IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received August 20, 2021, accepted September 10, 2021, date of publication September 13, 2021, date of current version September 21, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3112272

Horizontal Integrated Framework for Mobile Crowdsensing

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A part of this work was supported by JSPS KAKENHI Grant Number JP21K17729 and JST, ACT-I, Grant Number JPMJPR18UL, Japan.

ABSTRACT Mobile crowdsensing is a promising paradigm to leverage the power of people to collect large-scale spatially distributed data. This concept has been intensely studied to efficiently and securely complete sensing tasks at lower cost. The development of a unified platform designed to provide various types of sensing applications is among the major approaches to economical crowdsourcing. However, existing previous frameworks were not optimized for shared use among multiple organizers because they were largely vertically integrated systems. Security and user trust and confidence is also a significant issue a crowdsensing frameworks, given the potential security concerns. Therefore, in this study, we propose a network-side task allocation (NeSTA) framework to address the existing problems in mobile crowdsensing. The proposed framework enables the horizontal integration of sensing applications, in which mobile networks mediate communication among organizers and participants, significantly reducing the installation cost of individual applications. Privacy preservation is achieved by task distribution and allocation procedures, where the participants were obscured by organizers. The validity of the proposed NeSTA was confirmed by simulations with an analytical model using an open dataset. The results show that the proposed method exhibited computational efficiency over two orders of magnitude greater than the conventional approach. This advantage originates from the reduction of problem size by dividing the original problem into subproblems.

INDEX TERMS Crowdsourcing, mobile applications, mobile communication, mobile computing.

I. INTRODUCTION

Rec ent advances in sensor technology have enabled mobile devices including smartphones and tablets to be equipped with various embedded sensors such as cameras, gyroscopes, accelerometer, GPS, microphone, and light sensor. As mobile devices are increasingly becoming essential tools in our daily lives, they are expected to provide a powerful platform for large-scale data collection for human society and surrounding environments [1]. In this context, mobile crowdsensing is a promising concept designed to leverage the power of people to collect large-scale spatially distributed data [2]–[5].

The concept of crowdsensing involves the completion of large-scale sensing tasks with the cooperation of many mobile users. The advantage of crowdsensing is that it enables organizers to easily collect spatially distributed data at a lower cost, which is impossible for a single individual or a small group. Various types of sensing applications can be deployed based on this paradigm, e.g. monitoring systems for road surfaces, traffic flows, and urban environments, performing functions such as street parking availability statistics [2]. It can also be noted that sensing applications can collect data without participants' awareness, in contrast to participatory sensing [6], which behavior is classified as opportunistic sensing [3]. In other words, for instance, a sensing application may run as a background process in a mobile device, enabling it to automatically collect data without the active involvement of the mobile user.

Many works have reported the advantages of crowdsensing [4], [7], [8] in the recent past. In addition to these specific sensing applications, the development of unified platforms is expected to be an economical and efficient approach to provide various types of sensing applications [9]–[11]. The concepts of such unified platforms are based on the strong similarity of various sensing applications. On such platforms, sensing tasks are allocated to participants.

The associate editor coordinating the review of this manuscript and approving it for publication was Hong Xing.

A programmable platform called Medusa was developed in [9], which aimed to construct high-level abstractions of the crowdsensing task procedures. A distributed runtime system was employed in this platform to coordinate task execution between cloud computing systems and smartphones. Optimizing the allocation of sensing tasks among participants is considered a significant issue in the development of a unified crowdsensing platform of sensing tasks to the participants. This is issue is complex because each sensing task has different requirements, and each mobile user has different constraints, such as time budgets. Many research efforts have considered optimal task allocation algorithms to address this problem [11].

It has been reported that security, privacy, and data integrity are critical issues for crowdsensing frameworks [2], [12], because crowdsensing applications collect data from individuals, including sensitive private data. As a typical example, is GPS tracking sensors installed on all mobile devices can easily be utilized to infer private information such as users' home and work locations. With regard to data integrity and confidence, malicious individuals can easily affect sensing results by reporting erroneous data. Thus, it is important for sensing platforms to provide mechanisms to ensure the privacy of participants and the integrity of the collected data. Moreover, resource limitations are also important issues in the development of large-scale crowdsensing platforms [2]. Multiple sensing applications may share energy and computational resources of devices as well as the time and cost resources of participants. Thus, the diverse sensing capabilities and availability of mobile users and devices should be considered in task allocation across multiple sensing applications. Recently, methods relying on edge computing have gained popularity in aiming to address these resource limitations. The decentralized data aggregation and processing scheme proposed in [13] is a typical example.

Therefore, in this study, we propose a network-side task allocation framework to address the existing challenges in mobile crowdsensing. Although the basic idea was introduced in [14], this paper provides a detailed explanation of the proposed framework and simulation results. The proposed framework enables the horizontal integration of sensing applications, where mobile networks mediate organizers and participants. The installation and running costs for organizers of individual sensing applications are significantly reduced by the proposed approach. Privacy preservation is achieved by task distribution and allocation procedures, where the participants are obscured from organizers. This procedure is executed using an edge computing approach with a central controller and mobile edge nodes. The proposed confidence mechanism reduces erroneous data by excluding unreliable participants in subsequent sensing tasks.

The contribution of this work is to propose a horizontal integrated framework mediated by mobile networks. In the proposed framework, different organizers can issue their own tasks and collect data on the same platform. Mobile users can participate in different sensing applications and report the results of different tasks on this platform. The key advantage of the proposed framework is the integration by the minimal inclusion of a third party, because network connectivity is a mandatory component in mobile crowdsensing. That is, a third party is inevitably required to achieve horizontal integration of multiple sensing applications. Because network connectivity is a mandatory component in mobile crowdsensing, the proposed framework enables a horizontal integrated system with the minimal inclusion of a third party through the mediation of mobile networks. The security and privacy of participants are ensured by the system architecture; thus, it is not necessary to consider them in the task allocation. The reliability of the participants was considered in task allocation in the proposed task allocation algorithm using the proposed confidence mechanism.

The remainder of this work is organized as follows. In Section II, we describe the related work and contributions of this study. Section III introduces the proposed NeSTA framework. Regarding the proposed framework, we explain the problem definition for task allocation in Section IV. Then, the proposed task allocation algorithm is introduced in Section V. In addition, the confidence mechanism and analytical results are described in Section VI. Section VII provides a performance evaluation of the proposed framework with case studies using an open dataset. Finally, our conclusions are presented in section VIII.

II. RELATED WORK

Various incentive mechanisms have been proposed to motivated individuals to participate in crowdsensing platforms and collect sensor data, including both monetary and non-monetary approaches [15], [16]. A common monetary approach estimates the reservation wage, which is defined as the lowest wage rate at which a participant will accept a job. Non-monetary approaches include the use of social rewards, competition, and games. The goal of these approaches is to encourage volunteer participation of specific users. In [17], a practical reputation system was proposed for pervasive social networking. A hybrid trust and reputation management model was developed to evaluate node recommendation trust and content reputation. A mechanism for sustaining trust among trusted computing platforms was proposed in [18] aiming to ensure trust, which has been a significant issue in cyberspace context. The proposed mechanism establishes trust relationships based on the root trust module and ensures its sustainability. To consider the quality of the sensory data contributed by individual users, the quality of information aware [19] and a quality-driven auction-based [20] incentive mechanism was introduced. In [21], two system incentive mechanisms were developed, including a user-centric model in which participants have control over the payment, and a crowdsource-centric model where participants share the rewards provided by the organizer. In this study, we assume that both existing monetary and non-monetary approaches can be employed as incentive mechanisms.

