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False-name-proof mechanism for time window coverage tasks in mobile crowdsensing

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***Abstract*—Mobile crowdsensing has been regarded as an efficient paradigm for performing large-scale sensing tasks. In this paper, we consider a specific scenario, where the crowdsensing platform needs to collect the sensing data in a requested time window (RTW), and mobile users would bid for their sensing time windows. This process could be modeled as a reverse auction. In this context, the Vickrey-Clark-Groves (VCG) mechanism becomes a generic auction mechanism that uniquely guarantees both truthfulness and efficiency, but it is vulnerable to false-name bidding and generates high overpayment for the platform. Thus in this paper, we design the core-selecting mechanism to solve VCG's vulnerability and improve the revenue. We demonstrate that our proposed mechanism achieves the properties of RTW feasibility, efficiency, individual rationality, and false-name-proofness. Besides, to minimize the incentives of users to deviate from truthful-telling, we adopt a VCG-nearest payment rule and propose an efficient algorithm called CCG-TWC. Our extensive simulation results show that the core-selecting mechanism could reduce VCG's overpayment by about 10%.**

***Index Terms*—Mobile crowdsensing, Time window, Core-selecting,False-name-proof**

I. Introduction

In recent years, the number of mobile users with sensor-embedded smartphones has exploded, and mobile devices (e.g., smartphone, iPad, PDA, etc.) becomes more and more popular. According to the latest Ericsson mobility report[1], the number of worldwide mobile subscriptions has reached 7.5 billion in 2017 and will approach 9.1 billion in 2022. Besides, with the development of hardware technology, most mobile devices are embedded with various types of sensors (e.g., GPS, accelerometer, camera)[2]. Thus, devices such as smartphones, smart wearable devices (e.g., Google glasses, Apple Watch) could be used to collect information from the surrounding environment.

The aforementioned trends motivate the development of the mobile crowdsensing (MCS) [2], which provides an efficient paradigm to collect large-scale sensing data. Compared with the traditional sensor network, mobile crowdsensing, which utilizes hundreds of thousands of ordinary users, has a huge application potential due to its prominent advantages such as wide spatio-temporal coverage, low cost, and good scalability.

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In the crowdsensing market for time window coverage tasks, MCS system consists of two parts: the platform and smartphone users. The platform wants to buy continuous sensing data in the whole required time window (RTW). Each user bids with a user time window (UTW) in which she can collect the sensing data. There are some real-world examples of existing systems that fall into this scenario, such as bus arrival time prediction system[3] and Ear-Phone[4]. This process of mobile sensing could be modeled as a reverse auction, the goal is to design a suitable mechanism for the platform to determine which users to recruit, and how much to pay them.

The problem is hard because users may take some strategies, such as lying about their costs or UTWs. The well known Vickrey-Clark-Groves (VCG) mechanism is the unique efficient and truthful mechanism. However, it is not robust against false-name bids, which means the users can register fake accounts to get more profit. Thus, VCG mechanism may result in a high overpayment for the platform. In this paper, we relax the restriction of truthfulness and propose the core-selecting mechanism to address the economic problems of the VCG mechanism. Our main contributions are summarized as follows.

1) We model the auction in a graph and propose a new method to solve the winner determination problem, which has a better complexity of $O(|N|\log|N|)$ than the previous method [5] ($|N|$ is the number of users).
2) We design the core-selecting mechanism for crowdsensing market and demonstrate that this mechanism satisfies four desirable properties: RTW feasibility, efficiency, individual rationality, and false-name-proofness.
3) We adopt a quadratic payment rule to minimize the incentives of users to bid dishonestly and propose CCG-TWC algorithm to calculate the payment result efficiently.
4) Finally, we extensively evaluate the performance of our mechanism based on both real trace and randomly generated users. The results show that our mechanism is frugal and practical.

The rest of this paper is organized as follows. We present the related work in Section II. In Section III, we introduce the preliminary knowledge including the VCG mechanism, and demonstrate our new method for the winner determination problem. In Section IV, we propose the core-selecting mechanism for time window coverage crowdsensing tasks and offer theoretical results. Section V presents the VCG-nearest payment rule and the proposed CCG-TWC algorithm to compute the payment result. In Section VI, the simulation results and performance analysis are given. Finally, we conclude this paper in Section VII.

II. Related work

The unique auction mechanism that ensures both efficiency and truthfulness is the well-known VCG type of mechanisms due to Vickrey [6], Clarke[7] and Groves[8]. However, the VCG mechanism is rarely applied in practice directly, due to its low revenue [9] and vulnerability to false-name bids [10]. Core-selecting mechanism, originally proposed and developed by Day[11, 12, 13] has attracted substantial attention in economics as a more robust and profitable alternative to the VCG mechanism. It is widely used in auctions such as spectrum auctions [14, 15], TV advertising auctions [16] and electricity markets [17]. In this paper, we convert the core-selecting crowdsensing mechanism into a form of path auction, which is also related to the researches of core-selecting path auction [18, 19, 20].

Mobile crowdsensing (MCS) provides an efficient method to collect the sensing data [2, 21]. The time window coverage tasks in mobile crowdsensing were first studied by Xu [5], Xu modeled this problem as a reverse auction and proposed the truthful mechanisms for time window coverage tasks. Then, they proposed BFF-STI mechanism and FIMI mechanism to ensure budget feasibility and frugality, respectively [22, 23]. However, they relaxed the guarantee of efficiency and didn't consider the false-name manipulation, which is different from our mechanism.

Previous works also studied the false-name-proof mechanisms for MCS system [24, 25, 26, 27]. Lin studied the auction-based incentive mechanisms for crowdsensing and proposed the SPIM-S and SPIM-M mechanism which satisfy individual rationality, truthfulness, and sybil-proofness[24]. They also studied sybil-proof online incentive crowdsensing mechanisms and proposed SOS and SOM mechanisms [25]. Jiang considered time-sensitive crowdsensing tasks and proposed the sybil-proof TSSP-M and TSSP-S mechanisms [26]. However, they all relax the guarantee of maximum social welfare, which is different from our mechanism. Zhang proposed a sybil-proof mechanism to encourage users to both devote efforts to complete the task and refer other users to join into participation [27].

III. Problem formulation and preliminary knowledge

We consider a mobile crowdsensing system consisting of a platform $\mathcal{P}$ and a set of smartphone users $N = \{1, 2, ..., n\}$. Denote the total set by $\mathcal{N}$, where $\mathcal{N} = \mathcal{P} \cup N$. The platform publicizes a required time window (RTW) $\mathcal{W} = [T_S, T_E]$, where T_S and T_E are the start time and the end time, respectively. The platform requests the sensing data in the period from T_s to T_e. We set a time unit as the minimum sensing time and consider each point-in-time as the number of time unit from the start time. The part less than one unit will be removed for each user. Denote the length of RTW, i.e., the number of time unit, as $|\mathcal{W}|$.

