i}^{\text{Assess}}$ as the threshold of the region assessment, which is represented by

$$V_{i}^{\text{Assess}} = \alpha \times D_{\text{min}}^0 + \beta \times \frac{I_{\text{min}} \times A_i}{I_i \times A} \quad (3)$$

where $D_{\text{min}}^0$ denotes the minimum density of users during all tasks execution time. $I_{\text{min}}$ is the minimum value of the importance of the tasks, and $A_i$ is the average value of the sensing area. When $V_{i}^{\text{Assess}} > V_{T}^{\text{Assess}}$, we can say that the sensing region $V_i$ is a hot zone that has enough users to complete the task. On the contrary, when $V_{i}^{\text{Assess}} \leq V_{T}^{\text{Assess}}$, the sensing region $V_i$ is called a blank zone where may insufficient users or lower importance of the task which cannot motivate the user to participate in the task.

User willingness

Generally, the user’s willingness to participate in a sensing task is decided by several factors, such as the distance between the user and the task, the cost of the execution, the battery energy consumption of their smart devices, payment for completing the tasks, and so on. In this article, we mainly consider the three vital factors which are closely related to the user’s willingness.

In the sensing region, the distance between the user and the task is always one of the most concerned factors for users. The long distance will consume more energy of users and demotivate the users. Therefore, we deduce the relationship $w_{i, \theta}^{\text{dis}}$ between the distance and user willingness as follows

$$w_{i, \theta}^{\text{dis}} = \begin{cases} \frac{1-d_{i,\theta}}{d_{\text{max}}}, & d_{i,\theta} < d_{\text{max}}^0 \\ 0, & d_{i,\theta} \geq d_{\text{max}}^0 \end{cases} \quad (4)$$

where $d_{i,\theta}$ denotes the distance between the user $i$ and the task $\theta$, and $R_{\text{max}}$ is the maximum distance that a task can recruit users and the users can make contributions to the coverage for the tasks, which is calculated by $R_{\text{max}} = R_{\theta} + s_{ui}$.

The users choose to take part in the tasks and sense the data which will consume a lot of energy of users’ smart devices. The remaining energy of user mobile devices would be a great important consideration for the users since it shows whether the user has the ability to perform the tasks and collect the data. Hence, we use the RE to represent the remaining energy of user mobile devices, and $E_{ui}$ will be updated dynamically after the user $i$ completes the task. The relationship $w_{i, \theta}^{RE}$ between the remaining energy and the user willingness can be described as follows

$$w_{i, \theta}^{RE} = \begin{cases} \frac{E_{ui}}{E_{\text{max}}}, & E_{ui} \geq E_{\text{con}} \\ 0, & E_{ui} < E_{\text{con}} \end{cases} \quad (5)$$

where $E_{ui}$ denotes the full energy of the user mobile device, and $E_{\text{con}}$ is the consumption for completing the task $\theta$.

Obviously, the users are more likely to participate in tasks with higher importance; thus, they may get more rewards from the task. We assume that users are rewarded in terms of incentives, which will encourage users to take part in tasks and provide high-quality sensing data. Intuitively, the incentives will seriously affect the user’s willingness. The higher the importance of the task is, the more reward the users can get after they complete the tasks. That means the users will more likely to choose the task with higher importance to execute. So, the relationship $w_{i, \theta}^{I}$ between the importance of the task and the user willingness is given by

$$w_{i, \theta}^{I} = \frac{I_{\theta}}{I_{\text{max}}} \quad (6)$$

where $I_{\text{max}}$ is the maximum value of the importance in the tasks $\theta = (\theta_1, \theta_2, ..., \theta_N)$. Overall, we consider three factors, the distance, remaining energy, and task importance which all affect the user willingness, and deduce the user willingness $w_{i, \theta}$ as follows
\[ w_{u, \theta_j} = \sqrt{w_{u, \theta_j}^{dist} \times w_{u, \theta_j}^{RE} \times w_{u, \theta_j}^{l}} \] (7)

