

Received January 23, 2020, accepted February 8, 2020, date of publication February 18, 2020, date of current version March 20, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2974909

Privacy-Aware Sensing-Quality-Based Budget Feasible Incentive Mechanism for Crowdsourcing Fingerprint Collection

WEI LI¹, CHENG ZHANG¹, (Member, IEEE), AND
YOSHIKI TANAKA^{2,3}, (Life Senior Member, IEEE)

¹Department of Computer Science and Communications Engineering, Waseda University, Tokyo 169-8555, Japan

²Department of Communications and Computer Engineering, Waseda University, Tokyo 169-8555, Japan

³Global Information and Telecommunication Institute, Waseda University, Tokyo 169-8555, Japan

Corresponding author: Wei Li (liwei@akane.waseda.jp)

The work of Wei Li was supported by the China Scholarship Council (CSC) under Grant 201706690030.

ABSTRACT Mobile crowdsourcing (MCS) has shown great potential in received signal strength (RSS) fingerprint collection, in which an incentive mechanism plays a critical role to motivate users' participation. However, how to quantify the quality of the gathered fingerprint data is still not addressed well in the design of incentive mechanism for MCS-based fingerprint collection. In this paper, a sensing quality metric is proposed to characterize the joint impact of users' privacy protection and the spatial coverage of the submitted data. Given a limited budget, a basic incentive mechanism is devised to recruit appropriate users to maximize sensing quality. Considering that the cost of each user is regarded as private information and users may be attempted to misreport their costs to increase the revenue. Hence, an auction-based incentive mechanism is proposed to achieve the truthfulness of users' costs, which is truthful, individually rational, computationally efficient and budget feasible. Simulation results show that our proposed schemes outperform the baseline schemes and the experiment with real-world data is carried out to evaluate the performance of our proposed basic incentive mechanism.

INDEX TERMS Local differential privacy, incentive mechanism, auction theory, crowdsourced fingerprint collection.

I. INTRODUCTION

Mobile crowdsourcing (MCS) has emerged as a promising solution to leverage the power of mobile users (MUs) for massive data collection and processing [1]. A typical MCS-based system is mainly comprised of a platform residing in the cloud and a crowd of MUs, where MUs are recruited to participate in the required task and upload the sensing data back to the platform via the existing wireless network. Generally, it requires MUs' efforts and consumes diverse resources (e.g., data usage, time, battery) to participate in MCS activities. To incentivize MUs' participation, many incentive mechanisms have been developed with diverse optimization goals, e.g., reducing the platform's cost, maximizing social welfare [2].

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

Over the past decade, many research efforts have been dedicated to tailoring MCS to acquire received signal strength (RSS) fingerprint data from the inertial sensors of users' smartphones with the aim to relieve the burden of RSS fingerprint collection [3], [4]. However, the fingerprint data gathered through MCS lacks quality guarantee, which, in turn, has a significant effect on users recruitment [5]. This necessitates the need for measuring the quality of sensing data (namely "sensing quality") and designing a quality-based incentive mechanism for crowdsourced fingerprint collection. While the state-of-the-art studies [6], [7] have been conducted to characterize the quality of fingerprint data gathered in the MCS manner, they are not fully suitable in practical scenarios. The success of the work [6] strongly depends on experiments of users' sensed locations, which may lead to unpredictable factors. The work in [7] is under the assumption that the prior knowledge of the indoor space is perfectly known, including the indoor map and the physical locations

of reference points. Therefore, due to the lack of a perfect benchmark, it is quite challenging to evaluate sensing quality for MCS-based RSS fingerprint collection. Moreover, it is worth noting that none of the works mentioned above considers users' privacy protection and deals with the impact of the privacy issue on sensing quality measurement.

Nowadays, users' privacy issue has been one of the key concerns for MCS-based systems [8], since individuals' sensitive information can be inferred from sensing data [9]. Hence, users will suffer privacy breach when such sensitive data is disclosed to the unauthorized third party. Given this challenge, a great number of techniques from different aspects of privacy have been developed to protect users' privacy [10] that can be broadly categorized into four types: encryption [11], anonymity [12], differential privacy [13] and game theory [14]. Among those, local differential privacy (LDP) has been widely adopted by many technology companies such as Microsoft, Google, Apple, where users are permitted to perturb personal data by adding random noise to achieve privacy protection [15]. However, there is a conflict between the incentives of privacy preservation by users and data aggregation accuracy maximization by the platform [16], which increases the difficulty in the sensing quality evaluation for crowdsourced fingerprint collection.

It is still an open research topic to quantify sensing quality for MCS-based fingerprint collection without the prior knowledge of ground truth and users' historical data. Moreover, the consideration of privacy issue increases the difficulty for the quality measurement and the design of a quality-based incentive mechanism. In this study, a sensing quality metric is first proposed to capture the joint impact of privacy protection and the spatial coverage of users' submitted data. Subsequently, the proposed sensing quality metric is incorporated into the design of incentive mechanism for users selection under a budget constraint. The key contributions of this paper are summarized as follows:

- A sensing quality metric is proposed to characterize the joint impact of the privacy protection for users' sensory data and spatial coverage of the area covered by the submitted sensing data.
- The basic incentive mechanism is proposed to recruit users with an assumption that individual user truthfully reports its cost. To maximize sensing quality, a greedy algorithm is proposed for users selection constrained within a budget limit.
- An auction-based incentive mechanism is proposed to address the scenario where users misreport their costs, and theoretically analyzed to prove its truthfulness, individual rationality, computational efficiency, and budget feasibility.

The reminder of this article is organized as follows. Section II analyses the related works and Section III introduces the system model. The sensing quality maximization problem is described in Section IV and the basic mechanism is presented in Section V. Section VI presents the auction-based mechanism with theoretical analysis. Section VII and

Section VIII present the performance evaluation results. Section IX makes a conclusion of this paper.

II. RELATED WORK

In recent years, many incentive mechanisms have been developed for mobile crowdsourcing (MCS) to attract enough number of users to participate in sensing tasks.