Each user i reports a bid $B_i = ([s_i, e_i], b_i)$, where $[s_i, e_i]$ is the user time window (UTW) within which user i can perform. The start time s_i and the end time e_i can be any point-in-time. However, any $s_i < T_s$ or $e_i > T_e$ cannot bring extra benefit the platform, thus we don't consider the time outside the RTW $[T_s, T_e]$. b_i is the claimed cost that user i wants to charge for performing $[s_i, e_i]$. Each UTW $[s_i, e_i]$ is associated with a real cost c_i and c_i is only known by user i herself.

The reverse auction of MCS includes two phases, allocation phase and payment phase. In the allocation phase, also called winner determination, the platform selects a subset of users as winners and notifies them. Then the winners perform the sensing tasks in their UTWs and send data back to the platform. In the payment phase, each user i gets a payment p_i according to the payment rule that the platform formulates. Thus, the result of a mechanism is the winner set $S_w \subset N$ and a payment vector $P = (p_1, p_2, \ldots, p_n)$.

The utility of user i is defined through the following quasi-linear function:

$$u_i = \begin{cases} p_i - c_i & i \in S_w \\ 0 & other \end{cases} \tag{1}$$

The utility of the platform $\mathcal{P}$ is

$$u_{\mathcal{P}} = u(\mathcal{W}) - \sum_{i \in S_w} p_i \tag{2}$$

where $u(\mathcal{W})$ is the value of the platform when it obtains all data in the whole $\mathcal{W}$. $u(\mathcal{W})$ is considered to be a large enough constant in this paper. Social welfare is defined as the total utility of all the players, including the platform and users. Denoted by $\mathcal{SW}$, the social welfare is computed by

$$\begin{aligned} \mathcal{SW} &= u_{\mathcal{P}} + \sum_{i \in N} u_i \\ &= u(\mathcal{W}) - \sum_{i \in S_w} c_i \end{aligned} \tag{3}$$

According to Eq. (3), to get the maximum social welfare, the mechanism must select the optimal user group with the minimum cost. The cost minimizing user selection (CMUS) problem can then be formulated as

$$\begin{aligned} S_w &= \arg\min_{S \subset N} \sum_{i \in S} c_i \\ &s.t.\ W \subseteq \cup_{i \in S} [s_i, e_i] \end{aligned} \tag{4}$$

The constraint in (4) means that all the chosen UTWs should cover the RTW, i.e., the mechanism should assure that the winners can perform all the sensing tasks from T_s to T_e. To avoid the monopoly, we assume that there are enough users and exclude the situation where only one bid hits the arbitrary time unit in $[T_s, T_e]$ to avoid the monopoly.

In the crowdsensing market, users are selfish individuals and may lie about their costs or UTWs. In this paper, we assume that the platform can verify the veracity of the sensing data in the UTWs by using trusted time stamping such as Public Key Infrastructure Time-Stamp Protocol (TSP). This means users can't lie about the time windows.

The platform could only get each user's bid price b_i instead of the real cost c_i, thus we assume that the mechanism regards the users' bids as their costs. As a whole, we are interested in designing auction mechanism satisfying the following five desirable properties.

- **RTW Feasibility**. A mechanism $\mathcal{M}$ is RTW feasible if the UTWs of winners together can cover the whole RTW.
- **Efficiency**. A mechanism $\mathcal{M}$ is efficient if this mechanism achieves the maximum social welfare, i.e., the mechanism should select the optimal user group according to the bid profile.
- **Individual Rationality**. A mechanism $\mathcal{M}$ is individual rational if each user will have a non-negative utility according to her bid, i.e., $p_i \geq b_i, \forall i \in N$.
- **Truthfulness**. A mechanism $\mathcal{M}$ is truthful if no user can improve her utility by submitting a fake bidding price, no matter what others submit.
- **False-name-proofness**. A mechanism $\mathcal{M}$ is false-name-proof if each user cannot get more profit by creating fake names and submitting multiple bids under these names[28]. With the development of the internet, false-name bidding is easy to implement in a crowdsensing market, which may lead to serious consequences. Thus it is an essential property for the crowdsensing mechanism.

However, it is impossible to design a mechanism satisfying all the above properties, since VCG mechanism is the unique mechanism satisfying the first four properties, but it is not false-name-proof and may cause a large overpayment for the platform. We will state the problem of VCG later. In the next section, we first solve the CMUS problem by transforming it into the shortest path problem, which could be solved in polynomial time.

A. Winner determination algorithm

According to the RTW and UTWs, we create a directed weighted interval graph $G_I = (V_I, E_I, W_I)$ through the following two steps:

1) For each user's bid $([s_i, e_i], b_i)$, add a directed edge (v_a, v_b) with the weight of b_i in G_I, where $v_a = s_i, v_b = e_i$.
2) Sort the vertices in ascending order as $v_0, v_1, ..., v_k$. For each $i \in [1, k]$, add a directed edge (v_i, v_{i-1}) with the weight of 0.

These edges added in the second step represent the dummy users. Denote the set of dummy users by S_0. Each dummy user's payment and cost are assigned as zero, that is

$$p_i = c_i = 0 \quad \forall i \in S_0 \tag{5}$$

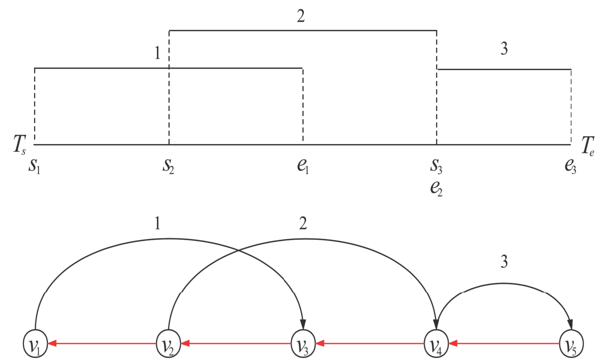

Fig. 1. The process of transformation. Top: original crowdsensing time windows. Bottom: The corresponding graph G_I.

Fig. 1 is an example for the transformation. The top in Fig. 1 demonstrates the UTW and RTW $[T_s, T_e]$ by the straight lines. According to this example, we could create the graph G_I as the bottom of Fig. 1, the black arrows represent the UTWs of mobile users, and the red arrows represent the UTWs of dummy users.

After creating the graph G_I, we could get the following theorem.

Theorem 1: The optimal solution to CMUS problem is just the non-dummy users in the shortest path from v_0 to v_k in G_I.

Proof 1: We sort the users in the optimal solution as $1, 2, ..., m$, where $s_1 \leq s_2 \leq \cdots \leq s_m$. Then we prove Theorem 1 from two steps. The first is proving the optimal solution could be transformed into a path from v_0 to v_k in G_I and the second is proving this path is the shortest path.

Firstly, we have the following inequality[1]

$$s_{i+1} \leq e_i \leq s_{i+2}, \forall i \in [1, m-1] \tag{6}$$

This could be proved by contradiction as follows.

Assume that $e_i < s_{i+1}$, then there must exist a UTW $[s_j, e_j]$ where $s_j \leq s_i, e_j \geq e_i$, otherwise the time window $[e_i, s_{i+1}]$ can not be covered. Thus, the RTW $[s_i, e_i]$ is redundant, which means this solution is not optimal. By this contradiction, the left part of inequality (6) is proved.