Privacy has also been a major concern in crowdsensing methods [22]. In [23], a trade-off between privacy and accuracy of acquired data was reported. A spatial cloaking technique for task assignment was proposed to obfuscate the locations of participants when they did not intend to share their locations [24]. For auction-based incentive mechanisms, a differentially private incentive mechanism was proposed in [25] to preserve the privacy of each participant's bids against others. Truth discovery is employed to identify truthful values from the sensory data. The authors of [26] proposed a cloud-enabled privacy-preserving truth discovery framework to protect the private information of participants and ensure their reliability scores. For location-privacy protection, a location aggregation method was proposed in [27], in which users were classified into several groups to preserve anonymity and mitigate information loss. An, an incentive mechanism was also developed to select efficient users based on the clustered groups generated in the location aggregation procedure. Although these techniques can improve the privacy of participants, obfuscation is not a fundamental solution, as it increases the computational complexity of the task considerably, leading to increased resource requirements of the associated sensing systems.

From a system perspective, mobile data cost and energy consumption are important factors that affect mobile users' willingness to participate in crowdsensing. An adaptive data uploading framework within fixed data uploading cycles was developed to improve energy and cost efficiency [28]. In [29], a hybrid framework combining mobile devices with static sensor nodes was proposed to address the issue of inadequate sensing opportunities caused by incentive mechanisms, that is, existing users in the target regions being fewer than the number of participants required for the sensing task. A framework called CCS-TA was developed in [30] to reduce the number of required tasks while ensuring data quality by leveraging the temporal and spatial correlations among the data collected in different sub-areas. A system framework that integrated data aggregation, data perturbation, and an incentive mechanism was developed in [31], [32]. In the proposed incentive mechanism, participants who were more likely to report reliable data were selected. The data perturbation scheme also ensured the privacy of the participants and suitable accuracy for the perturbed results. To effectively allocate dynamic and heterogeneous tasks to participants from a large number of mobile users, a dynamic participant recruitment scheme was developed to minimize cost while ensuring coverage [33]. An efficient participant selection scheme that aims for multitask environments was also proposed in [34]. In addition to the conventional approach, the concept of fog-based vehicular crowdsensing is an emerging paradigm. The goal of this concept was to meet the requirements for location-specific applications with communication between vehicular ad hoc networks and fog nodes that provide location-aware data management functions [35]. The proposed framework has a similar feature, using a fog-based approach allocate location-specific tasks. However, previous frameworks, including fog-based approaches, have not considered the development of an efficient method to integrate multiple organizers and applications using a horizontal integration approach. Therefore, in this study, we propose a novel horizontal integrated framework in which a mobile network mediates communications between organizers and participants in crowdsensing operations.

III. NeSTA FRAMEWORK

This section introduces the proposed NeSTA framework for mobile crowdsensing.

A. CONCEPT

The concept and advantages of the proposed framework are summarized here. The difference between the proposed NeSTA and conventional crowdsensing schemes is shown in Fig. 1 and is introduced in the following.

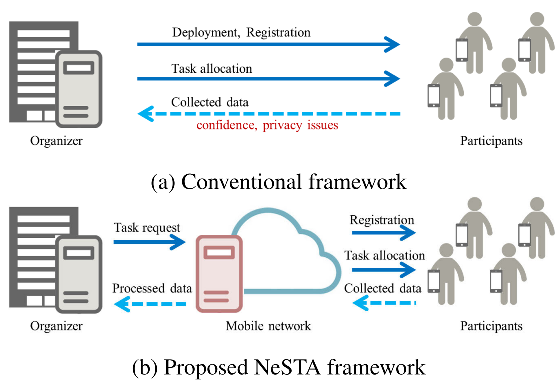


FIGURE 1. Relationship between organizer and participants in crowdsensing frameworks.

1) CONVENTIONAL CROWDSENSING FRAMEWORK

Fig. 1a shows the general crowdsensing framework. It includes two components; participants and an organizer. A sensing application is arranged by the organizer to acquire required data. A sensing application defines and issues sensing tasks. A sensing task is composed of multiple spatially distributed targets and required specifications, such as required sampling frequencies and coverage. Here we define participants as the people who registered with this sensing application. The participants register their attributes, e.g. their spatial and temporal availability, restrictions for data acquisition, and smart device specifications. An issued sensing task is allocated to the participants considering their registered attributes. Then, the participants started to collect data according to the results of task allocation using the sensors of their mobile devices. The collected data are automatically reported to the organizer.

Privacy, confidence, and cost are the major concerns for this conventional approach. First, the privacy issue is caused by data management schemes in which organizers can easily obtain and utilize the private information of participants included in the collected data, for example, time and spatial movement records of the participants. With regard to confidence, the quality of data deteriorates if there are unreliable participants, such as malicious individuals and mobile users whose devices are equipped with inoperable sensors. The cost issue originates from the vertically integrated system architecture. With this architecture, the cost of installing and running sensing applications cannot be shared among multiple organizers. That is, when an organizer arranges an application, they must deploy a new application, even if a similar application has already been deployed. It is also required for each organizer to register mobile users for the sensing task.

Here we explain the difference in horizontally and vertically integrated systems. A horizontal integrated framework provides a platform for various sensing applications. Different organizers can issue their own tasks and collect the required data on the same platform. In addition, users can participate in different sensing applications and report the results of different tasks on this platform. A vertical framework aims to provide a single or specific sensing application easily and efficiently. Most existing frameworks have worked on task allocation algorithms considering a wide variety of indices, such as computational efficiency, requirements of sensing applications, and user privacy. The contribution of this work is the proposal of a horizontal integrated framework mediated by mobile networks. A major advantage of the proposed framework is the integration of the minimum inclusion of a third party, because network connectivity is a mandatory component in mobile crowdsensing.

2) NeSTA FRAMEWORK

Fig. 1b shows the proposed NeSTA framework. Its key difference from the conventional framework is the existence of the mobile network as a third component. The participants and the organizers are mediated by the mobile network in the NeSTA. In other words, the deployment, registration, and data collection of sensing applications are executed via a mobile network. This framework enables the horizontal integration of sensing applications. Because a single unified platform is shared among multiple organizers, the installation and running costs of individual sensing applications are drastically reduced. Also, the proposed framework employs an edge computing approach. The task allocation and data collection procedure are processed in mobile networks, and thus the private information of participants is obscured by organizers. If there are unreliable participants, they can be excluded in subsequent sensing tasks because the unreliability flag for each participant is updated with the error reports from the mobile edges.

The goal of the NeSTA framework is to address the challenges of conventional approaches.

Privacy: The privacy of the participants is ensured by obscuring their data from the organizer. The organizer requests a sensing task and receives the processed data without any participant information. The mobile edge allocates sensing targets that compose a sensing task to the participants based on mobile user information. Spatially distributed targets were allocated to neighboring participants of the applications included in the mobile users. The collected data are anonymized, and then sent to the organizer. With this framework, the private information, e.g., movement records and spatial and temporal availability) of the participants are hidden from the organizer. Importantly the third-party included in the proposed approach is a mobile network operator, i.e. mobile edge nodes are deployed and operated by a mobile network operator. Because mobile network operators generally collect and store mobile users' data, including their profiles and locations, no additional private information of mobile users is collected with the proposed scheme. As long as the stored data are properly maintained by mobile edge nodes in the same way as existing mechanisms, privacy protection is not a concern for the proposed approach.