Game-theoretic incentive mechanisms have received increasing popularity, since they are capable to deal with users' strategic behaviors [17]–[19]. Yang *et al.* [17] proposed a platform-centric model to encourage users' participation within which the relationship between the platform and users is modeled as Stackelberg game. Pang *et al.* [18] proposed a Bayesian game based incentive mechanism for spatial crowdsourcing. Nie *et al.* [19] proposed a Bayesian game-theoretic incentive mechanism for social crowdsensing service, where the information of social network effects is incomplete.

Considering that selfish individual users seek to maximize their own gain by misreporting their truthful costs. To tackle this issue, auction theory has been an invaluable tool for MCS-based systems to discover users' truthful costs and effectively control the payment for the selected users. In the literature, many researchers have studied the auction-based incentive mechanisms for MCS-based applications [20]–[24]. For example, Zhao *et al.* [20] investigated an online auction-based incentive mechanism for mobile crowdsourced sensing and Ji and Wang [21] proposed an auction-based incentive mechanism to study the correlated tasks allocation problem. The authors in [22] and [23] considered the user-centric model where each mobile user could ask for the reserve price, and further proposed a revenue maximizing reverse auction mechanism. In [24], authors proposed an incentive mechanism to maximize the social welfare including the worker-centric task selection phase and the platform-centric worker selection phase. However, none of these studies considers the issue of estimating users' data quality.

In this study, we first propose a metric of sensing quality to characterize the joint impact of users' privacy protection and spatial coverage. Then, we incorporate this metric into the design of the basic incentive mechanism to maximize sensing quality, and the auction-based incentive mechanism to achieve the truthfulness of users' costs, respectively.

III. SYSTEM OVERVIEW

The system model considered in our work is described in more detail in this section. For convenience, Table 1 lists the frequently used notations.

A. SYSTEM MODEL

This system consists of a mobile crowdsourcing platform (MCP) and a crowd of MUs $\Omega = \{u_1, u_2, \dots, u_m\}$.¹ Given a limited budget, MCP aims to recruit a sufficient

¹In the next of this paper, we refer to the terms "mobile user", "user" and "participant" interchangeably.

TABLE 1. Notations.

Symbol	Description
$\Omega = \{u_1, u_2, \dots, u_m\}$	MU set
$L = \{l_1, l_2, \dots, l_n\}$	PoI set
$W = \{\omega_1, \omega_2, \dots, \omega_n\}$	PoIs' weight set
c^s	Individual MU's unit sensing cost
c^p	Cost for unit privacy leakage
ϵ	Privacy budget
d	Trajectory distance
$\mathcal{X} = \{\mathcal{X}_{u_1}, \mathcal{X}_{u_2}, \dots, \mathcal{X}_{u_m}\}$	PoI cover set for each MU
B	The limited budget

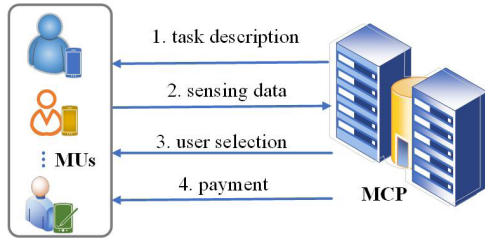


FIGURE 1. Interactions between MUs and MCP.

number of MUs to contribute to sensing data for RSS fingerprint collection.² The system architecture is depicted in Fig. 1, where the interactions between MUs and MCP are as follows:

- **Step 1:** The MCP announces the task to MUs and similar to [25], the upper bound of ϵ is also broadcasted.
- **Step 2:** The interested MUs perform the task and send the data perturbed by adding random noise with the claimed cost (sensing cost, privacy cost) to MCP.
- **Step 3 & 4:** The MCP selects a subset S of MUs (*winners*) to maximize the sensing quality and determines the payment for winners to compensate their costs, while the total cost does not exceed the budget B .

B. USER COST

In this paper, the cost of each user comes from two aspects:

(1) Sensing Cost: When participating in a MCS activity, it incurs nontrivial sensing cost to a user in terms of the effort to collect data, the charge to transmit data, the computing power of devices to process data, etc. Referring to [26], sensing cost for individual MU is modeled as a function of its trajectory distance d . Based on [27], a linear function $c^s d$ is adopted to formulate sensing cost, in which c^s scales the value of unit movement cost for each MU.

(2) Privacy Cost: Individuals' sensitive information can be derived from MUs' sensed data, which leads to users' privacy loss (also termed as "privacy cost") if such data is leaked. To quantify MUs' privacy, the celebrated notion of local differential privacy [13] is adopted.

Definition 1 (Local Differential Privacy): An algorithm F is ϵ -local differentially private (ϵ -LDP), if and only if for any

²In this context, individual MU's indoor trajectory is regarded as sensing data, which includes walking steps, barometer readings, RSS value, time slots.

input κ and κ' , the following inequation can hold:

$$Pr[F(\kappa) = \mathcal{K}] \leq e^\epsilon Pr[F(\kappa') = \mathcal{K}] \tag{1}$$

where $\mathcal{K} \in Range(F)$ and $Range(F)$ is the set of all possible outputs of the algorithm F . Pr is the probability that F maps the input κ or κ' to \mathcal{K} . $\epsilon \in (0, 1)$ denotes the privacy protection level (or privacy budget) achieved by \mathcal{F} , where data is strongly protected when ϵ approaches to 0.

According to [25], for any user, its privacy cost is positively correlated with ϵ . Assuming that there is a positive relation between privacy cost and d , since more sensitive information is provided as d increases. In this paper, a linear model $c^p \epsilon d$ is adopted to quantify privacy cost, where c^p reflects how much a MU cares about its privacy.

In summary, MU i 's cost is denoted as follows³:

$$c_i = (c_i^s + c_i^p \epsilon_i) d_i \tag{2}$$

IV. PROBLEM FORMULATION

This section defines a sensing quality metric, and presents the budget-constrained sensing quality maximization problem.

A. SENSING QUALITY FORMULATION

This subsection studies the joint impact of privacy protection and spatial coverage of the target area to characterize sensing quality for crowdsourced RSS fingerprint collection.