For the right part, we know $e_{m-1} \leq s_{m+1}$ is true. Assuming that $e_i > s_{i+2}$ for each $i \in [1, m-2]$, then in chronological order, the UTWs of users $i, i+1, i+2$ could be represented as

$$s_i \cdots s_{i+1} \cdots s_{i+2} \cdots e_i \cdots (e_{i+1}) \cdots e_{i+2} \cdots (e_{i+1})$$

We know that the UTW $[s_{i+2}, e_{i+2}]$ is redundant if e_{i+2} is in the left of e_i, thus the order of the three UTWs is right. But the position of e_{i+1} is uncertain, this could be considered according to the relationship with e_{i+2} into two cases:

- Case 1: If $e_{i+1} < e_{i+2}$, we can see that the UTW $[s_{i+1}, e_{i+1}]$ would be covered by the other two UTWs, thus $[s_{i+1}, e_{i+1}]$ is redundant.

[1]Let $s_{m+1} = T_e$

- Case 2: If $e_{i+1} \geq e_{i+2}$, the UTW $[s_{i+2}, e_{i+2}]$ would be redundant because it is covered by $[s_{i+1}, e_{i+1}]$.

Overall, the solution is not optimal, either. By this contradiction, the left part is proved so that inequality (6) is established. Then, we could construct a path in G_I as

$$s_1 \to e_1 \to s_2 \to e_2, \ldots, s_m \to e_m$$

The edge $s_i \to e_i$ represents the UTW $[s_i, e_i]$ of user i. The edge $e_i \to s_{i+1}$ represents the subpath from e_i to s_{i+1}. Since $e_i \geq s_{i+1}$, these subpaths consists of the dummy users when $e_i < s_{i+1}$ and doesn't include any users when $e_i = s_{i+1}$. According to inequality (6), these subpaths don't have overlap between them. Therefore, this path transformed by the optimal solution is one existent path from v_0 to v_k in G_I. Besides, the length of this path is just the total cost of the solution.

Also, we next prove that this path is the shortest path by contradiction. Assuming that it isn't the shortest, we denote the shortest path by $\mathcal{SP}$. Then we sort the non-dummy users as $1, 2, \ldots, m'$, in the order that $\mathcal{SP}$ passes their corresponding edges. Thus SP becomes

$$s_1 \to e_1 \to s_2 \to e_2, \ldots, s_{m'} \to e_{m'}$$

Similarly, the edge $s_i \to e_i$ represents user i's UTW. The edge $e_i \to s_{i+1}$ represents the subpath from e_i to s_{i+1} or empty. There exist only the dummy edges in these subpaths, so we have $e_i \geq s_{i+1}$. Due to that $s_1 = T_s, e_{m'} = T_e$, the users $1, 2, \ldots, m'$ could form a feasible user group for the CMUS problem, whose cost is lower than the original optimal solution. This produces a contradiction, thus Theorem 1 is true.

For example in Fig. 1, the solution is users $1, 2, 3$, which is corresponding to the path $v_1 \to v_3 \to v_2 \to v_4 \to v_5$ in the graph G_I.

In this paper, we compute the shortest path by Dijkstra's algorithm, whose time complexity is $O(|E_I| + |V_I| \log |V_I|)$ in graph G_I. We can see that $|V_I| \leq 2|N|$,
$|E_I| \leq 2|N| - 1$, so the time complexity of our method is $O(|N| \log |N|)$ in the worst case. Thus, compared with the complexity of $O(|N|^2)$ in [23], our new proposed method would be better to handle the large-scale crowdsensing tasks.

Given this method, the maximum social welfare in the auction could be computed by

$$\mathcal{SW}(\mathcal{N}) = u(\mathcal{W}) - d(v_0, v_k, G_I) \tag{7}$$

where $d(v_0, v_k, G_I)$ is the cost of the shortest path from v_0 to v_k in G_I. Note that $d(v_0, v_k, G_I) = \infty$ if there exists no path from v_0 to v_k.

B. VCG mechanism

We state the famous VCG mechanism briefly in this section. VCG mechanism selects the optimal user group as the winner set such that it is efficient. For each user i in the winner set, its utility is given by

$$u_i^{VCG} = \mathcal{SW}(\mathcal{N}) - \mathcal{SW}(\mathcal{N} - i) \tag{8}$$

where $\mathcal{SW}(N-i)$ is the social welfare if user i's bid is ignored.

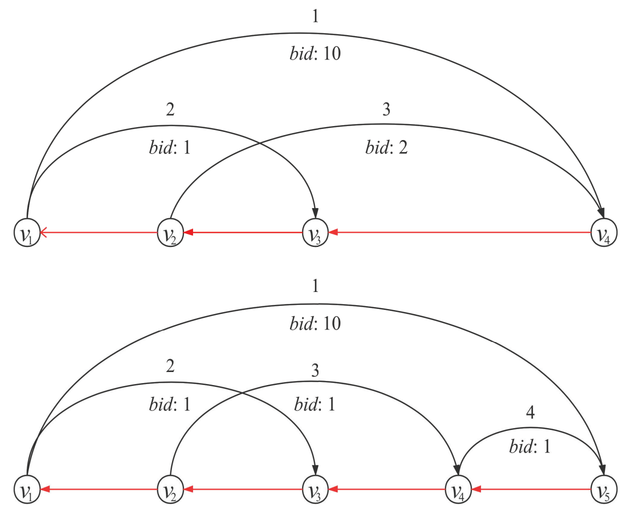

Fig. 2. False-name manipulation in VCG mechanism. Top: the truthful bid profile. Bottom: the false-name bid profile.

According to Eq. (7), the VCG payment to winner i is

$$p_i^{VCG} = -d(v_0, v_k, G_I) + d(v_0, v_k, G_I - i) + b_i \tag{9}$$

where $G_I - i$ stands for the graph that removes the edge of user i in G_I. Compared with G_I, $G_I - i$ lacks one edge, thus we have $d(v_0, v_k, G_I) \leq d(v_0, v_k, G_I - i)$. According to Eq. (9), $p_i^{VCG} \geq b_i$ such that VCG mechanism satisfies individual rationality. The VCG mechanism is also dominant strategy truthful. Note that in Eq. (9), i's bid b_i also appears in $d(v_0, v_k, G_I)$, so it can be cancelled with the last term. The VCG payment is thus not dependent on user i's bid price b_i. Therefore, it is a weakly dominant strategy for users to report their true costs: $\forall i \in N, b_i = c_i$.

VCG mechanism is the unique mechanism that guarantees efficiency, individual rationality, and truthfulness. However, it is vulnerable to false-name manipulation, which may cause a large overpayment for the platform.