**Coverage ability**

In the urban environment, many sensing tasks need not only a higher task completion rate but also to possibly achieve the maximum coverage efficiency. In our MCS system model, we try to achieve the two goals at the same time. The recruited users have the best ability to guarantee the task completion rate; meanwhile, they can achieve the maximum coverage for the whole sensing region. We assume that \( c_{u, \theta_j}^{cov} \) denotes the coverage that the user \( u \) can sense for the task \( \theta_j \), and \( C_{\theta_j}^{cov} \) is the whole sensing area of the task \( \theta_j \) which is needed to be sensed. Hence, we can get the coverage ability \( C_{u, \theta_j}^{cov} \) of the user for the task described by

\[ C_{u, \theta_j}^{cov} = \frac{c_{u, \theta_j}^{cov}}{C_{\theta_j}^{cov}} \] (8)

The higher the coverage ability \( C_{u, \theta_j}^{cov} \), the greater possibilities the user is to be recruited.

**Process of WAUR strategy based on task attributes**

In our MCS system model, we assume that the platform \( P \) releases the \( n \) sensing tasks \( \theta = (\theta_1, \theta_2, \ldots, \theta_n) \) about certain regions. Then, we introduce the weighted Voronoi diagram to divide the whole sensing region into \( n \) sub-regions according to the tasks attributes that contain the task location \( l_{\theta_j} \) and the importance \( I_{\theta_j} \). Furthermore, we conduct a region assessment about the sub-regions based on the density of users in this region in their durations, the importance of the tasks, and the whole area of the sub-regions which are closely related to the region assessment. Then, we can categorize the \( n \) sensing sub-regions as hot zones and blank zones.

After categorization, let \( C_{\theta_j} = (u_1, u_2, \ldots, u_k) \) denotes the candidate set of users who will be potentially selected to finish the task \( \theta_j \) in the sub-region \( V_{\theta_j} \). In addition, we analyze the user willingness \( w_{u, \theta_j} \) in terms of the distance, remaining energy, and task importance which all affect whether users are more likely to take part in the tasks. Then, we further evaluate the coverage ability \( c_{u, \theta_j}^{cov} \) of the user for the task for the purpose of improving the task completion rate and achieving a higher coverage.

To help the platform \( P \) find the most suitable user to accomplish the tasks, and based on the different purposes in the hot region and blank region, we, respectively, build the fitness functions to evaluate the user’s sensing ability based on the user willingness and the coverage ability. In the hot regions, there are plentiful users to participate in the tasks who have the great ability to accomplish the tasks and achieve the higher coverage for the tasks. Hence, the fitness function in hot zones aiming at improving the tasks completion rate and reaching the maximum coverage for the tasks is given as follows

\[ f_H = \lambda w_{u, \theta_j} + \mu c_{u, \theta_j}^{cov} \] (9)

where \( \lambda \) and \( \mu \) denote the balancing coefficients ranging from 0 to 1, and \( \lambda + \mu = 1 \). In blank regions, if \( C_{\theta_j} = \emptyset \), it means that the region \( V_{\theta_j} \) may have no active users in the candidate set to participate in the task which will lead to failure of the task completion. In order to guarantee a better task completion rate, we can find the candidate users out of the region \( V_{\theta_j} \) to achieve the optimal coverage for the task \( \theta_j \), but the distance \( d_{\theta_j} \) between the user and the task should be closer than \( R_{\theta_j}^{max} \), where \( R_{\theta_j}^{max} \) is equal to \( R_{\theta_j}^{max} = R_\theta + \Delta u \). Therefore, we deduce the fitness function in blank regions given by

\[ f_B = \begin{cases} \lambda w_{u, \theta_j} + \mu c_{u, \theta_j}^{cov}, & u_i \in C_{\theta_j}, C_{\theta_j} \neq \emptyset, \\ \mu c_{u, \theta_j}^{cov}, & u_i \notin C_{\theta_j}, C_{\theta_j} = \emptyset, \ RE_{u_i} \geq E_{\theta_j}^{cov} \end{cases} \] (10)

For different tasks in hot regions and blank regions, we integrally consider a variety of parameters and build different equations (9) and (10) to select the most suitable user who has the maximum value of \( f \). We compute the whole users’ fitness for each task, and the user with the highest value of \( f \) will be recruited to finish the tasks. Then, we introduce a greedy algorithm to help our user recruitment strategy to compute the whole users’ fitness scores and choose the best one for the task. The specific process of our user recruitment strategy is shown in Algorithm 1.