(i) The Impact of Privacy Protection: Basically, MUs' raw sensory data is perturbed with random noise to achieve ϵ -LDP. However, this perturbation influences MCP's data aggregation accuracy. To quantify the accuracy of the aggregated result, the notation (α, β) -accuracy is introduced.

Definition 2 (α, β)-Accuracy: An algorithm \mathcal{R} with a perturbation mechanism F is (α, β) -accurate where $\alpha, \beta \in (0, 1)$, if the following inequality can be held:

$$Pr\{|\mathcal{R}(D) - \mathcal{R}(F(D))| \geq \alpha\} < \beta \tag{3}$$

where \mathcal{R} is adopted by the platform to aggregate the uploaded data and the algorithm \mathcal{F} is adopted to achieve ϵ -LDP. D is the corresponding dataset and β is a predetermined constant selected by the platform. α denotes the difference between the aggregation result before and after perturbation.

Finally, by combining Definition 1 and 2, we can obtain the relationship between ϵ and α : as ϵ is small, large noise is locally added to MUs' raw data, which causes larger α and furthermore reduces the aggregation accuracy. Based on [28], the function⁴ $q(\alpha)$ is exploited to characterize the impact of privacy protection on sensing quality, which decreases in α .

(ii) The Impact of Spatial Coverage: Generally, a larger number of fingerprints measured from diverse places contribute to enhancing the system performance. Meanwhile, the coverage scale of areas visited by participants is affected by the randomness of MUs' movement. To describe the places

³Note that in this article, for ease of presentation, we use a linear function to formulate MUs' cost.

⁴Based on Definition 2, β is determined by the platform. Here, we omit β and mainly use $q(\alpha)$ to quantify the impact of α in the next of this paper.

where users complete different activities (e.g., walking, turning), points of interest (PoIs) $L = \{l_1, l_2, \dots, l_n\}$ are introduced that can be extracted from users' indoor trajectories. Successively, Shannon Entropy [29] is used to capture the popularity of different PoIs, which denotes that how many unique users have visited a specific PoI as well as how many times each user have visited a PoI.

$$E(l_j) = - \sum_{u_i \in \Omega} \lambda_j^i / \Psi_j \log(\lambda_j^i / \Psi_j) \quad (4)$$

where λ_j^i denotes the number of visits of user $u_i \in \Omega$ to PoI l_j and $\Psi_j = \sum_{u_i \in \Omega} \lambda_j^i$. The entropy for a PoI is regarded as the probability that the PoI is visited by users.

Definition 3 (Spatial Coverage): Given a collection of PoIs L and an associated weight set $W = \{\omega_1, \omega_2, \dots, \omega_n\}$, the spatial coverage of the target area is characterized by (5):

$$\Phi_{\Omega}(L) = \frac{1}{n} \sum_{j=1}^n w_j E(l_j) \quad (5)$$

where different weights in W are assigned to different PoIs to capture the information heterogeneity since different valuable information is provided by different PoIs, in which all elements in W sum up to 1. It is assumed that a higher weight is assigned to the PoI with lower entropy, since it has a smaller chance of being visited by users.

(iii) Sensing Quality Metric: Referring to [17], the power property of \log function is used to characterize sensing quality with considering privacy protection and spatial coverage.

$$Q_{\Omega}(L) = \log(1 + q(\alpha)\Phi_{\Omega}(L)) \quad (6)$$

where the logarithm function is applied to reflect the MCP's diminishing returns on participating MUs while the total cost does not violate the predefined budget B .

B. PROBLEM STATEMENT

The MCP aims to select a subset S MUs to maximize the sensing quality given a limited budget B , in which the budget B could be intuitively represented by the total reward that all the selected users obtain.

$$\max_{S \in \Omega} Q_S(L) \quad (7)$$

$$\sum_{i \in S} c_i \leq B \quad (8)$$

V. BASIC INCENTIVE MECHANISM DESIGN

This section presents a basic incentive mechanism within the budget limitation to recruit users to maximize sensing quality, which is called **Budgeted Sensing Quality Maximization (BTSQM)** problem. Similar to [30], this mechanism is designed under an assumption that MUs do not misreport their costs, which means that the costs claimed by MUs are treated as their real costs.

A. PROBLEM REDUCTION

To address this problem, we first claim that the BTSQM problem could be transformed into the *budgeted maximum coverage problem* [31].

Definition 4 (Budgeted Maximum Coverage Problem [31]): A collection of sets \mathcal{S} with associated costs is defined over a domain of weighted elements X . The objective is to find a subset of $\mathcal{S}' \subseteq \mathcal{S}$ such that the total cost of all elements in \mathcal{S}' is at most of the budget B and the total weight of all elements covered by the subset \mathcal{S}' is maximize.

Similar to [30], given a PoI set L , $\mathcal{X}_{u_i} = \{\lambda_j^i\}_{j=1}^n$ is used to denote the PoIs visited by u_i . Then, the collection of all MUs' cover set $\mathcal{X} = \{\mathcal{X}_{u_1}, \mathcal{X}_{u_2}, \dots, \mathcal{X}_{u_m}\}$ with associated cost set $\Theta = \{c_1, c_2, \dots, c_m\}$ is acquired. Consequently, the transform relation between our BTSQM problem and the *budgeted maximum coverage problem* is as follows: $\mathcal{X} \rightarrow \mathcal{S}, L \rightarrow X$ with the corresponding target set $S \rightarrow \mathcal{S}'$. As a result, our BTSQM problem is proved to be NP-hard, since the budgeted maximum coverage problem has been proved to be NP-hard [31]. To solve the BTSQM problem, the objective function is proved to be non-decreasing submodular such that the submodular function [32] could be exploited.

Definition 5 (Submodular Function): Let \mathfrak{h} be a finite set, a function f on the subsets of \mathfrak{h} is submodular if

$$f(A \cup a) - f(A) \geq f(A' \cup a) - f(A') \quad (9)$$

for any $A \subseteq A' \subseteq \mathfrak{h}$ and $a \in \mathfrak{h} \setminus A'$. Moreover, the function f is denoted to be *non-decreasing* if $f(A) \leq f(A')$ where $\forall A \subseteq A' \subseteq \mathfrak{h}$.