Confidence: The horizontal integration of multiple crowdsensing applications also improves the confidence of the acquired data. Because the list of participants is stored in the central controller, the allocation results of the sensing application can be utilized in other applications. The unreliability flag for each participant was updated with the error reports from the mobile edges at the end of the allocation sequence. That is, unreliable participants can be excluded from subsequent sensing tasks. This feature improves the confidence by excluding malicious users and mobile users with broken sensors. Also, the proposed framework can improve the confidence considering the network environment. If there are multiple candidate participants for task allocation, mobile users in unstable environments are excluded to minimize network errors. In addition, the mobile network can set the optimum quality of service (QoS) setting for the data flow based on the requirements of the application, such as bandwidth and latency. The collected data are forwarded in the network based on QoS policies.

Cost: The horizontal integration of multiple crowdsensing applications drastically reduces the installation cost of sensing applications. Fig. 2 depicts the proposed horizontal integration model. Different organizers provide their own sensing applications through the same mobile network. The mobile network manages the registration information for the mobile users. Mobile users can individually select whether to participate in each sensing application in a unified manner. With this model, the deployment

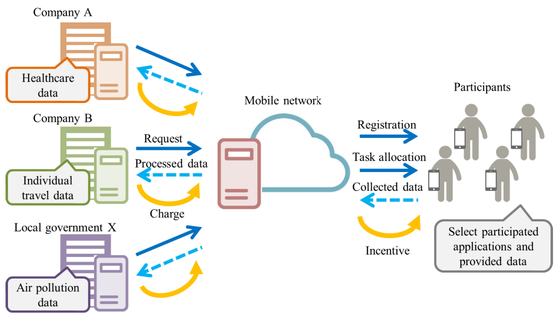


FIGURE 2. Proposed horizontal integration model.

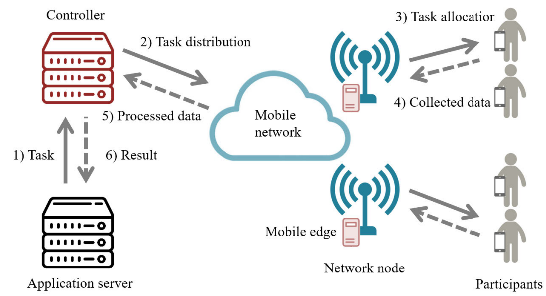


FIGURE 3. Sequence flow of NeSTA framework.

cost of a sensing application for an organizer is significantly lower than that of a conventional vertically integrated crowdsensing model. The mobile network operator receives charge from the organizers to provide the sensing platform service. The organizers decide and offer the incentive for sensing that the participants receive. The priority of sensing applications for the participants can be differentiated with the incentive setting; higher incentives attract more people. The incentive is paid for the participants by totaling the mobile bill. Furthermore, the proposed model improves the efficiency of task allocation for multiple applications by considering the participation states, spatial and temporal availability, and movement cost of mobile users.

These advantages originate from the model of the proposed NeSTA framework, in which the spatially distributed mobile network manages and links mobile users with spatially distributed sensing tasks. Furthermore, the spatial distribution in the proposed task allocation provides the benefit of reducing the allocation problem size.

A third party is inevitably required to achieve horizontal integration of multiple sensing applications. Because network connectivity is a mandatory component in mobile crowdsensing, the proposed framework enables a horizontal integrated system with the minimum inclusion of a third party through the mediation of mobile networks. If the organizers collaborate to allocate tasks, some information of the participants must be shared among the organizers. With the proposed framework, each organizer can virtually collaborate on the platform without sharing participants' information. This scheme has significant merit because it is difficult to evaluate the confidence of each organizer. In addition, because the time and location of the collected data themselves include private information of participants, it is beneficial not to report them to the organizers with the proposed framework.

B. SEQUENCE FLOW

Fig. 3 depicts the sequence flow of the proposed framework. The controller and application server are installed in the mobile core network. The application server provides the platform for installing sensing applications. The controller establishes control channels with the mobile edges linked with each network node. A network node was assumed to be a mobile base station (BS). If the centralized radio access network (C-RAN) architecture is employed, a network node is a remote radio head (RRH).

The sequence is performed as follows.

1) A sensing application which is installed in an application server issues a sensing task. The issued task was forwarded to the controller.
2) The controller distributes the received task to mobile edges based on the spatial distribution of the targets included in the task.
3) Each mobile edge assigns the received targets to the participants in the coverage area.
4) The participants collect data for the allocated targets and report the results to mobile edges.
5) The mobile edges process the received data including anonymization and statistical processing, and send the results to the controller.
6) The controller aggregates the received data and send the results to the application server.

The issued task is competed with the sequence above.

C. DATA MANAGEMENT

The data management in the proposed NeSTA framework is explained here with the detailed sequence shown in Fig. 4). Based on the received task, the controller distributes the task into a set of targets in each mobile cell. The controller stores the user database (DB), which records user information such as participant states and incentive settings. In other words, the registration data for each mobile user are stored in the user DB. The mobile users register or update their attributes in the user DB. The user attributes include participation states for each application, spatial and temporal availability, and smart device specifications.

When a mobile edge node receives a sensing task, it sends a user DB query to the controller with the list of user IDs in the cell. As a result, it receives a query result from the user DB that contains the list of mobile users who participate in the task. Based on the received participant list, the mobile edge allocates the sensing task to the participants using the proposed task allocation algorithm. The participants send the ACK to let the mobile edge know the acceptance of the

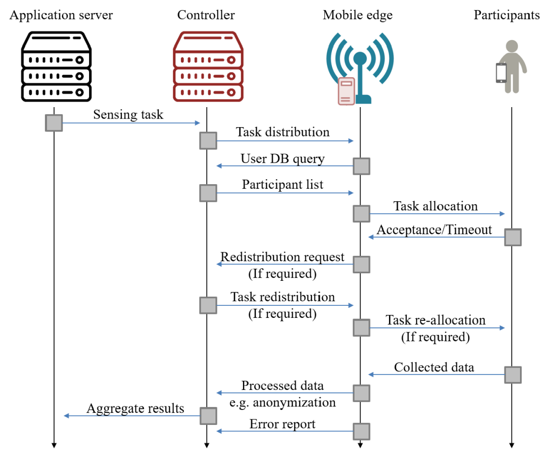


FIGURE 4. Data management in proposed sequence.

allocated tasks. Note that if a moving user is assigned a target that is not located in the direction of movement, he/she can simply decline the offer by sending NACK. If the mobile edge receives NACK, which indicates that the allocation was refused, or timeout occurs, that is, the mobile edge receives no ACK/NACK from a participant in a certain time, these tasks are re-allocated. Moreover, if there are not enough participants in the cell, the mobile edge requests a task redistribution to the controller. The participants then collect and report data in accordance with the result of allocation. The mobile edge processes the collected data, including anonymization, and sends the processed data to the controller. Finally, the application server receives the aggregated data from the controller. At the same time, the mobile edge reports a list of user IDs who send erroneous or unreliable data. With this process, the proposed scheme improves the confidence of the acquired data in sensing tasks by excluding unreliable participants such as malicious users and mobile users with broken sensors.

In the sequence above, the controller only receives the list of mobile users in each cell, which is included in the user DB query. The allocation results and collected data are only stored in the mobile edge nodes. Thus, although the controller has a user DB, it cannot link mobile users with the allocation results and collected data. In addition, the application server only receives aggregated results, where no private information of participants is included. Therefore, the proposed data management can achieve privacy protection of the participants.

IV. PROBLEM DEFINITION

A. VARIABLES

Table. 1 summarizes the variables used to explain the proposed framework. The details of each variable are introduced in the following sections.