C. Problems with VCG mechanism

We demonstrate the problems of VCG mechanism through an example as Fig. 2. At the top of Fig. 2, there are three users $1, 2, 3$ with the cost of $10, 1, 2$. The selected winners are users 2 and 3, and their VCG payments are 8 and 9, respectively. If user 3 bids with two different fake names $3, 4$, like the bottom of Fig. 2, the total payment for user 3 will be $p'_3 + p'_4 = 7 + 7 = 14$ with the same sensing task. Thus, user 3 obtains more profit by using false names, which forms a false-name manipulation.

Besides, the VCG mechanism often leads to a high overpayment. At the top of Fig. 2, the minimum cost is 4 but the final VCG payment is 17, which brings a high overpayment for the platform. These problems make VCG mechanism difficult to apply in the crowdsensing market, thus we introduce the core-selecting mechanism to address these problems.

IV. Core-selecting mechanism in the mobile crowdsensing market

In this section, we propose the core-selecting mechanism for the time window coverage crowdsensing tasks. Firstly, we model the reverse auction as a cooperative game $(\mathcal{N}, \mathcal{SW})$ and use the core as our solution concept.

$\mathcal{N} = \mathcal{P} \cup N$ represents all the players in this game. The dummy users are involved by default. For an arbitrary coalition $L \subset \mathcal{N}$, its coalition value is defined as the maximum social welfare in the auction held by players in L. It is computed by

$$\mathcal{SW}(L) = \begin{cases} u(\mathcal{W}) - d(v_0, v_k, G_I^L) & \text{if} \quad \mathcal{P} \in L \\ 0 & \text{if} \quad \mathcal{P} \notin L \end{cases} \tag{10}$$

where G_I^L is the graph created by L. Note that if a coalition does not include the platform, then its coalition value equals 0. We can now define the concept of the core. An outcome is in the core when the total utility of $\mathcal{N}$ equals $\mathcal{SW}(\mathcal{N})$, and the total utility to every coalition L is at least $\mathcal{SW}(L)$.

Definition 1 (Core outcome): A core outcome in the auction is an allocation and payment profile such that the utility profile $U = \{u_1, \ldots, u_n\}$ satisfies

$$(C0) : \sum_{i \in \mathcal{N}} u_i = \mathcal{SW}(\mathcal{N}) \tag{11}$$

$$(C1) : \sum_{i \in L} u_i \geq \mathcal{SW}(L) \tag{12}$$

Given a bid profile B, we let $core(B)$ be the total set of the core outcomes, which is our solution concept. It is worth noting that in our setting, the first-price (pay what you bid) payment vector is always a core outcome, and thus the core is always non-empty. Then we can define the core-selecting mechanism.

Definition 2 (Core-selecting mechanism): In the crowdsensing market, a mechanism is core-selecting if (1) it selects the optimal user group; and (2) the payment vector P is computed so that $P \in core(B)$.

A. Theoretical results

According to the above definition, we can see that core-selecting mechanism guarantees RTW feasibility and efficiency. Let $L = \{i\}$ in constraint $(C1)$, and we have

$$u_i \geq 0 \quad \forall i \in N \tag{13}$$

This constraint means the core-selecting mechanism also satisfies individual rationality. Next, we introduce two theorems for our mechanism. The first is that core-selecting mechanism is always more frugal than VCG mechanism, that is, core payments are never higher than VCG payments.

Theorem 2: In the crowdsensing market, the payment to user i in core-selecting mechanism is no more than that in VCG mechanism. That is, if $p_i \in core(B)$, then we have

$$p_i \leq p_i^{VCG} \quad \forall i \in N$$

Proof 2: By subtracting the constraint $(C1)$ from $(C0)$, we could get,

$$\sum_{i \in \mathcal{N}} u_i - \sum_{i \in L} u_i \leq \mathcal{SW}(\mathcal{N}) - \mathcal{SW}(L) \tag{14}$$

Let $L = \mathcal{N} - i$, and we have

$$u_i \leq \mathcal{SW}(\mathcal{N}) - \mathcal{SW}(\mathcal{N} - i) \tag{15}$$

Note that $u_i = p_i - b_i$, thus we have $p_i \leq p_i^{VCG}$.

Therefore, the revenue for the platform is no less than VCG mechanism with the same bid profile. The second theorem is that core-selecting mechanism is robust against false-name manipulation.

Theorem 3: In the core-selecting mechanism for the crowdsensing market, no user can earn more than her VCG utility by generating false-name bids.

Proof 3: Let $S \subset N$ be a coalition of users, they might be the false names generated by one user. The condition requires that these players can not obtain more utility than if they were to submit their merged bid in the VCG mechanism, which means $\sum_{i \in S} u_i \leq u_S^{VCG}$, $\forall S \subset N$.

Note that the VCG utility of S is

$$u_S^{VCG} = \mathcal{SW}(\mathcal{N}) - \mathcal{SW}(\mathcal{N} - S) \tag{16}$$

Then this condition becomes

$$\sum_{i \in S} u_i \leq \mathcal{SW}(\mathcal{N}) - \mathcal{SW}(\mathcal{N} - S) \tag{17}$$

Since the core-selecting mechanism is efficient, we have $\mathcal{SW}(\mathcal{N}) = \sum_{i \in \mathcal{N}} u_i$. Then, Eq. (17) is equivalent to

$$\sum_{i \in \mathcal{N} - S} u_i \geq \mathcal{SW}(\mathcal{N} - S) \tag{18}$$

Eq. (18) is just a constraint of $(C1)$ where $L = \mathcal{N} - S$. Thus, the condition is satisfied for arbitrary coalition S in core-selecting mechanism.

Therefore, core-selecting mechanism is false-name-proof. So far we have assumed that bids are truthful, then we will study how to design the payment rule to maximize users' intention of truthful bidding in Section V.

V. Payment rule

Note that there may be many feasible payment vectors in the type of core-selecting mechanism, thus In this section we state how to choose a specific payment vector to make up for the untruthfulness.

A. VCG-nearest payment rule

Firstly, to evaluate users' incentive to deviate from truthful reporting, we introduce the definition of the incentive profile for a core-selecting mechanism.

Definition 3: The incentive profile for a core-selecting auction mechanism at bid profile B is $\{\theta_i(B)\}$ where $\theta_i(B)$ is i's maximum utility gain by deviating from truthful reporting.

The idea is to minimize these incentives to deviate from truthful bidding, subject to the core-selecting rule. We use a Pareto-like criterion, that is, a core-selecting mechanism

$\mathcal{M}$ provides optimal incentives, if there is no core-selecting mechanism $\mathcal{M}'$ such that for every user i, $\theta_i^{\mathcal{M}'}(B) \leq \theta_i^{\mathcal{M}}(B)$ with strict inequality for some users.

Day and Milgrom [11] proved that a core-selecting mechanism provides optimal incentives if and only if it chooses a user-Pareto-optimal outcome.

Definition 4 (User-Pareto-optimal core outcome): A core outcome is user-Pareto-optimal if there is no other core outcome weakly preferred by every user in the winner set.

According to the definition of user-Pareto-optimality, we have the following theorem.

Theorem 4: A core outcome is user-Pareto-optimal if it produces the maximum total payment in the core.