Lemma 1: Given an arbitrary subset $S_1 \subseteq \Omega$ and a PoI set L , the function $Q_{S_1}(L)$ is non-decreasing submodular.

The proof can be found in Appendix A.

B. ALGORITHM DESIGN

Based on [31], a greedy algorithm is proposed to obtain the approximate solution that is illustrated in Algorithm 1.

- First, the collection H of Ω of the cardinality less than the fixed integer $\tau > 0$ is obtained, where the total cost of each set in H does not exceed B . Among them, the set with the largest sensing quality is selected as the candidate solution (**line 1**).
- Second, all subsets of Ω of the cardinality τ are enumerated to acquire a feasible solution, whereas the total cost of each subset is at most of B (**line 2**). The greedy algorithm is used to complement all the subsets. At each iteration, MU u_i is added to the candidate subset when meeting the following requirements: (1) the ratio $(Q_{H \cup u_i} - Q_H)/c(u_i)$ is maximized; (2) the total cost of MU u_i and the current candidate set does not violate B . Then, the set with the highest sensing quality is chosen as the targeted solution (**lines 3-14**).
- Finally, the approximation solution of BTSQM problem is achieved (**lines 15-16**).

Algorithm 1 Algorithm Design for BTSQM Problem

Input: PoI set L with weight set W , user set Ω with associated cost set Θ and cover set \mathcal{X} , and the budget B

Output: Final candidate set S where $S \subseteq \Omega$

```

1:  $G_1 \leftarrow \arg \max\{Q_H(L)\}$ , where  $H \subseteq \Omega$ ,  $|H| < \tau$  and  $c(H) \leq B$ ;  $G_2 \leftarrow \emptyset$ 
2: for all  $H \subseteq \Omega$ , where  $|H| = \tau$ , and  $c(H) < B$  do
3:    $\Pi \leftarrow \Omega \setminus H$ 
4:   repeat
5:     select  $u_i \in \Pi$  that maximize  $(Q_{H \cup u_i} - Q_H)/c(u_i)$ 
6:     if  $c(H) + c(u_i) \leq B$  then
7:        $H \leftarrow H \cup \{u_i\}$ 
8:        $\Pi \leftarrow \Pi \setminus \{u_i\}$ 
9:     end if
10:  until  $\Pi = \emptyset$ 
11:  if  $Q_H(L) > Q_{G_2}(L)$  then
12:     $G_2 \leftarrow H$ 
13:  end if
14: end for
15: if  $Q_{G_1}(L) > Q_{G_2}(L)$  then
16:    $S \leftarrow G_1$ , otherwise  $S \leftarrow G_2$ 
17: end if

```

C. PERFORMANCE ANALYSIS

1) COMPUTATIONAL COMPLEXITY

It firstly takes $O(m^\tau)$ time to enumerate all subsets of Ω . Secondly, at each stage, the greedy selection is employed to obtain the feasible solution, which takes $O(m \log(m))$ time. In summary, the complexity is $O(m^{\tau+1} \log(m))$, where τ is a integer and not less than 3.

2) APPROXIMATION RATIO

Given $\tau \geq 3$, an approximation factor of $(1 - 1/e)$ is achieved by Algorithm 1.

The proof can be found in Appendix B.

VI. AUCTION-BASED INCENTIVE MECHANISM

In the previous section, a basic mechanism is proposed to maximize sensing quality under the assumption that each MU truthfully reports its cost. However, the cost is private information from MUs' perspective that is not public to MCP. To achieve the truthfulness of MUs' costs, a sensing quality-aware auction-based mechanism is presented in this section.

A. PROBLEM FORMULATION

As depicted in Fig. 2, the trade-offs between MCP and MUs are modeled as a reverse auction, where MCP acts as the *auctioneer* that purchases indoor trajectories from MUs who act as *bidders*. The utility of each winner is defined as (10):

$$\pi_i = \begin{cases} p_i - c_i & \text{if } i \in S \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where p_i denotes the payment to winner i

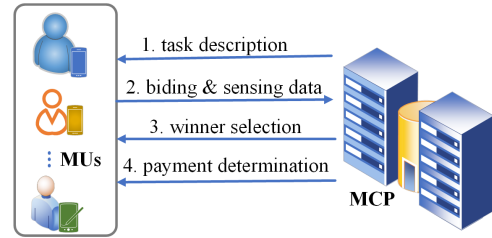


FIGURE 2. Interactions between MUs and MCP.

Based on MUs' contributed sensing data, MCP is able to provide different kinds of location-based services to the public. Under this circumstance, the valuation of the platform is characterized as follows:

$$v(S) = \mu \log(1 + \sum_{j=1}^n q(\alpha) w_j E(l_j)/n) \quad (11)$$

where $\mu > 0$ is the coefficient that transforms the sensing quality metric into the platform's valuation function.

This auction-based mechanism aims to maximize the MCP's valuation under a constrained budget.

$$\max_{S \in \Omega} v(S) \quad (12)$$

$$\sum_{i \in S} p_i \leq B \quad (13)$$

Meanwhile, this mechanism also aims to satisfy the following desirable properties:

- **Truthfulness:** No MU can improve its utility by submitting a bid different from its true cost, no matter what others submit.
- **Individual Rationality:** The utility of individual winner is non-negative.
- **Computational Efficiency:** The result of this auction-based mechanism can be obtained in polynomial time.

B. AUCTION BASED ALGORITHM DESIGN

To meet the above properties, the designed mechanism mainly depends on Myerson's well-known characterization [33] and budget feasibility [34].

Based on Lemma 1, given $\mu > 0$, it is easily found that the platform's valuation function is submodular and monotonically non-decreasing. To select winners, the *marginal contribution per bid* of user $i \in \Omega \setminus S$ is defined as $\zeta_i = \frac{v_i(S)}{b_i}$ with respect to S , where $v_i(S) = v(S \cup \{i\}) - v(S)$. In this study, Algorithm 2 contains the following phases:

Winner Selection: First, the winner set is initialized as empty and MUs are sorted in the non-increasing order of ζ , in which the candidate user is selected with the largest marginal contribution per bid (**line 2**). Second, the difference between the candidate user's ζ and the value per budget of S is acquired. If the difference is positive, this user is added to S and the next iteration is continued until the difference is negative. Otherwise, the candidate user is discarded and this phase terminates (**lines 3-6**).