**Simulation and numerical results**

In this section, several experiments and simulations are conducted for our WAUR strategy based on task attributes, and the performance is compared with other methods. In order to simulate the realistic urban scenarios, we use a custom simulator called CrowdSenSim39 which allows the researchers to conduct the analysis for MCS activities. In this article, we perform the experiments in a real city of Luxembourg, the center area of which is 1.1 km². A certain number of users ranging from 1000 to 10,000 are randomly distributed in the city and moving at a speed 1 m/s from 8:00 to 18:00. Each user carries a smart device that can sense and transmit the data, and the initial remaining energy of which is randomly distributed in \([0.5, 1.0]\). For each round of the task, the recruited user’s remaining energy will be reduced by the consumption of this task. The number of the tasks varies in \([10, 100]\) and the task will be divided into several timeslots. For each timeslot of


Algorithm 1. A willingness-aware user recruitment (WAUR) strategy based on task attributes.

```
Input: input U, θ
Output:
1: for u in U do
2: d(l_u, l_o)/w_θ ≈ d(l_u, l_o)/w_θ
3: Region partition V_θ = {u ∈ U} θ
4: end
5: Assess the regions V_θ = α × D_u + β × l_u × A_u
6: if V_θ ∈ V_θ
7: V_θ ∈ V_θ
8: else if V_θ ∈ V_θ
9: Calculate user willingness w_u, θ and coverage ability C_u, θ
10: for u in V_θ do
11: Select u ∈ U that maximize f
12: Calculate f_u of u ∈ U
13: Select u ∈ U that maximize f
14: end if
15: Calculate f_u of u ∈ U
16: Select u ∈ U that maximize f
17: end
```

Table 2. Simulation settings.

| Parameters                  | Value         |
|-----------------------------|---------------|
| Number of users             | [1000, 10000] |
| Number of tasks             | [10, 100]     |
| Coverage radius of task     | [10, 50]      |
| Initial remaining energy    | [0.5, 1.0]    |
| Task importance             | [0.2, 1.0]    |
| Sensing radius of user      | [10, 50]      |
| Evaluation period           | 8:00–18:00    |
| Task duration               | 30 min        |
| Timeslot duration           | 3 min         |
| Balancing coefficient α, β, λ, μ | 0.7, 0.3, 0.6, 0.4 |

The SGRS approach user characteristic aware participant selection (UCPS) for mobile crowdsensing. The WAUR approach displays a better performance than the other benchmarks in task completion rate and coverage rate. Our WAUR approach integrally considers the user willingness and coverage ability which are sensitive for the tasks so that it can get the better users to improve the performance.

Table 4 indicates that our proposed WAUR approach has obvious significant advantages over other two algorithms. We explore the relationship between task completion rate and average rates of the three approaches are basically equal. And with more and more users, the WAUR approach and other benchmarks present an upward trend. This is because there are more possibilities for the tasks to recruit the appropriate user who has the great sensing ability and coverage ability to finish the tasks, which leads to the improvement of the task completion rate and coverage rate. Our WAUR approach integrates the user willingness and coverage ability which are sensitive for the tasks so that it can get the better users to improve the performance.