B. SENSING TASK

A crowdsensing application issues a sensing task, which is denoted as T. Multiple sensing targets are included in a sensing task. It is necessary for participants to acquire data at all sensing targets using mobile devices to complete the task. Here, we define $\mathcal{S}_T$ as the set of sensing targets for the Tth task. Let $s \in \mathcal{S}_T$ denote the identifier for the targets. Let c_s denote the required coverage for the sth target, which represents the required number of allocated participants. This coverage requirement is defined to ensure redundancy in sensing to guarantee the quality of the acquired data by reducing the effect of measurement errors.

TABLE 1. Variables.

Variable	Definition
T	A sensing task
$\mathcal{S}_T$	Set of sensing targets for task T
s	Sensing target identifier, $s \in \mathcal{S}_T$
c_s	Required coverage for sth target
$\mathcal{J}$	Set of deployed mobile network nodes
j	Node identifier
$\mathcal{S}_T^j$	Set of sensing targets for task T in the jth coverage area
s^j	Sensing target identifier, $s^j \in \mathcal{S}_T^j$
$\mathcal{U}_j$	Mobile users in jth coverage area
$\mathcal{U}_T$	Participants of task T
$\mathcal{P}_T^j$	Participants of T in jth coverage area
p	Participant identifier, $p \in \mathcal{P}_T^j$
q_{sp}	Incentive for sth target reported by p
w_p	Weight for pth participant
$\mathcal{O}_T^j$	Overloaded targets in jth coverage area
o	Target identifier, $o \in \mathcal{O}_T^j$

C. MOBILE USERS

The relationship between mobile users and participants is shown in Fig. 5. Mobile network nodes are assumed to be widely deployed by mobile network operators to provide mobile connectivity to users. Let $\mathcal{J}$ denote the set of mobile network nodes, their coverage areas, and the corresponding mobile edges. They are identified with $j \in \mathcal{J}$. The mobile users are potential participants for deployed sensing applications. They can selectively join or leave each sensing task considering their purpose, incentive, burden, and so forth. Note that a mobile user can join different tasks at the same time. Let $\mathcal{U}_j$ denote the set of mobile users in jth coverage area. The set of mobile users who join Tth task is described as $\mathcal{U}_T$. The set of participants in the Tth task in the jth coverage area is defined as $\mathcal{P}_T^j := \mathcal{U}_T \cap \mathcal{U}_j$. They are identified with $p \in \mathcal{P}_T^j$. Unreliable participants can be excluded from $\mathcal{P}_T^j$ to improve data quality, as described in the following sections.

D. PROBLEM DEFINITION

The problem definition for task allocation in the proposed NeSTA is introduced here. The task allocation in the proposed framework consists of two steps, including Step 1) task distribution to the mobile edges by the controller, and Step 2) task allocation to participants in each mobile cell. That is, the original task allocation problem is divided into subproblems to be solved in each mobile cell. This procedure ensures the privacy of mobile users. Moreover,

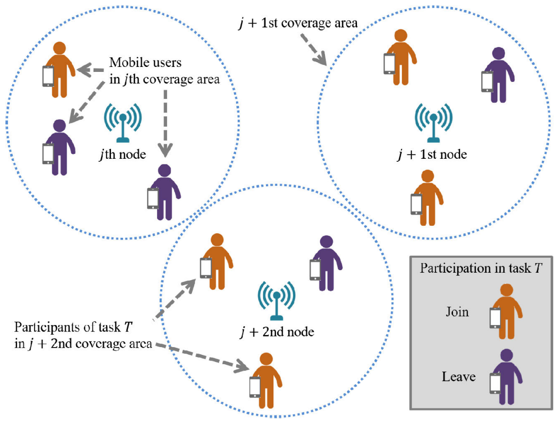


FIGURE 5. Mobile users and participants.

the computational efficiency and scalability of the allocation problem is improved.

1) TASK DISTRIBUTION

The controller distributes the targets of the Tth task to the mobile network edges based on their location. The set of sensing targets for the Tth task in the jth coverage is denoted as $\mathcal{S}_T^j$. Obviously, $\mathcal{S}_T^j$ is a subset of $\mathcal{S}_T$. The targets in $\mathcal{S}_T^j$ are identified with s^j. This task distribution process can automatically and easily be executed with inside/outside determination based on the coverage areas and coordinates of the targets.

2) TASK ALLOCATION

The sensing targets in mobile cell $j \in \mathcal{J}$, that is, $\mathcal{S}_T^j$, are allocated to the participants $\mathcal{P}_T^j$. Because the mobile cell size is spatially limited, targets are assigned to neighboring participants. That is, the original problem is divided into subproblems to be solved independently in each mobile cell. This problem-size reduction is a great advantage of the NeSTA. The travel cost of participants to assigned targets is negligible because of the limited cell size, which simplifies the allocation algorithm. We define q_{sp} as the incentive paid when the sth target is reported by the pth participant. The goal of the task allocation problem is to minimize the total incentive, which is equivalent to minimizing the cost of the organizers. The participants can define the acceptable range of incentive values based on the characteristics of sensing applications. The minimum acceptable value of the pth participant is denoted as $q_{p,Min}$, which is stored in the user DB and obtained by mobile edges using the user DB query. The required coverage c_s must be satisfied for all the targets. Let x_{sp} denote a binary variable that represents the allocation state. If the sth target is assigned to the pth participant $x_{sp} = 1$; and otherwise, $x_{sp} = 0$. Therefore, the objective function and the constraints are formulated as

$$\text{Min} \sum_{s \in \mathcal{S}_T^j} \sum_{p \in \mathcal{P}_T^j} q_{sp} x_{sp} \tag{1}$$

$$\text{s.t.} \sum_{p \in \mathcal{P}_T^j} x_{sp} \geq c_s \quad \forall s \in \mathcal{S}_T^j$$
$$x_{sp} \in \{0, 1\}. \tag{2}$$

V. NeSTA ALGORITHM

Based on the problem definition, this section introduces the task allocation algorithm in the proposed framework. Fig. 6 depicts the overall sequence of the proposed algorithm. When the controller distributes sensing targets to mobile edges, each mobile edge independently executes this sequence. The allocation problem solved by each edge is a subproblem of the entire problem, and thus, the computational complexity for each mobile edge is limited by the size of the coverage area. In addition, the private information of mobile users is hidden from organizers, as introduced in III-C.

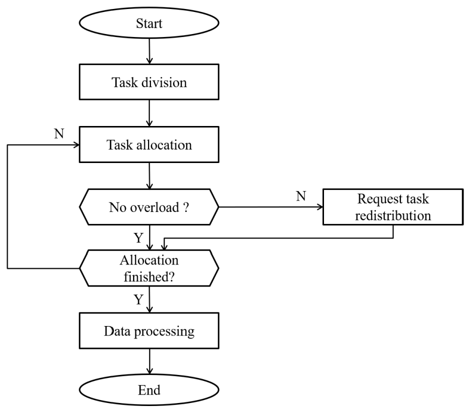


FIGURE 6. Sequence of NeSTA algorithm.

A. TASK DIVISION

The set of sensing targets of task T is defined as $\mathcal{S}_T$. A task division process is executed when the controller distributes the sensing targets $s \in \mathcal{S}_T$ to the network edge $j \in \mathcal{J}$. The purpose of the task division is to reduce the problem complexity while satisfying the coverage constraint formulated in (2). In this process, the sth target is further divided into c_s independent targets, all of which are associated with the same location in the same manner as in [11]. For example, if the required coverage of the sth target is $c_s = 3$, it is divided into three targets that are located at the same position. The new sensing targets generated from the sth target are denoted as $s_k (k = 1, 2, \ldots, c_s)$. For ensuring data quality, these new targets are assigned to different participants. Let y_{skp} denote a binary variable that represents the allocation state; if the s_kth target is assigned to the pth participant, $y_{skp} = 1$; otherwise, $y_{skp} = 0$.