Algorithm 2 Budgeted Auction Mechanism

Input: PoI set L with associated weight set W , potential user set Ω with associated cost set Θ , and a limited budget B

Output: A set of winning mobile users $S \subseteq \Omega$ and payment profile P

```

1: // phase 1: winner selection
2:  $S \leftarrow \emptyset, i \leftarrow \arg \max_{j \in \Omega} \frac{v_j(S)}{b_j}$ ;
3: while  $b_i \leq \frac{B}{2} \frac{v_i(S)}{v(\Gamma \cup \{i\})}$  do
4:    $S \leftarrow S \cup \{i\}$ ;
5:    $i \leftarrow \arg \max_{j \in \Omega \setminus S} \frac{v_j(S)}{b_j}$ ;
6: end while
7: // phase 2: critical payment determination
8: for each  $i \in \Omega$  do;
9:    $P \leftarrow \emptyset$ ;
10: end for
11: for each  $i \in S$  do;
12:    $\Omega_{-i} \leftarrow \Omega \setminus \{i\}, \Gamma \leftarrow \emptyset$ ;
13:   repeat
14:      $i_j \leftarrow \arg \max_{j \in \Omega_{-i} \setminus \Gamma} \frac{v_j(\Gamma)}{b_j}$ ;
15:      $p_i \leftarrow \max\{p_i, \min\{\frac{v_i(\Gamma)b_{i_j}}{v_{i_j}(\Gamma)}, \frac{Bv_i(\Gamma)}{2v(\Gamma \cup \{i\})}\}\}$ ;
16:      $\Gamma \leftarrow \Gamma \cup \{i_j\}$ ;
17:   until  $b_{i_j} > \frac{B}{2} \frac{v_{i_j}(\Gamma)}{v(\Gamma \cup \{i_j\})}$  or  $\Gamma = \Omega_{-i}$ ;
18:   if  $\Gamma = \Omega_{-i}$  then
19:      $p_i \leftarrow \max\{p_i, \frac{Bv_i(\Gamma)}{2v(\Gamma \cup \{i\})}\}$ 
20:   end if
21: end for
22: return  $S, P$ 

```

Payment Determination: First, the payment set P is initialized as empty for all users (lines 8-10). Second, the winner set is recomputed over $\Omega_{-i} \leftarrow \Omega \setminus \{i\}$ and MUs in Ω_{-i} are sorted based on ζ to obtain the first j users denoted as Γ_j , where the j^{th} user is denoted as i_j in this sorting. Third, the largest bid that winner i can submit is achieved where MU i is selected not the user at j -th position in this sorting. This process is repeated until the position after the last winner over Ω_{-i} . Finally, for all candidate payments, the maximal payment is selected as the final payment to winners (lines 11-20).

C. MECHANISM ANALYSIS

In this subsection, our designed mechanism is proved to satisfy the predefined properties.

Theorem 1: The auction-based mechanism is truthful.

The proof can be found in Appendix C.

Theorem 2: The proposed auction-based mechanism is individually rational.

Proof: According to (10), if user i is not selected as a winner, its payoff is zero, otherwise its claimed cost should be lower than or equal to the critical value. Moreover, this auction-based mechanism is proved to be truthful, user i could report its true cost. Hence, winner i 's utility $p_i - c_i$ is non-negative. ■

Theorem 3: The proposed auction-based mechanism is computationally efficient.

Proof: In Phase 1, it takes $O(|\Omega|)$ time to obtain the user with the maximal marginal contribution per bid (line 2) and the process of the while-loop (lines 3-6) runs about $O(|\Omega|)$ time. It takes $O(|\Omega|)$ time to repeat the iteration (lines 11-20) in Phase 2. To summarize, the complexity of the auction-based mechanism is $O(|\Omega|^3)$. ■

Assume that there are two arbitrary user sets $S \subset \mathcal{G} \subseteq \Omega$ and $\eta_0 = \arg \max_{\eta \in \mathcal{G} \setminus S} \frac{v_\eta(S)}{b_\eta}$, based on [35], we have

$$\frac{v(\mathcal{G}) - v(S)}{b(\mathcal{G}) - b(S)} \leq \frac{v_{\eta_0}(S)}{b_{\eta_0}} \quad (14)$$

where $b(S) = \sum_{g \in S} b_g$.

By utilizing (14), we can obtain the following lemma.

Lemma 2: For the winner $r \in S$, its critical payment p_r has an upper bound $\frac{v_r(S)B}{v(S)}$.

The proof can be found in Appendix D.

Theorem 4: The auction-based mechanism is budget feasible.

Proof: By using Lemma 3, we have $\sum_{i \in S} p_i \leq \frac{\sum_{i \in S} v_i(S)B}{v(S)} = B$. Hence, the sum of the payment to all winners does not exceed the budget. ■

VII. NUMERICAL SIMULATIONS

This section presents the simulation results of our proposed mechanisms. The basic incentive mechanism is made comparison with the following schemes: (i) Random selection algorithm: in each round, users are randomly added to the candidate user set with satisfying the budget constraint; (ii) Maximum sensing quality (MSQ) algorithm: at each iteration, the user who maximizes sensing quality is selected, where the budget constraint is satisfied. However, in the basic mechanism, a user who maximizes the ratio between the increased sensing quality and the cost will be added to the candidate user set. The auction-based mechanism is compared against the following two benchmark schemes: Greedy-SM and Random-SM [35].