Proof 4: When the total payment is the maximum in the core, there exists no core outcome that could improve one's utility without hurting others' utilities in the winner set. Thus, it is a user-Pareto-optimal core outcome.

Therefore, we use the maximum total payment as the final payment to ensure users' incentives. However, there is still a lack of precision because these points are not unique. A simple method is that among all the core points with maximum total payment, selecting the one that minimizes the distance from one reference point. In this paper, we adopt the VCG-nearest rule, which minimizes the Euclidean distance from VCG payment point [13]. For a payment vector P, denote the distance from VCG payment by $D(P, P^{VCG})$, which is

$$D(P, P^{VCG}) = \sum_{i \in S_w} (p_i - p_i^{VCG})^2 \tag{19}$$

Therefore, the final result is to compute the VCG-nearest payment vector based on the maximum total payment. We will apply the method of core constraint generation (CCG) to solve this problem in Section V-B.

B. Computation of VCG-neatest payment

After solving the winner determination problem, the winner set S_w is fixed. Then we have to consider the constraints in $(C1)$ to get the final payment result. However, in an auction with n users, the number of constraints in $(C1)$ is $2^{n+1} - 1$, which is insufferable for the platform.

Thus, we reorganize the core constraint set format at first.

1) Core constraint set formulation: Recall the constraint in $(C1)$,

$$\sum_{i \in L} u_i \geq \mathcal{SW}(L) \tag{20}$$

For the case $\mathcal{P} \notin L$, the constraint becomes

$$\sum_{i \in L} u_i \geq 0 \tag{21}$$

This constraint could be derived by the individual rational constraint $p_i \geq b_i$. Thus, we only need to consider the remaining constraints where $\mathcal{P} \in L$. According to the definition in Eq. (10), these constraints become

$$\sum_{i \in L} u_i \geq u(\mathcal{W}) - d(v_0, v_k, G_I^L) \tag{22}$$

Notice that $u_i = 0, \forall i \notin S_w \cup \{\mathcal{P}\}$, so we have

$$\begin{aligned} \sum_{i \in L} u_i &= u_{\mathcal{P}} + \sum_{i \in L \cap S_w} u_i \\ &= u(\mathcal{W}) - \sum_{i \in S_w} p_i + \sum_{i \in L \cap S_w} (p_i - b_i) \\ &= u(\mathcal{W}) - \sum_{i \in S_w \setminus L} p_i + \sum_{i \in L \cap S_w} b_i \end{aligned} \tag{23}$$

Bring Eq. (23) into Eq. (22), we obtain

$$\sum_{i \in S_w \setminus L} p_i \leq d(v_0, v_k, G_I^L) - \sum_{i \in L \cap S_w} b_i \tag{24}$$

Eq. (24) is the constraint format we would use to compute the final VCG-nearest payment. In this format, the left part is the payment variable for the final result, and the right is the fixed quantities. Note that L is an arbitrary nonempty subset satisfying that $L \subset \mathcal{N}$ and $\mathcal{P} \in L$, thus the number of constraints is $2^{|N|} - 1$.

2) CCG-TWC algorithm: Setting $\beta_L = d(v_0, v_k, G_I^L) - \sum_{i \in L \cap S_w} b_i$, and denoting the vector of all β_L values as $\boldsymbol{\beta}$, we can reformulate Eq. (24) as

$$\boldsymbol{p}\boldsymbol{A} \leq \boldsymbol{\beta}$$

where $\boldsymbol{A}$ is a $|S_w| \times (2^{|N|} - 1)$ matrix. In each column of $\boldsymbol{A}$, the i-th entry equals 0 if winner i is in set L and equals 1 otherwise. $\boldsymbol{p}$ is the payment vector for the winners. Then we can compute the maximum total payment by solving the following linear program:

$$\begin{aligned} LP: \quad & \alpha = \max \boldsymbol{p} \times \mathbf{1} \\ s.t. \quad & \boldsymbol{p}\boldsymbol{A} \leq \boldsymbol{\beta} \\ & \boldsymbol{p} \geq \boldsymbol{b} \end{aligned} \tag{25}$$

where $\boldsymbol{b}$ is the bid vector corresponding to the payment vector $\boldsymbol{p}$. After getting the maximum total payment α, we need to minimize the Euclidean distance from the VCG point subjecting to the total payment of α. Thus, we can formulate a quadratic program to determine the final payment vector $\boldsymbol{p}$:

$$\begin{aligned} QP: \quad & \min(\boldsymbol{p} - \boldsymbol{p^{VCG}})(\boldsymbol{p} - \boldsymbol{p^{VCG}})^T \\ s.t. \quad & \boldsymbol{p}\boldsymbol{A} \leq \boldsymbol{\beta} \\ & \boldsymbol{p} \geq \boldsymbol{b} \\ & \boldsymbol{p} \times \mathbf{1} = \boldsymbol{\alpha} \end{aligned} \tag{26}$$

Solving the QP (26) and we could get the final VCG-nearest payment vector. Throughout the optimization problem, the number of the inequality constraints is $2^{|N|} + |S_w| - 1$. Among them, the individual rational constraints $\boldsymbol{p} \geq \boldsymbol{b}$ are easy to obtain. For the remaining constraints in the format (24), each requires to run the shortest path algorithm once to obtain the value of $d(v_0, v_k, G_I^L)$. Thus, the shortest path algorithm needs to be run $2^{|N|} - 1$ times, which is formidable in practice.

A core-constraint generation (CCG) procedure can be employed to reduce the complexity. Instead of enumerating all the possibilities of non-empty coalitions L, it finds blocking coalitions effectively by reducing payments from the VCG payment point. This iterative algorithm actually continues to reduce the payments of the winners, until there is no blocking coalition, reaching a core outcome. Each blocking coalition is corresponding to a constraint in (24). Finally, after adding all the necessary constraints, there is no blocking coalition, and the generated payment vector satisfies the total payment maximization rule and hence the VCG-nearest rule.

Algorithm 1 Core Constraint Generation for the time window coverage crowdsensing tasks (CCG-TWC)

Require: Directed graph $G_I = (V_I, E_I, W_I)$; source vertex v_0; target vertex v_k; the winner set S_w.

Ensure: VCG-nearest payment vector

    # 1. Solve the LP **(25)**

1: $t \leftarrow 0$

2: Compute p_i^{VCG}, $p_i^t \leftarrow p_i^{VCG}$

3: CCG-SET $\leftarrow \{p_i \leq p_i^t, p_i \geq b_i | i \in S_w\}$

    # CCG-SET is the constraint set for CCG-TWC.

4: $\forall i \in S_w, w_i \leftarrow p_i^t$, thus the graph G_I^t is created.

5: Compute the winner set S_w^t in G_I^t by Dijkstra's algorithm.

6: **while** $\sum_{i \in S_w} p_i^t > \sum_{i \in S_w^t} w_i$ **do**

7:     $t \leftarrow t + 1$

8:     $z \leftarrow S_w \cap S_w^t$

9:     CCG-SET $\leftarrow$ CCG-SET $\cup \{\sum_{i \in S_w \setminus z} p_i \leq \sum_{i \in S_w^t \setminus z} w_i\}$

10:     Solve the LP and get payment $P^t = (p_1^t, p_2^t, \ldots, p_m^t)$

11:     $\forall i \in S_w$, $w_i \leftarrow p_i^t$, compute the new winner set S_w^t.