B. TASK ALLOCATION

A mobile edge node starts the task allocation based on the received list of participants in the cell. The jth edge has $\mathcal{P}_T^j$, which is the participant list of T in the coverage area. First, the incentive q_{sp} is determined based on the base value b_T, which is determined by the organizer. If b_T is higher than other tasks, the task T is more attractive to the participants, and thus this task is likely to be completed quickly and smoothly. To improve the acceptance rate of the allocation, a target is allocated only if the offered incentive exceeds the minimum acceptable value, that is, $q_{sp} \geq q_{p,Min}$. With the base value b_T, the incentive can be determined using the existing mechanisms described in Section II.

Regarding the task allocation problem, the proposed NeSTA framework employs load balance as a novel concept in the field. The concept of load balance is introduced to fully utilize the horizontal integration of multiple sensing applications, which is enabled by the proposed framework. The load for each participant can be balanced by allocating additional tasks, considering the tasks currently allocated to each participant. A newly issued task is expected to be completed smoothly and quickly by considering the load balance. Let w_p denote the weight for the pth participant, which is determined by the allocation status managed by the mobile edge. A simple example of the weight determination process is that w_p is formulated as

$$w_p = \alpha n_p, \tag{3}$$

where n_p is the number of allocated tasks, and α is a parameter. n_p is stored and updated at each mobile edge. Equation (3) represents that

the weight is incremented when a new task is allocated and decremented when an allocated task is finished. The load-balancing effect is intensified with larger α.

With divided tasks and redefined variables, the task allocation problem is reformulated as.

$$\text{Min} \sum_{s \in \mathcal{S}_T^j} \sum_{k=1}^{c_s} \sum_{p \in \mathcal{P}_T^j} q_{sp} w_p y_{skp} \tag{4}$$

$$\text{s.t.} \sum_{p \in \mathcal{P}_T^j} y_{skp} = 1 \quad \forall s \in \mathcal{S}_T^j,\ 1 \leq k \leq c_s \tag{5}$$

$$\sum_{k=1}^{c_s} y_{skp} \leq 1 \quad \forall s \in \mathcal{S}_T^j,\ \forall p \in \mathcal{P}_T^j \tag{6}$$

$$\begin{aligned} &q_{sp} y_{skp} \geq q_{p,Min} y_{skp} \quad \forall s \in \mathcal{S}_T^j,\ \forall p \in \mathcal{P}_T^j \\ &y_{skp} \in \{0, 1\}. \end{aligned} \tag{7}$$

The task allocation problem defined above is a 0-1 integer programming problem (ILP), which is well-known as being NP-complete [36]. There have been significant research efforts on this problem, such as heuristics, and high-performance solvers are available [37]. Note that the problem size is significantly reduced from its original size owing to the task distribution. Thus, the solution for (4) – (7) can be obtained in a short time using an available solver.

C. TASK REDISTRIBUTION

If an overload of sensing targets occurs in the jth cell, the jth edge requests the redistribution of targets to the controller. The controller redistributes the overloaded targets to neighboring mobile nodes to address overload. Let $\mathcal{O}_T^j$ denote the set of overloaded targets in jth mobile coverage. The overload problem occurs in two conditions: a) high target density and b) high decline/timeout rate. The redistribution request for each condition is explained in the following.

1) HIGH TARGET DENSITY

This condition occurs if there are too many targets in the cell compared to the number of participants. To satisfy the constraint formulated in (6), $|\mathcal{P}_T^j|$ must satisfy

$$|\mathcal{P}_T^j| \geq c_s \quad \forall s \in \mathcal{S}_T^j. \tag{8}$$

If (8) is not satisfied, $\mathcal{O}_T^j$ is generated by extracting targets from $\mathcal{S}_T^j$ to satisfy (8). Subsequently, the allocation problem is solved using $\mathcal{S'}_T^j = \mathcal{S}_T^j - \mathcal{O}_T^j$.

2) HIGH DECLINE/TIMEOUT RATE

A participant to whom a sensing target is allocated may decline the offer by sending NACK to the edge. Alternatively, timeout occurs if the mobile edge does not receive any ACK/NACK from a participant in a certain time period. The edge considers these participants are currently unavailable for some reasons. Let $\mathcal{P}_{unavailable}^j$ denote the set of unavailable participants. The set of participants is updated as $\mathcal{P'}_T^j = \mathcal{P}_T^j - \mathcal{P}_{unavailable}^j$. The allocation state y_{skp} is also updated as

$$y_{skp} = 0, \quad p \in \mathcal{P}_{unavailable}^j. \tag{9}$$

In addition, the set of remaining targets $\mathcal{S'}_T^j$ is generated as the set of s_k that satisfies $\sum_p y_{skp} = 0$, that is, the targets that have been allocated to the unavailable participants. Based on the updated $\mathcal{P'}_T^j$ and $\mathcal{S'}_T^j$, reallocation is executed, as depicted in Fig. 6. If (8) is not satisfied in the reallocation process, $\mathcal{O}_T^j$ is generated in the same manner as in V-C1 to request redistribution.

Algorithm 1 shows the task redistribution algorithm executed in the controller.

Algorithm 1 Task Redistribution Algorithm

```
begin
    while O_T^j ≠ ∅ do
        g = GetNeighbourMobileEdge (j)
        o = GetTargetFrom (O_T^j)
        if |P_T^g| ≥ c_o then
            O_T^j = O_T^j − o
            S_T^g = S_T^g + o
        end if
    end while
end
```

The overloaded targets are redistributed to other mobile edges until there is no overloaded target. It selects a mobile edge geographically adjacent to jth edge. The selected edge is denoted as g. A candidate target o is selected from $\mathcal{O}_T^j$. If (8) is satisfied in the gth cell, o is extracted from $\mathcal{O}_T^j$ and assigned to the gth edge.

D. DATA PROCESSING

When mobile edge nodes receive the collected data reported from the participants, they process the data, including anonymization. After that, mobile edges report the processed data to the controller. The controller integrates the received data and reports aggregated data to the application server. In this sequence, the allocation results and collected data are stored only in the mobile edge nodes. The controller cannot link mobile users with the collected data. In addition, the application server receives aggregated results in which no private information of the participants is stored. Therefore, organizers cannot access the private information of participants.

VI. CONFIDENCE MECHANISM

This section describes the details of the confidence mechanism in the proposed NeSTA and the analytical results.

A. MECHANISM

The controller stores an unreliability flag for each participant in the user DB, which is updated with the error report from the mobile edge nodes at the end of the proposed allocation sequence. The unreliability flag represents whether the participant is legitimate or not. If a participant is determined to be unreliable, he/she is excluded from subsequent sensing tasks. The goal of this procedure is to improve confidence by excluding unreliable participants, such as malicious users and mobile users with broken sensors. In the following, the analytical model and numerical results for the proposed confidence mechanism are introduced.

B. ANALYTICAL MODEL

The detection accuracy of unreliable participants is theoretically analyzed in the following manner. For simplicity, it is assumed that one sensing application is deployed in the proposed framework, and all users participate in the application. Here, the sensing tasks issued by this application are identified with $T = 1, 2, \ldots$. $c_s = 1$ is assumed for all $s \in \mathcal{S}_T \forall T$. The expected number of targets in a task is defined as $E[S]$. The study area consists of multiple mobile cells that are identified with $j = 1, 2, \ldots$. Let us define $N_T := \sum_j |\mathcal{P}_T^j|$ for simplicity, which represents the total number of participants in the study area. It is assumed that the number of participants in the study area is stable, and mobile users can move in the area without going in or out. Let U_T and D_T denote the expected number of undetected and detected unreliable participants at the Tth allocation, respectively. From the definition,

$$N_{T+1} = N_T - D_T, \tag{10}$$

which represents that detected unreliable participants are excluded in the subsequent task allocation.