A. SIMULATION SETTINGS

Assuming that MUs' unit sensing cost c^s and unit privacy cost c^p are randomly distributed within the range $(0, 1)\$/m$ and the trajectory distance d for each user is normalized into a scale of 0-10m. The weights for different PoIs are randomly distributed over $(0, 1)$ and the value of the platform's valuation parameter μ is fixed as 1000\$. Different types of $q(\alpha)$ ($0 < \alpha < 1$) are adopted to study the impact of privacy protection on sensing quality, in which ϵ is randomly distributed within the range $(0, 1)$. Meanwhile, we assume that a PoI is visited by the same user at most twice. MUs' number m is varied from 200 to 1000 with the increment of 200 and the budget B is within the range from 0 to 300\$.

B. SIMULATION RESULTS

As shown in Fig. 3, the impact of the budget on sensing quality is investigated. We observe that as the budget

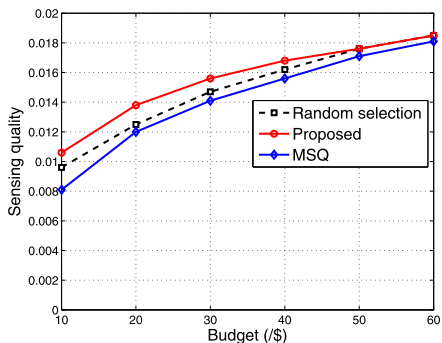


FIGURE 3. Budget vs sensing quality.

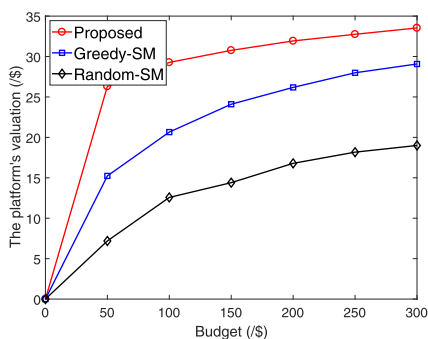


FIGURE 4. Budget vs the platform's valuation.

increases, the proposed sensing quality metric satisfies the law of diminishing returns. Meanwhile, our proposed algorithm can achieve a higher sensing quality as compared to the random selection algorithm and MSQ algorithm. Due to the simulation setting, when the budget is greater than a threshold, sensing quality of our proposed algorithm is same to that of the random selection algorithm.

In Fig. 4, we fix MUs' number $m = 200$. It is notable that the platform's valuation increases with the increasing budget and satisfies the diminishing returns rule. As shown in Algorithm 2, at the phase of winner selection, the user with the largest marginal contribution per bid is selected, hence our proposed mechanism can achieve a higher valuation in comparison with the baseline schemes.

Fig. 5 shows the impact of m on the valuation of the platform, in which we fix $B = 100\$$. It is found that the valuation indeed demonstrates diminishing returns as m increases. At the same time, our proposed auction-based mechanism outperforms the baseline schemes since the user with a larger marginal contribution per bid is chosen.

As illustrated in Fig. 6, our proposed auction-based mechanism is budget feasible by investigating users' total payment given different amount of budget. We observe that the total payment increases with the increasing users since more users are selected to perform the task. In Fig. 7, we note that the valuation is impacted by different types of $q(\alpha)$. Based on Definition 2, the larger α leads to lower accuracy achieved by the aggregation algorithm. Hence, the valuation of the platform's decreases with the increasing value of α .

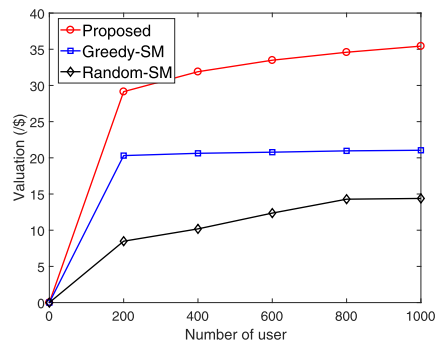


FIGURE 5. MUs' number vs the platform's valuation.

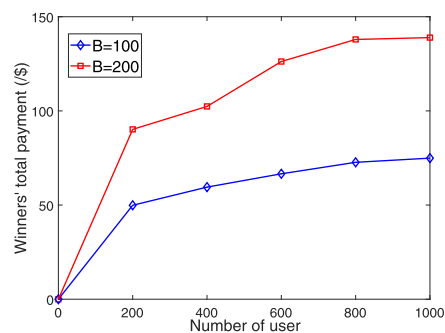


FIGURE 6. MUs' number vs total payment.

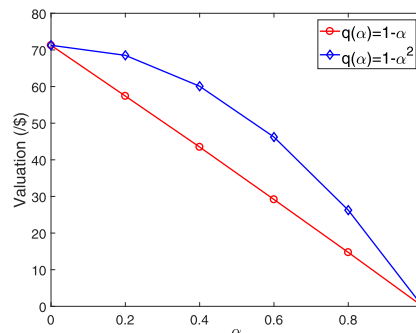


FIGURE 7. $q(\alpha)$ vs the platform's valuation.

VIII. EXPERIMENT RESULTS

In this section, the performance of the basic incentive mechanism is evaluated on UJIIndoorLoc database [36]. This database contains wireless local area network (WLAN) RSS measurements of three buildings of Universitat Jaume I with four or more floors, which is often utilized to evaluate indoor localization solutions that depend on RSS fingerprints.

A. EXPERIMENT SETTINGS

In this experiment, the location data of the first floor of the first building is adopted to validate the proposed mechanism, where the physical coordinate or location is comprised by the longitude and the latitude in the dataset.⁵

Considering that the indoor scenario is roughly divided into subareas based on the signal coverage of access points (APs)

⁵For convenience, we make an assumption that the unit of both the longitude and the latitude is meter and each user provides a RSS sequence.