Table 4 indicates that our proposed WAUR approach has obvious significant advantages over other two algorithms. We explore the relationship between task completion rate and various number of tasks when the number of users is fixed in Figure 4. From the figure, with the growing number of tasks, our WAUR approach and other benchmarks show a decline in the task completion rate. The reason is that with more and more tasks, there will be more sub-regions where the candidate users in this region will decrease due to the fixed whole number of users. Although when the number of tasks reaches 100, our WAUR approach gets decreasing from almost 85% to 51% in task coverage rate, which is still much better than other benchmarks.

To evaluate the performance of our proposed user recruitment strategy, we compare the WAUR approach with the two benchmark algorithms, including a stability-based group recruitment system (SGRS)\(^{40}\) and user characteristic aware participant selection (UCPS)\(^{41}\) for mobile crowdsensing. The SGRS approach focuses on the coverage of the sensing area and considers the parameters such as requirements of the sensing task, user mobility, and distribution. The UCPS approach estimates the regional heat and integrally considers the parameters to select the proper users to finish the tasks. The goal of our proposed WAUR approach is to improve the task completion rate and achieve a higher task coverage quality. So, we try to conduct the experiments with these three approaches over 100 runs under the same circumstances in the simulator CrowdSenSim and get the average values to show the different performance from several evaluation metrics of task completion rate, task coverage rate with the change of user numbers, task number, task coverage radius, user coverage radius, task importance, and initial remaining energy of user in order to highlight the strengths of our algorithms in these two metrics.

More evident from Table 3, our proposed WAUR approach displays a better performance than the other two benchmark methods in task completion rate and task coverage rate. In terms of the relationship between the various number of users and the average task completion rate, Figure 2 demonstrates that with growing numbers of users, the tasks will have a bigger user-pool and can attract more users to voluntarily take part in the tasks and make their contributions. As a result, more users can be the candidates to accomplish the task. The task completion rate will have a great increase. From Figure 2, no matter how many users grow, the WAUR approach outperforms the other two benchmarks. When the number of users reaches 10,000, the task completion rate of the WAUR approach has reached above 90%, which is much better than the 79% of the UCPS and 65% of the SGRS.

Figure 3 further illustrates the advantage of our proposed WAUR approach over the other two algorithms. At first, when the number of users is 1000, the task coverage rates of the three approaches are basically equal. And with more and more users, the WAUR approach and other benchmarks present an upward trend. This is because there are more possibilities for the tasks to recruit the appropriate user who has the great sensing ability and coverage ability to finish the tasks, which leads to the improvement of the task completion rate and coverage rate. Our WAUR approach considers the user willingness and coverage ability which are sensitive for the tasks so that it can get the better users to improve the performance.

Table 4 indicates that our proposed WAUR approach has obvious significant advantages over other two algorithms. We explore the relationship between task completion rate and various number of tasks when the number of users is fixed in Figure 4. From the figure, with the growing number of tasks, our WAUR approach and other two benchmarks show a decline in the task completion rate. The reason is that with more and more tasks, there will be more sub-regions where the candidate users in this region will decrease due to the fixed whole number of users. Although when the number of tasks reaches 100, our WAUR approach gets decreasing from almost 85% to 51% in task coverage rate, which is still much better than other benchmarks.
Similar to Figures 4 and 5, we compare our WAUR approach with the other two benchmarks in terms of the task coverage rate under a various number of tasks. The tendency of the rate keeps going down with the increasing number of tasks. From the beginning, our WAUR approach can get an 80% task coverage rate when the number of tasks equals 10, better than the 73% of SGRS and 57% of UCPS in Figure 5.

**Table 3.** Task completion rate and task coverage rate under a various number of users for three approaches.

| Number of users ranging from 1000 to 10,000 | Task completion rate | Task coverage rate |
|-------------------------------------------|----------------------|--------------------|
| WAUR                                      | 30.6%–95.6%          | 19.2%–79.9%        |
| UCPS                                      | 21.2%–79.1%          | 17.2%–68.0%        |
| SGRS                                      | 15.8%–63.6%          | 18.8%–70.6%        |

WAUR: willingness-aware user recruitment; UCPS: user characteristics aware participant selection; SGRS: stability-based group recruitment system. Bold value indicates the superiority of the WAUR algorithm.