When the tth task is issued, $E[S]$ targets are allocated to N_T participants. With the proposed mechanism, an unreliable participant is identified if a sensing target is allocated to the participant, and the reported value is detected as erroneous. Assuming that the targets and participants are uniformly distributed, the expected number of detected unreliable participants is:

$$D_T = \theta E[S] \frac{U_T}{N_T}, \tag{11}$$

where θ denotes the probability that the reported value is successfully detected as erroneous. The relationship between U_T and D_T is

$$U_{T+1} = U_T - D_T. \tag{12}$$

Note that $U_0 = \rho N_0$, where ρ denotes the ratio of unreliable participants to all participants.

Let $E[x]_T^{cnv}$ denote the expected number of erroneous data in the Tth task without the proposed scheme, and it is formulated as

$$E[x]_T^{cnv} = E[S]\rho. \tag{13}$$

With the proposed scheme, it is improved as

$$E[x]_T^{prp} = E[S] \frac{U_T}{N_T}. \tag{14}$$

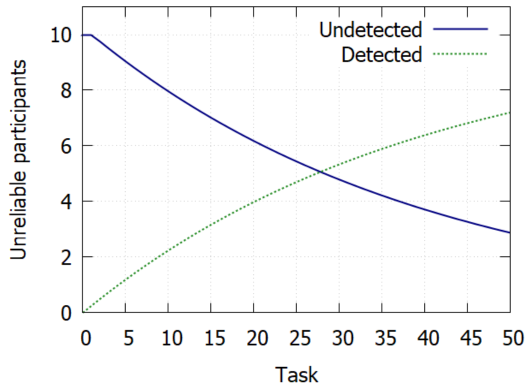


FIGURE 7. Detection of unreliable participants.

C. NUMERICAL RESULTS

The numerical results for the proposed confidence mechanism is introduced in the following. Here, we set $N_0 = 1000$, $E[S] = 100$, $\rho = 0.01$, and $\theta = 0.25$. First, the numbers of detected and undetected unreliable participants are calculated using (10), (11), and (12), as shown in Fig. 7. The unreliable participants are successfully detected with the proposed mechanism. In addition, the expected numbers of erroneous data with and without the proposed scheme are computed using (13) and (14), as shown in Fig. 8. Erroneous data can be reduced as task allocation proceeds with the proposed approach, whereas the expected value is stable with the conventional approach.

VII. NUMERICAL RESULTS

This section introduces the simulation results for the proposed approach.

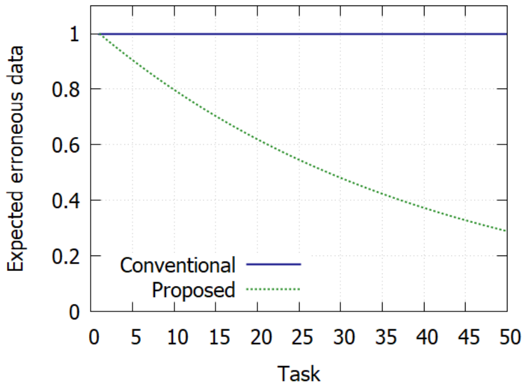


FIGURE 8. Expected number of erroneous data.

A. SIMULATION CONDITION

1) DATASET

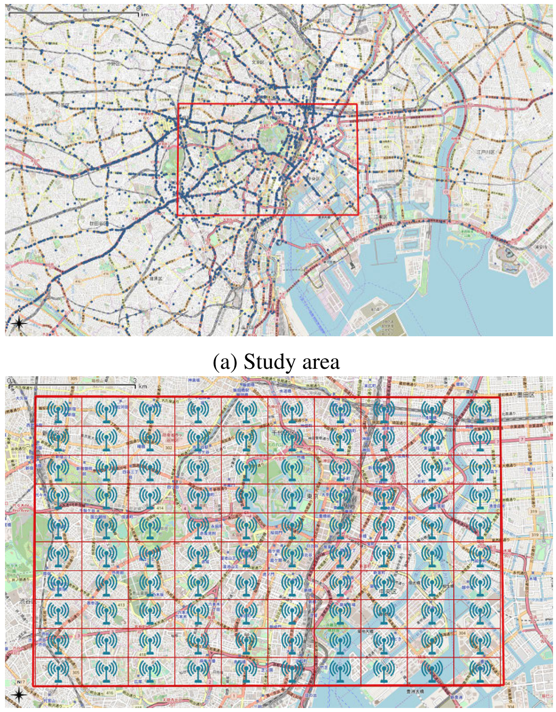
Open data on human mobility in Tokyo [38] were used in the simulations as the distribution of participants. This dataset includes the location and timestamp of mobile users' SNS posts in the Tokyo Metropolitan Area, Japan. Approximately 70000 records are included in the dataset for each day. It is assumed that each mobile user is a participant for sensing applications. Each participant's movement course can be traced from the records using user ID. The dates for simulation were selected as July 1, July 7, October 7, October 13, December 16, and December 22, 2013. The distributions of participants at certain times were generated with user ID.

2) STUDY AREA

The study area for the simulations was set as the red box depicted in Fig. 9a). The study area was approximately 6 km × 9 km, and it was located around the city center of Tokyo. In Fig. 9a, the blue points represent the locations of the participants that were plotted with the dataset on July 1, 12:00. The coverage of mobile network nodes was assumed, as depicted in Fig. 9b). The study area was divided into a 10 × 10 grid, assuming that 100 mobile BSs were deployed at regular intervals. Under these conditions, each mobile BS provides a roughly 1 km-wide cell, which is a general cell size in macro or micro-cellular networks in cellular systems such as LTE and LTE-Advanced.

3) APPLICATIONS

It was assumed that three sensing applications (App.1, App.2, and App.3) were registered in the controller. To clarify that the proposed framework can be employed for various applications as a multi-objective horizontal integrated framework, different time and spatial distributions required by different organizers were set for each sensing application. Table. 2 summarizes the specifications of simulated tasks. Each application independently issues a sensing task in a certain time interval between 6:00 and 21:00 each day. The average number of targets and required coverage (c_s) were different among the applications. The coordinates of the



(a) Study area

(b) Mobile coverage

FIGURE 9. Simulation condition.

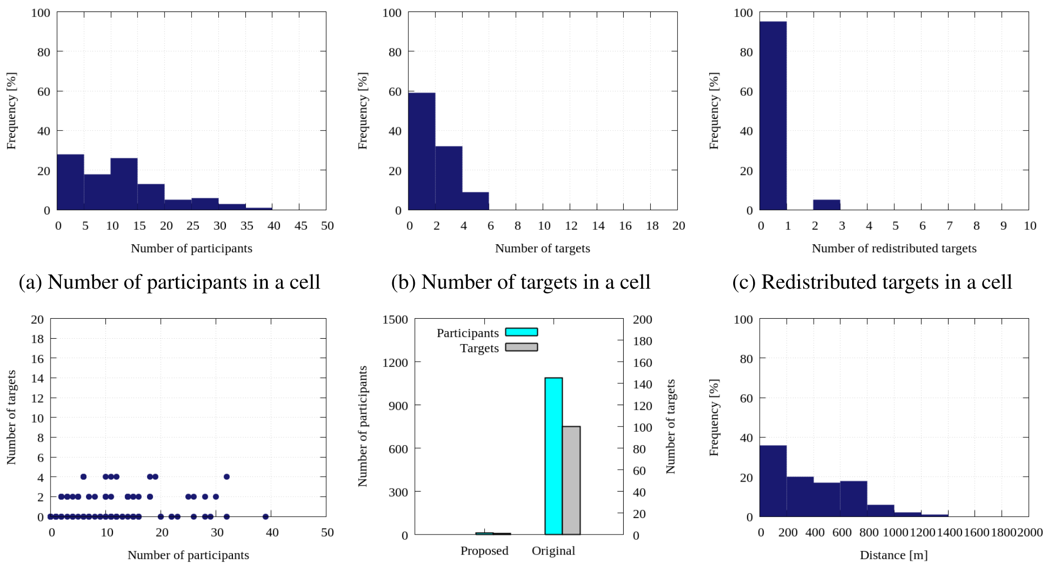
TABLE 2. Simulated tasks.