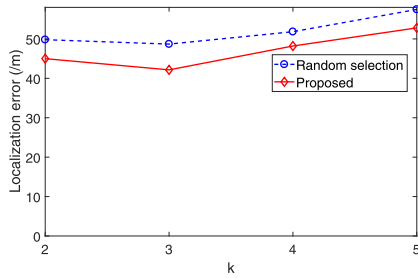


FIGURE 8. The impact of KNN on localization error.

deployed in the building. Hence, APs can be utilized to denote the mentioned PoIs in Section III. Here, the assumption is that if the RSS reading of an AP in a POI can be detected, it means that its corresponding PoI is covered by users. As mentioned in the previous sections, the mechanism performance is greatly influenced by privacy protection achieved by adding noise to raw data. Moreover, the study [13] has shown that the Laplace mechanism can be used to achieve ϵ -local differential privacy. Therefore, the noise drawn from a Laplace distribution with zero mean is added to the training data to investigate the impact of privacy protection, where the standard deviation σ is approximately proportional to $1/\epsilon$. Moreover, k -nearest neighbors (KNN) [37] is adopted to evaluate the performance, where our proposed basic mechanism is compared with the random selection algorithm. Meanwhile, the total cost of each candidate user is distributed over (1, 10)\$ and the number of candidate users is fixed as $m = 20$ and $m = 30$, respectively. Moreover, the average indoor localization error of 50 testing data is adopted as the metric to evaluate the system performance.

B. RESULTS

In the KNN solution, k neighbors of the target are selected based on Euclidean distance or other distances to estimate the target location. Fig. 8 investigates the impact of k on the localization error. It is noted that when $k = 3$, both the random selection algorithm and our proposed basic incentive mechanism can achieve a lower localization error compared to other values of k . Meanwhile, the localization error of our proposed incentive mechanism is smaller than that of the random selection algorithm.

Fig. 9 studies the effect of the limited budget on different mechanisms under different user number, respectively, where $k = 3$. As shown in Fig. 9, on one hand, the localization error becomes lower with the increasing budget; on the other hand, the localization error decreases with the increasing user number. Compared to the random selection algorithm, the proposed basic incentive mechanism can achieve a lower localization error. Moreover, this experiment result is found in line with the numerical simulation result.

Fig. 10 demonstrates the localization error under different σ , in which σ denotes the standard deviation of the Laplace distribution. The studies [13], [38] have shown that with larger σ , larger noise has to be added to users' data such

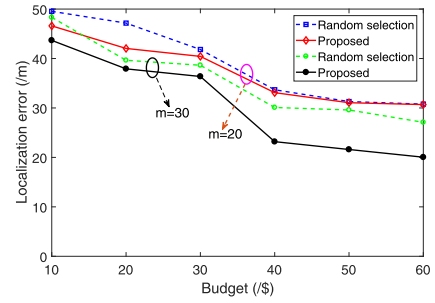


FIGURE 9. Budget vs localization error.

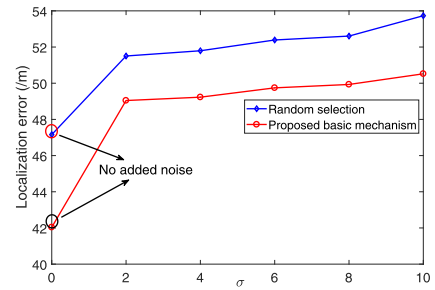


FIGURE 10. Privacy protection vs localization error.

that higher privacy protection level can be achieved which increases the localization error.

IX. CONCLUSION AND FUTURE WORK

In this study, a novel metric of sensing quality for MCS-based RSS fingerprint collection was proposed to characterize the joint impact of privacy protection and spatial coverage. In the basic incentive mechanism, a greedy-based algorithm was proposed to obtain an approximation solution for the sensing quality maximization problem under a constrained budget. Aiming to achieve the truthfulness of users' private costs, an auction-based incentive mechanism was proposed and theoretically proved to meet the predefined properties. Simulation results verified that our proposed mechanisms outperformed the baseline schemes. Moreover, an experiment based on real-world data was carried out to evaluate the proposed basic incentive mechanism.

In the future, the P2P or D2D networking paradigm [39] would be used as a cost and energy effective way to provide the spatial coverage for crowdsourcing fingerprint collection.

APPENDIXES

**APPENDIX A
PROOF FOR LEMMA 1**

Proof: Based on (6), it is easily found that $Q_{S_1}(L) = 0$ given $S_1 = \emptyset$. Then, consider that there are two arbitrary subsets $S_1 \subseteq S_2 \subseteq \Omega$: (1) if $\mathcal{X}_{S_2} - \mathcal{X}_{S_1} = \emptyset$, we have $Q_{S_1}(L) = Q_{S_2}(L)$; (2) given $\mathcal{X}_{S_1} < \mathcal{X}_{S_2}$, we have $Q_{S_1}(L) < Q_{S_2}(L)$. Consequently, $Q_{S_1}(L)$ is proved to be non-decreasing.

According to Definition 4, to prove that the sensing quality function is submodular, we need to demonstrate that

$$Q_{S_1 \cup \{u\}}(L) - Q_{S_1}(L) \geq Q_{S_2 \cup \{u\}}(L) - Q_{S_2}(L) \quad (15)$$

By leveraging MUs' cover sets, $|\mathcal{X}_{S_1 \cup \{u\}}| - |\mathcal{X}_{S_1}|$ denotes the amount of covered PoIs in MU u 's cover set \mathcal{X}_u and not in the set \mathcal{X}_{S_1} given a MU $u \in \Omega \setminus S_2$. It is found that $\mathcal{X}_{S_1 \cup u} - \mathcal{X}_u \geq \mathcal{X}_{S_2 \cup u} - \mathcal{X}_u$. Hence, it suffices to show that the inequality (15) can hold. Moreover, the marginal sensing quality from adding an additional user is non-negative which demonstrates that the objective function satisfies the law of diminishing returns.

To summarize, we have proved that the objective function is non-decreasing submodular. ■

APPENDIX B PROOF FOR APPROXIMATION RATIO OF ALGORITHM 1

Proof: The study [31] has shown that: (1) the candidate solution with the largest weight is selected as the approximation solution, whose associated cost does not exceed the limited budget; (2) the value of coverage quality achieved by the approximation solution is at least $1 - 1/e$ times greater than the optimal value of the coverage quality achieved by arbitrary subset. In this context, we have reduced our problem to the classical budgeted maximum coverage problem as well as captured the relation between these two problems. Therefore, for $\tau \geq 3$, the approximation factor achieved by our designed algorithm is greater than $(1 - 1/e)$. ■

APPENDIX C PROOF FOR THEOREM 1

Proof: To prove the truthfulness of our proposed auction-based mechanism, it requires to show that our proposed mechanism meets Theorem 1. On one hand, base on marginal contribution per bid, user i who submits a lower bid will be sorted in the same or a prior position; on the other hand, the platform's valuation function is monotone. Hence, the monotonicity can be maintained.