12: $\alpha = \sum_{i \in S_w} p_i$

    # 2. Solve the QP **(26)**

13: $t \leftarrow 0$

14: CCG-SET $\leftarrow$ CCG-SET $\cup \{\sum_{i \in S_w} p_i = \alpha\}$

15: Solve the QP and get a payment $P^t = (p_1^t, p_2^t, \ldots, p_m^t)$.

16: $\forall i \in S_w, w_i \leftarrow p_i^t$, compute the new winner set S_w^t.

17: **while** $\sum_{i \in S_w} p_i^t > \sum_{i \in S_w^t} w_i$ **do**

18:     $t \leftarrow t + 1$

19:     $z \leftarrow S_w \cap S_w^t$

20:     CCG-SET $\leftarrow$ CCG-SET $\cup \{\sum_{i \in S_w \setminus z} p_i \leq \sum_{i \in S_w^t \setminus z} w_i\}$

21:     Solve the QP and get payment $P^t = (p_1^t, p_2^t, \ldots, p_m^t)$

22:     $\forall i \in S_w$, $w_i \leftarrow p_i^t$, compute the new winner set S_w^t.

23: **return** $(p_1^t, p_2^t, \ldots, p_m^t)$

Based on this method, we propose a efficient two-stage algorithm called CCG-TWC to compute the VCG-nearest payment vector. The pseudo code is shown in Alg. 1. The first stage is solving the LP (25) to get the maximum total payment α, which is corresponding to step 1-12. The second stage is solving the QP (26) to get the final vector, which is step 13-23.

VI. Simulation Results

We conduct thorough simulations to investigate the performance of the core-selecting mechanism. We first evaluate our mechanism based on the dataset of real-world traces. Then the simulations based on the randomly generated users are conducted in order to reveal the impacts of the key parameters. We measure the number of winners, the total payment, and

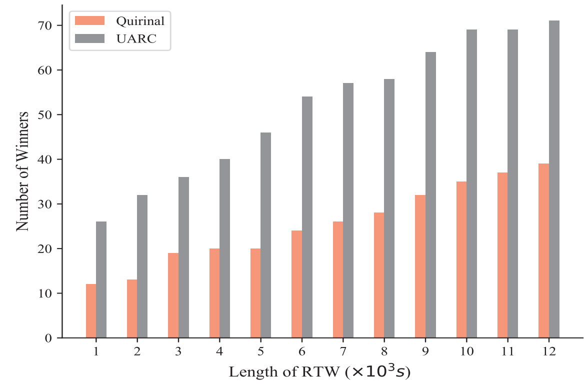

Fig. 3. Taxis involved at different end time of RTWs.

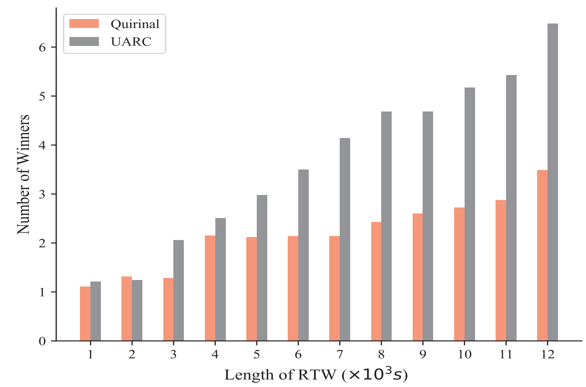

Fig. 4. Number of winners involved at different end time of RTWs.

the running time in each instance. The bid price is uniformly distributed in $[1, 100]$ in our simulations. The experiments are run on a Mac os machine with Intel Core i5-5350U CPU and 8 GB memory. All the results are averaged over 1,000 runs.

A. Evaluation based on real traces

We use the real mobility traces of 370 taxis that report their positions every 15 seconds around the city of Rome from 2014-02-01 to 2014-03-02[29]. In this paper, we use the traces on 2014-02-01. We consider that the time window coverage tasks are launched in some specific geographical areas. We choose two places, Quirinal Palace (Quirinal) and the University of Arkansas Rome Center (UARC), as the centers of the specific circular areas with a radius of 1 km. We assume that a smartphone is carried by the passenger or the driver of each taxi. For each circular area, we fix the maximum RTW and measure the performance with different end times. The RTWs of Quirinal area and UARC area are [09:00:00, 12:20:00] and [20:00:00, 23:20:00], respectively, both with length of 12,000 seconds. The time unit is set as 10 seconds. The users of each area are taxis who are in this area during the RTW and we select the maximum length time interval in the RTW of each taxi as the UTW. The number of taxis involved with different RTWs is shown in Fig. 3.

The average number of winners with different RTWs is shown in Fig. 4, we can see that the number of winning taxis

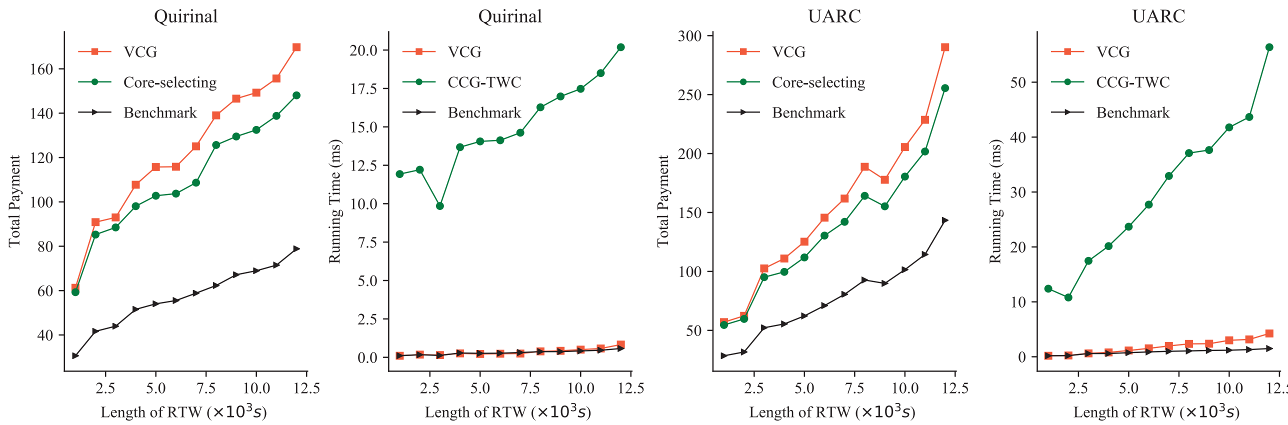

Fig. 5. Performance of Core-selecting mechanism with different end time of RTWs. From left to right: (1) Total payment in Quirinal. (2) Running time in Quirinal. (3) Total payment in UARC. (4) Running time in UARC.

increases with the increase of $|\mathcal{W}|$ because the platform has to recruit more users to accomplish the sensing tasks in large RTWs.