Application	Time interval	Avg. targets	Coverage
App.1	2 hour	50	2
App.2	3 hour	150	1
App.3	6 hour	40	3

generated sensing targets were randomly determined with a uniform distribution in the study area. For simplicity, the minimum acceptable values and the offered incentive values were also randomly determined. The initial value for the allocation weight was set to $w_p = 1$ for all participants. The weight is incremented when a new task is allocated and decremented when a task is completed.

4) EVALUATION METHOD

The contribution of this study lies in the proposed system model and the data management mechanism. Correspondingly, the major advantages of the proposed framework include privacy, confidence, and cost, which originate from the system design. Thus, it was very difficult to directly compare the performance with existing schemes in the simulation. The main purpose of the simulation was to confirm the feasibility of the proposed approach. To this end, it was confirmed in the simulation that the task allocation process could be properly executed with the proposed algorithm. tasks issued by each sensing application are adequately distributed to each mobile edge, and in each coverage area, the distributed targets are efficiently allocated to the participants. To confirm the efficiency of the proposed algorithm, the size of the allocation problems and the distance



(a) Number of participants in a cell (b) Number of targets in a cell (c) Redistributed targets in a cell

(d) Participants vs targets in a cell (e) Problem size (f) Travel distance of a participant

FIGURE 10. Simulation results (App.1).

between the sensing targets and assigned participants were evaluated. Because scalability is one of the major advantages of the proposed allocation algorithm, it is reasonable to confirm the effect of problem size reduction.

The evaluation criteria were as follows. 1) Verify platforming different applications, and 2) reduce the problem size. The discussion on privacy preservation and cost reduction of the proposed NeSTA is also provided in Section VII-C.

B. SIMULATION RESULTS

First, the performance of the proposed algorithm was confirmed using the allocation results for each application at certain time periods. Figs. 10 – 12 shows the results for App.1, App.2, and App.3, respectively.

The result for App.1 at 12:00 on July 1 is summarized in Fig. 10). Figs. 10a and 10b show the distribution of participants and targets in each mobile cell, respectively. In this condition, there were several tens of participants and several sensing targets in each mobile coverage area. Fig. 10c shows the histogram of the number of redistributed targets in each cell. Fig. 10d shows the relationship between the number of sensing targets and participants after the redistribution process. It was confirmed from these results that the task-redistribution was correctly executed; the overloaded targets were redistributed to neighboring cells if there were insufficient participants. Fig. 10e shows the size of task allocation problem. The original task allocation problem in the study area included more than 1000 participants and 100 targets. The proposed task distribution process reduced the problem size by 99% by dividing the original problem into subproblems. Finally, the travel distance of participants is summarized in Fig. 10f. The distance from the starting point to the allocated sensing targets was successfully limited to approximately 1 km. This is because the allocation process is basically executed in a mobile cell.

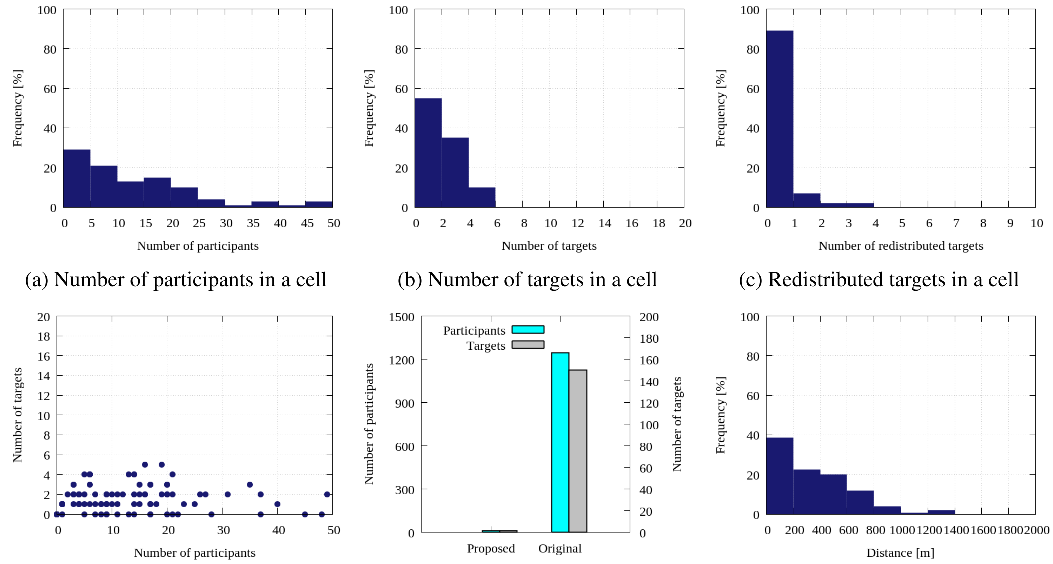
The results for App.2 at 15:00 on July 1 and App.3 at 18:00 on July 7 are summarized in Figs. 11 and 12, respectively. These results imply that the proposed algorithm can efficiently solve the task-allocation problems in these conditions in the same way as the result for App.1. The reduction in the problem size increased in accordance with the increase in the number of participants. The original problems can be appropriately divided into subproblems, irrespective of the changes in the distributions of the sensing targets and participants. Thus, it was confirmed that the proposed framework provides an efficient platform for various sensing applications.

The relationship between the mobile cell size and the problem size in this case of App.3 at 18:00 on July 7 is shown in Fig. 13). The problem size drastically decreases with the reduction in the mobile cell size. Although the actual values depend on the situation in the target area, the effect of the proposed approach does not depend on it. Considering that the mobile cell size has been reduced by network operators to increase the mobile data rate and the future increase in the number of participants and sensing applications, the benefit from the scalability improvement of the proposed scheme will increase.