Next, we show that the payment for each winner is the critical value. In the payment determination phase, users are essentially sorted according to their marginal contribution per bid. For user i , if $b_i > p_i$, it will be pushed backward after the position of the last user $i_j \in \Omega_{-i}$. Since its marginal contribution per bid is lower than that \mathcal{N}^{th} user, it will not be selected after the $(\mathcal{N} + 1)^{th}$ iteration. If $b_i < p_i$, it is selected as a winner according to the winner selection rule.

In summary, our designed auction mechanism is truthful. ■

APPENDIX D PROOF FOR LEMMA 2

Proof: First, consider that $\emptyset = S \subset \dots \subset S_k \subseteq \Omega$, due to the submodularity of the platform's valuation function, we have $\frac{v(S)}{b(S)} \geq \frac{v(S_k)}{B}$. Then, for contradiction, we assume that user $r \in S_k$ reports a bid $b_r > \frac{v_r(S)B}{v(S_k)}$ and it still can be selected as a winner. Before user r is added to the winner set, we have $r = \arg \max_{i \in \Omega \setminus S} \frac{v_i(S)}{b_i}$. Based on the threshold set in the winner selection phase, we have $\frac{v_r(S)}{b_r} \geq \frac{2v(S \cup \{r\})}{B}$.

We make an assumption that $S \cup \{r\} \subsetneq S_k \cup S$. If not we have $S \cup \{r\} = S_k \cup S$ and then

$$\frac{v_r(S)}{b_r} \geq \frac{2v(S \cup \{r\})}{B} \geq \frac{2v(S_k)}{B} \geq \frac{v(S_k)}{B} \quad (16)$$

Therefore, we have $b_r \leq \frac{v_r(S)B}{v(S_k)}$ and get a contradiction.

Then, we set $\mathcal{M} = S_k \setminus S$ and incorporate r and Lemma 2 into $S_k \cup S$ and $S \cup \{r\}$, respectively. For $g_0 \in \mathcal{M} \setminus \{r\}$, according to Lemma 2, we have

$$\frac{v(S_k \cup S) - v(S \cup \{r\})}{b(S_k \cup S) - b(S \cup \{r\})} \leq \frac{v_{g_0}(S \cup \{r\})}{b_{g_0}} \leq \frac{v_r(S)}{b_r} \quad (17)$$

Meanwhile, we have obtained that $b_r > \frac{v_r(S)B}{v(S_k)}$ and thus we have $\frac{v_r(S)}{b_r} < \frac{v(S_k)}{B}$. Combined with (17), we can get

$$\frac{v(S_k \cup S) - v(S \cup \{r\})}{b(S_k \cup S) - b(S \cup \{r\})} < \frac{v(S_k)}{B} \quad (18)$$

Thus, we get $b(S_k \cup S) - b(S \cup \{r\}) \leq b(S_k)$.

According to the inequality (17), for $j \in [k]$, we have $\frac{v_1(S)}{b_1} \geq \dots \geq \frac{v_k(S)}{b_k} \geq \frac{2v(S_k)}{B}$. Besides, it is proved that winning user truthfully reports its bid. Therefore, we could get $b(S_k) = \sum_{j=1}^k b_j \leq \frac{B}{2} \sum_{j=1}^k \frac{v_j(S_k)}{v(S_k)} = B/2$. Based on these analytics, we can have

$$\frac{v(S_k) - v(S \cup \{r\})}{B/2} < \frac{v(S_k)}{B} \quad (19)$$

As a result, we have $v(S_k) < 2v(S \cup \{r\})$. Besides, we know that $\frac{v_r(S)}{b_r} \geq \frac{2v(S \cup \{r\})}{B}$ and we have $\frac{v_r(S)}{b_r} > \frac{v(S_k)}{B}$. Hence, the contradiction with $b_r < \frac{v_r(S)B}{v(S)}$ is proved.

In summary, the critical payment for winner r has a upper bound $\frac{v_r(S)B}{v(S)}$. ■

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WEI LI received the B.S. degree in automation and the M.S. degree in control engineering from the University of Technology, China, in 2014 and 2017, respectively. He is currently pursuing the Ph.D. degree with the Department of Computer Science and Communications Engineering, Waseda University. His research interests include mobile crowdsourcing, network economics, and indoor localization.



CHENG ZHANG (Member, IEEE) received the Ph.D. degree from Waseda University, Tokyo, Japan, in 2015. From 2008 to 2015, he was a Research Engineer with Sony Digital Network Applications, Japan, and HGST Japan, Inc. (ex Hitachi Global Storage Technologies), where he researched and developed control algorithms for image stabilization module of Sony digital camera and servo control algorithms for next-generation high-capacity HDD. He is currently an Assistant Professor of Graduate Program for Embodiment Informatics (Program for Leading Graduate School) with the Graduate School of Fundamental Science and Engineering, Waseda University. His research interests include machine control algorithm, embedded software, game theory, network economics, and machine learning. He is a member of IEICE. He received the IEICE Young Researcher's Award, in 2013.



YOSHIAKI TANAKA (Life Senior Member, IEEE) received the B.E., M.E., and D.E. degrees in electrical engineering from The University of Tokyo, Tokyo, Japan, in 1974, 1976, and 1979, respectively. He became a Staff at the Department of Electrical Engineering, The University of Tokyo, in 1979, where he has been engaged in teaching and researching in the fields of telecommunication networks, switching systems, and network security. He is currently a Professor with the Department of Communications and Computer Engineering, Waseda University. He is also an Honorary Member of IEICE. He received the IEICE Best Paper Award, the IEICE Achievement Award, the IEICE Distinguished Achievement and Contributions Award, the Okawa Publication Prize, the Commendation by Minister for Internal Affairs and Communications, and so on.

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