B. Performance based on real traces

We first study the payment performance of our mechanism. The result is shown in Fig. 5. We can see that the total payment increases when $|\mathcal{W}|$ goes up in Quirinal and UARC. The total payment in core-selecting mechanism is always lower than that in VCG mechanism in the two areas and the gap between them increases as the RTW goes up. We also compute the benchmark of the CMUS problem for each RTW. The performance measure we used is the overpayment factor, which is defined as the ratio between its total payment and the true cost in the benchmark:

$$OF = \frac{\sum_{i \in S_w} p_i}{\sum_{i \in S_w} b_i} \tag{27}$$

The overpayment factors of core-selecting mechanism are 1.93 and 1.79 in Quirinal area and UARC area on average, compared with 2.15 and 2.01 for VCG mechanism on the same true costs. Thus, core-selecting mechanism is more frugal than VCG mechanism.

For the time performance, as shown in Fig. 5, the running time of CCG-TWC algorithm increases when $|\mathcal{W}|$ goes up because the running time depends on the number of winners. In general, The average running time of CCG-TWC is 15.0 ms and 30.1 ms in Quirinal area and UARC area, respectively. Its running time is bounded by 20.2 ms and 56.4 ms respectively when $|\mathcal{W}| = 12,000s$. In contrast, the running time of benchmark and VCG mechanism nearly remain zero, while VCG running time may increase slightly from zero to 5.6 ms in UARC. Their running times are negligible compared with that of CCG. However, the running time of CCG-TWC algorithm is still in an acceptable range for the real applications.

C. Impact of the key parameters

There are three common key parameters: the number of users n, the length of RTW $|\mathcal{W}|$, and the upper limit ratio of UTW δ. For our simulations, the UTW length of each bid is uniformly distributed in the interval $[1, \delta|\mathcal{W}|]$. The UTWs are placed in the whole $\mathcal{W}$ with uniform distribution. We set $n = 1000, |\mathcal{W}| = 100, \delta = 0.2$ as the default values and vary them for exploring the impacts of these parameters. The impact of $|\mathcal{W}|$ has been investigated on the real traces. Thus we measure the impacts of other key parameters here.

1) Impact of the upper limit ratio of UTW: The length of UTWs depicts the interest and suitability of users for participating in mobile crowdsensing. We set the UTW length of each bid in $[1, \delta|\mathcal{W}|]$ with uniform distribution, and then vary δ from 0.1 to 0.28. As shown in the top of Fig.6, the number of winners and the total payment decrease dramatically with increasing δ. This is because the platform can select fewer users to perform the tasks when each UTW could be longer. The total payment in core-selecting mechanism is lower than that of VCG auction in all cases. Besides, the overpayment ratios of core-selecting mechanism are 1.70 on average, compared with 1.85 of VCG mechanism. This verifies the frugality of core-selecting mechanism. The running time of CCG-TWC decreases sharply with the increasing δ, from 170.6 ms to 53.4 ms, with an average of 87.7 ms. In contrast, the running time of VCG decreases slightly from 25.1 ms to 13.4 ms, with an average of 17.6 ms. The benchmark for the winner determination algorithm is only 2.5 ms on average.

2) Impact of the number of users: To investigate the scalability of our mechanism, we vary the number of users from 1,000 to 2,000. The bottom of Fig.6 shows the impact of the number of users on the performance of core-selecting mechanism. The number of winners decreases slightly when users go up, from 8.97 to 8.55. We can see that the total payment goes down with increasing number of users since the platform can find more cheap users in the more competitive market. The total payment of core-selecting mechanism decreases sharply, from 58.44 to 31.23. The payment of VCG mechanism also drops from 63.22 to 33.77. Through all the cases, the total payment of core-selecting mechanism is always lower than that of VCG mechanism, and the overpayment ratios of core-

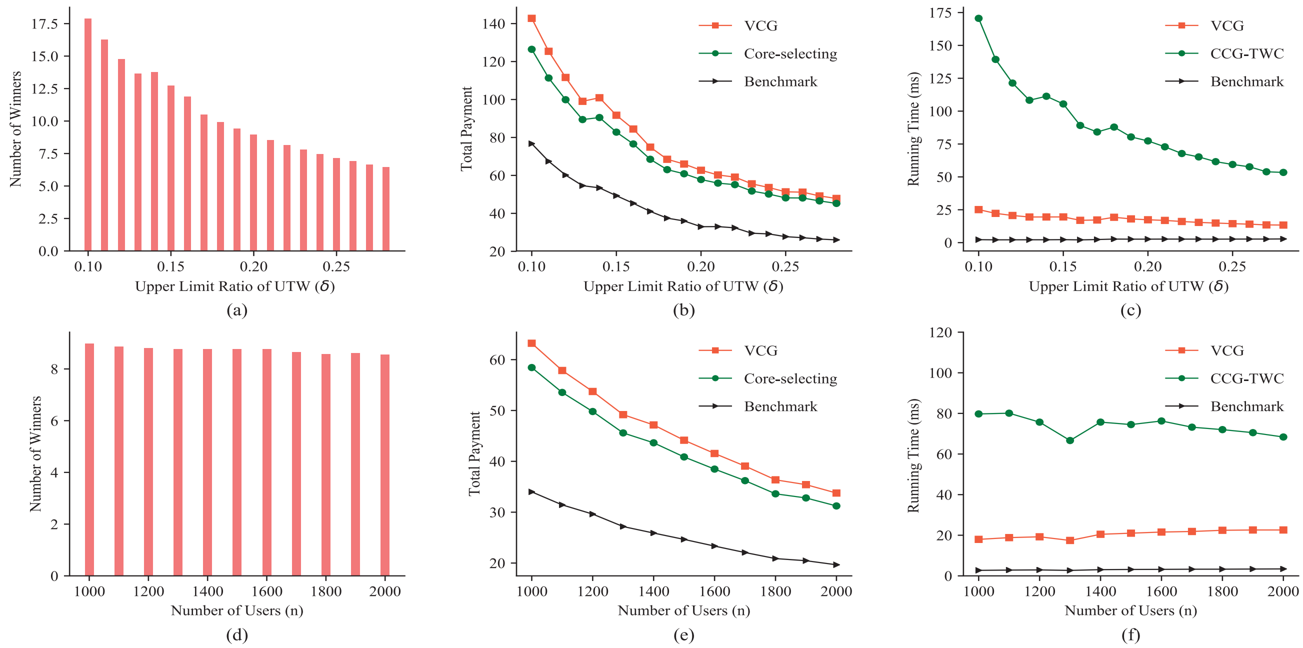

Fig. 6. Top: Impact of the upper limit ratio of user time window δ. (a) Winners. (b) Total payment. (c) Running time. Bottom: Impact of the number of users n. (d) Winners. (e) Total payment. (f) Running time.

selecting and VCG are 1.66 and 1.80 on average. For the time performance, all the running times remain steady with the increasing user scale. The running time of CCG-TWC algorithm is 65.4 ms on average, compared with 20.5 ms and 3.1 ms for VCG mechanism and the benchmark, respectively. Although the complexity of core-selecting mechanism is higher, its running time is the same order of magnitude as VCG in this evaluation.