C. DISCUSSION

1) PRIVACY

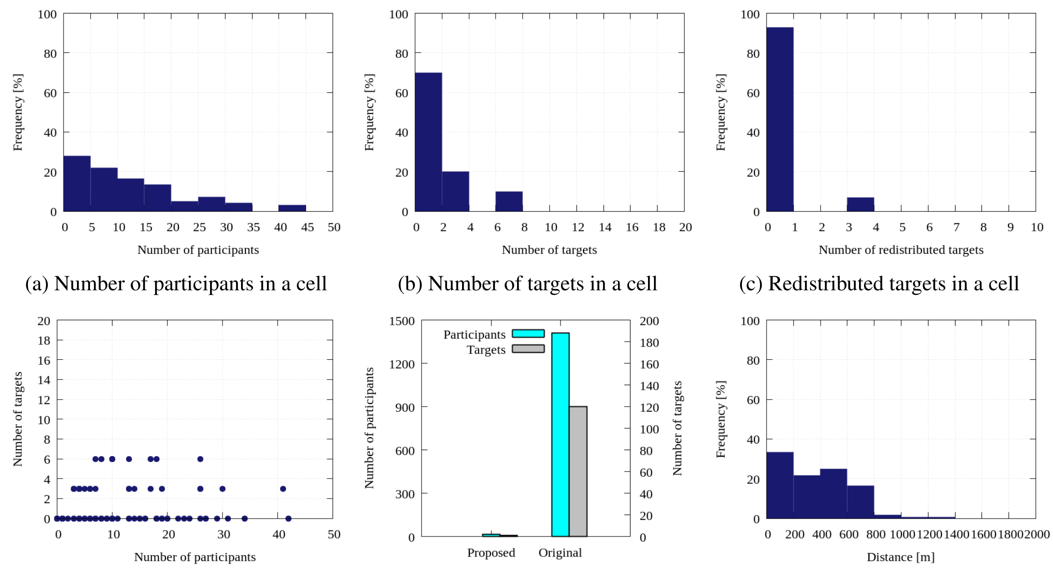
The basic assumption of the present work is that the mobile network can be trusted. This assumption is reasonable because mobile networks, which are fully managed by a single operator, are expected to be secure compared with general networks managed by various operators that are used by existing frameworks. In addition, it is easy to judge the trustworthiness of the mobile network, while a participant must judge whether an organizer is trustworthy or



(a) Number of participants in a cell (b) Number of targets in a cell (c) Redistributed targets in a cell

(d) Participants vs targets in a cell (e) Problem size (f) Travel distance of a participant

FIGURE 11. **Simulation results (App.2).**



(a) Number of participants in a cell (b) Number of targets in a cell (c) Redistributed targets in a cell

(d) Participants vs targets in a cell (e) Problem size (f) Travel distance of a participant

FIGURE 12. **Simulation results (App.3).**

not for each application when conventional frameworks are employed. Moreover, existing privacy preservation schemes, such as spatial cloaking, can be employed in the proposed framework.

Based on the above assumption, privacy preservation in the proposed framework is explained here. As illustrated in the simulation, there was no direct communication between the organizers and participants. Thus, when the mobile network is trusted, which is the basic assumption stated above, user privacy is ensured as long as the user information is not included in the data reported to the organizers. In the proposed scheme, the mobile edge anonymizes the collected data using existing data anonymization methods to store them without any information about the participants. Subsequently, the collected data are integrated to be reported to the organizers. Therefore, privacy is preserved in principle with the proposed framework based on the basic assumption of trustworthiness.

The discussion above assumed that mobile edge nodes can be trusted. When we assume the existence of malicious edge nodes, we can ensure further security by employing secure computation, such as secure multi-party computation (MPC) [39]. MPC enables a set of parties to compute the joint function of their private inputs using encrypted data. With this type of technology, mobile users can upload encrypted data for further processing.

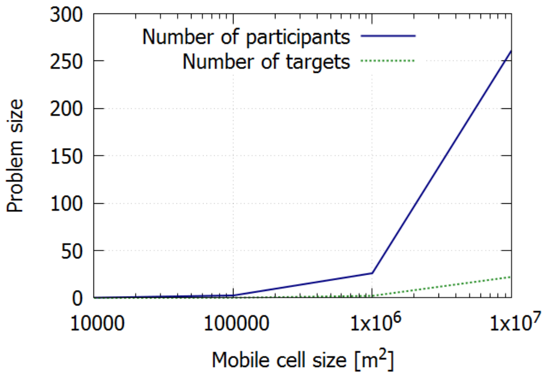


FIGURE 13. **Mobile cell size vs problem size.**

Note that the simplicity of the allocation problem is an advantage of the proposed framework. This is because the novelty and contribution of this work lie in horizontal integration with the minimum inclusion of a third party, as explained above. The security and privacy of participants are ensured by the system architecture; thus, it is not necessary to consider them in the task allocation problem. The reliability of the participants was considered in task allocation in the proposed task allocation algorithm using the confidence mechanism.

2) COST

The cost issue is discussed here. The cost to consider should include not only the system installation cost, but also running costs such as labor costs and advertising costs for recruiting participants. This is because it is essential and costly for mobile crowdsensing to ensure a sufficiently large number of participants who are willing to collect and report data. Because the proposed approach is a horizontal integrated platform, a new sensing application can be easily and inexpensively deployed on the basis of the users already registered for the platform. Thus, the proposed scheme is expected to reduce the total cost owing to this feature compared with existing vertically integrated systems. However, a cost evaluation with regard to advertising cost is very difficult and almost unfeasible because such data are unavailable. Therefore, we avoid numerical cost evaluation in this paper. Instead, we provide some discussion on cost below.

Because the proposed framework achieves horizontal integration of various crowdsensing applications, different organizers can share the same system installed by a mobile network operator. The mobile network operator manages all the information for mobile users, such as the registration and participation states. This feature is enabled by introducing an authorized party into the sensing platform. With this model, the deployment cost of each sensing application is significantly reduced from existing vertically integrated crowdsensing models. The organizers can also reduce operating costs because of easy operation, which is enabled by outsourcing user management processes to the mobile network operator. In the simulation scenario, the three organizers share the sensing system installed and managed by the mobile network operator. Thus, compared with conventional frameworks where each sensing application is individually installed and managed by each organizer, the total system installation cost is reduced by two-thirds. The running cost required for managing the installed system was also reduced in the same manner. Note that with the proposed NeSTA, edge servers must provide computation resources that are sufficient for allocating multiple tasks in parallel. From this perspective, the required computing resources are rather small because the problem size is reduced by the task division process, as shown in the simulation results. Therefore, it is implied that the organizers can expect a sufficient cost reduction effect from the proposed NeSTA framework.

3) MOBILE USERS

The proposed NeSTA also contributes for managing participants. The trust issues and mobility of mobile users are discussed in the following. The proposed task allocation can consider the trustworthiness of mobile users by setting the weight to a large value. For example, it can avoid allocating a task to unreliable participants such as malicious users and users with inoperable sensors. If a participant reports unreliable data for a sensing application, this result can be considered in a task allocation process for another application. This trust management is easily executed with the proposed framework. With regard to mobility, the travel cost of mobile users is limited by the task allocation process, which is executed in each mobile cell, as shown in the simulation results. The reduction in the travel distance can also contribute to reduce energy consumption. This distance limitation is an advantage of the proposed framework.

VIII. CONCLUSION

Mobile crowdsensing has been intensely studied to provide an efficient scheme for large-scale data collection. This concept can leverage the power of mobile users to rapidly collect a large amount of data. In particular, the development of unified platforms for various types of sensing platforms is a popular approach for enabling the efficient deployment of sensing applications. However, existing vertically integrated frameworks have not been optimized for shared use among multiple organizers. The privacy and confidence are also significant challenges for crowdsensing frameworks. To address these problems, we have proposed the NeSTA framework for crowdsensing in this work. The proposed approach enables the horizontal integration of sensing applications. The organizers and participants were mediated by mobile networks to obscure participants from the organizers. The cost of installing and running individual applications is significantly reduced. The proposed confidence mechanism reduces erroneous data by excluding unreliable participants in subsequent sensing tasks, which was confirmed by the analytical results. The validity of the proposed framework was also confirmed by the results of computer simulations using an open dataset. The reduction of problem size by dividing the original problem into subproblems contributes to improving the computational efficiency of task allocation problems. The benefit from the scalability improvement will increase in accordance with an increase in the number of sensing applications and participants. The proposed framework is expected to contribute to various industry sectors, including beyond 5G mobile and social/environmental monitoring services.

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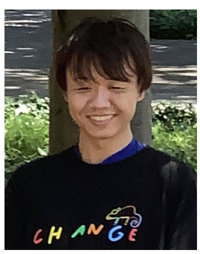

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