**Figure 2.** Task completion rate under a various number of users.

**Figure 3.** Task coverage rate under a various number of users.

**Table 4.** Task completion rate and task coverage rate under a various number of tasks for three approaches.

| Number of tasks ranging from 10 to 100 | Task completion rate | Task coverage rate |
|----------------------------------------|----------------------|--------------------|
| WAUR                                   | 84.6%–51.2%          | 80.2%–50.2%        |
| UCPS                                   | 76.3%–45.3%          | 56.8%–35.1%        |
| SGRS                                   | 73.8%–40.0%          | 73.5%–40.8%        |

WAUR: willingness-aware user recruitment; UCPS: user characteristics aware participant selection; SGRS: stability-based group recruitment system.

**Figure 4.** Task completion rate under a various number of tasks.

Compared to the SGRS approach which focuses on the coverage of the sensing area, our WAUR approach not only assesses the coverage ability of users but also chooses the users with coverage guarantee to complete the tasks in the blank regions. Therefore, our WAUR can provide a guarantee for the task completion rate and meanwhile achieve the higher task coverage quality.

Figure 6 shows that when the coverage radius of tasks gets higher and higher, it means the area needed to be sensed is getting larger and larger. Hence, the tasks will have higher and higher requirements for users. It will demand that the users not only ensure they have the ability to finish the tasks but also sense and cover as large a coverage area as possible. As we know, users with smart devices only have limited sensing ability. Although our WAUR approach considers
the user coverage ability, it still cannot maintain the coverage rate when the task coverage radius gets higher and higher. However, the WAUR approach outperforms in terms of the task coverage rate than the other two benchmarks.

On the contrary, in Figure 7, we can see that when users get higher and higher sensing radius, which means the sensing and coverage ability of users get stronger. This will lead the users to have more willingness to take part in the tasks and more possibilities to finish more tasks and get more awards. Our WAUR approach comprehensively considers the user willingness and coverage ability, so the performance is much better than UCPS and SGRS methods.

From equation (7), we can know that the task importance and initial remaining energy for user smart devices have a great impact on the user willingness. Users are more likely to participate in the most important tasks so that they may get attractive rewards. And with the more initial remaining energy of user devices, users are more willing to participate in the tasks, meanwhile, they will have a stronger sensing ability. From Figures 8 and 9, we discuss how the task importance and initial remaining energy affect the task coverage rate and task completion rate, respectively. Figures 8 and 9 indicate that our WAUR approach has more significant performance than the
other two benchmarks and is consistently ahead by a 10% advantage.

Conclusion

In this article, we are concentrated on dealing with the problem that how to improve the whole task completion rate and meanwhile achieve the optimal coverage. We design a WAUR strategy based on the task attributes to provide a guarantee for a higher task completion rate and maximize the coverage for the sensing region. First, we introduce a weighted Voronoi diagram to divide the whole sensing region into several sub-regions based on the tasks attributes. Then we conduct the assessment about the sub-regions according to the density of users in the region, importance of the task, and the area of the region, and categorize the sensing sub-regions as hot regions and blank regions. In addition, we analyze the influence of the user willingness on the user recruitment and the task completion rate, and then integrally consider the distance between the user and the task, remaining energy, and the task importance to evaluate the user willingness. Moreover, we assess the coverage ability for the candidate users which may achieve the optimal coverage for the tasks. Finally, in the hot regions and blank regions, our proposed WAUR algorithm focuses on different needs for the tasks. In the hot regions, we aim to guarantee maximum coverage and improve the task completion rate. In the blank regions, we try to ensure that the tasks have the optimal coverage, meanwhile, guarantee the completion rate of tasks. In addition, we use the greedy method to optimize the user recruitment for each task. Simulation results show that the WAUR approach can improve the task completion rate and achieve a higher task coverage quality compared with other algorithms.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the Fundamental Research Funds for the Central Universities (3102017zy026).

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