Overall, we can see that core-selecting mechanism is scalable since it could achieve higher revenue and nearly constant running time with the increasing users. Meanwhile, it is false-name-proof so the platform could protect her revenue from the false-name bids, which VCG mechanism can not achieve.

VII. Conclusion

In this paper, we investigate the false-name-proof mechanism for time window coverage tasks in mobile crowdsensing. We model the mobile crowdsensing system as a reverse auction and formulate the CMUS problem. Then, we propose a new algorithm to solve the CMUS problem, which has a better complexity. After that, we apply the core-selecting mechanism to time window coverage tasks. Through rigorous theoretical analyses, we demonstrate that the proposed mechanism achieves RTW feasibility, efficiency, individual rationality, false-name-proofness. Furthermore, we adopt a VCG-nearest payment rule to minimize the incentive of untruthfulness. Finally, we design the CCG-TWC algorithm to solve the computation problem. The results of extensive simulation show that our mechanism can reduce the total payment to 89% of that in VCG mechanism on average, and it is scalable by using CCG-TWC algorithm.

In future work, we will consider the more complex scenarios, where each user's bid includes multiple time windows. On the other hand, we will also study the relationship between constraints to accelerate the CCG-TWC algorithm.

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References

[1] N. Heuveldop *et al.*, "Ericsson mobility report," *Ericsson AB, Technol. Emerg. Business, Stockholm, Sweden, Tech. Rep. EAB-17*, vol. 5964, 2017.

[2] R. K. Ganti, F. Ye, and H. Lei, "Mobile crowdsensing: current state and future challenges," *IEEE communications Magazine*, vol. 49, no. 11, pp. 32–39, 2011.

[3] P. Zhou, Y. Zheng, and M. Li, "How long to wait? predicting bus arrival time with mobile phone based participatory sensing," in *Proceedings of the 10th international conference on Mobile systems, applications, and services*, 2012, pp. 379–392.

[4] R. K. Rana, C. T. Chou, S. S. Kanhere, N. Bulusu, and W. Hu, "Ear-phone: an end-to-end participatory urban noise mapping system," in *Proceedings of the 9th ACM/IEEE international conference on information processing in sensor networks*, 2010, pp. 105–116.

[5] J. Xu, J. Xiang, and D. Yang, "Incentive mechanisms for time window dependent tasks in mobile crowdsensing," *IEEE Transactions on Wireless Communications*, vol. 14, no. 11, pp. 6353–6364, 2015.
[6] W. Vickrey, "Counterspeculation, auctions, and competitive sealed tenders," *The Journal of finance*, vol. 16, no. 1, pp. 8–37, 1961.
[7] E. H. Clarke, "Multipart pricing of public goods," *Public choice*, vol. 11, no. 1, pp. 17–33, 1971.
[8] T. Groves, "Incentives in teams," *Econometrica: Journal of the Econometric Society*, pp. 617–631, 1973.
[9] L. M. Ausubel and P. R. Milgrom, "Ascending auctions with package bidding," *The BE Journal of Theoretical Economics*, vol. 1, no. 1, 2002.
[10] M. Yokoo, Y. Sakurai, and S. Matsubara, "The effect of false-name bids in combinatorial auctions: New fraud in internet auctions," *Games and Economic Behavior*, vol. 46, no. 1, pp. 174–188, 2004.
[11] R. Day and P. Milgrom, "Core-selecting package auctions," *international Journal of game Theory*, vol. 36, no. 3-4, pp. 393–407, 2008.
[12] R. W. Day and S. Raghavan, "Fair payments for efficient allocations in public sector combinatorial auctions," *Management science*, vol. 53, no. 9, pp. 1389–1406, 2007.
[13] R. W. Day and P. Cramton, "Quadratic core-selecting payment rules for combinatorial auctions," *Operations Research*, vol. 60, no. 3, pp. 588–603, 2012.
[14] P. Cramton, "Spectrum auction design," *Review of industrial organization*, vol. 42, no. 2, pp. 161–190, 2013.
[15] Y. Zhu, B. Li, H. Fu, and Z. Li, "Core-selecting secondary spectrum auctions," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 11, pp. 2268–2279, 2014.
[16] J. Hartline, N. Immorlica, M. R. Khani, B. Lucier, and R. Niazadeh, "Fast core pricing for rich advertising auctions," in *Proceedings of the 2018 ACM Conference on Economics and Computation*, 2018, pp. 111–112.
[17] O. Karaca and M. Kamgarpour, "Core-selecting mechanisms in electricity markets," *IEEE Transactions on Smart Grid*, vol. 11, no. 3, pp. 2604–2614, 2019.
[18] L. Zhang, H. Chen, J. Wu, C.-J. Wang, and J. Xie, "False-name-proof mechanisms for path auctions in social networks," in *Proceedings of the Twenty-second European Conference on Artificial Intelligence*, 2016, pp. 1485–1492.
[19] H. Cheng, L. Zhang, Y. Zhang, J. Wu, and C. Wang, "Optimal constraint collection for core-selecting path mechanism," in *Proceedings of the 17th international conference on autonomous agents and multiagent systems*, 2018, pp. 41–49.
[20] H. Cheng, W. Zhang, Y. Zhang, L. Zhang, J. Wu, and C. Wang, "Fast core pricing algorithms for path auction," *Autonomous Agents and Multi-Agent Systems*, vol. 34, no. 1, pp. 1–37, 2020.
[21] A. Capponi, C. Fiandrino, B. Kantarci, L. Foschini, D. Kliazovich, and P. Bouvry, "A survey on mobile crowdsensing systems: Challenges, solutions, and opportunities," *IEEE communications surveys & tutorials*, vol. 21, no. 3, pp. 2419–2465, 2019.
[22] J. Xu, J. Xiang, and Y. Li, "Incentivize maximum continuous time interval coverage under budget constraint in mobile crowd sensing," *Wireless Networks*, vol. 23, no. 5, pp. 1549–1562, 2017.
[23] J. Xu, J.-R. Fu, D.-J. Yang, L.-J. Xu, L. Wang, and T. Li, "Fimi: A constant frugal incentive mechanism for time window coverage in mobile crowdsensing," *Journal of Computer Science and Technology*, vol. 32, no. 5, pp. 919–935, 2017.
[24] J. Lin, M. Li, D. Yang, G. Xue, and J. Tang, "Sybil-proof incentive mechanisms for crowdsensing," in *IEEE INFOCOM 2017-IEEE Conference on Computer Communications*. IEEE, 2017, pp. 1–9.
[25] J. Lin, M. Li, D. Yang, and G. Xue, "Sybil-proof online incentive mechanisms for crowdsensing," in *IEEE INFOCOM 2018-IEEE Conference on Computer Communications*. IEEE, 2018, pp. 2438–2446.
[26] L. Jiang, X. Niu, J. Xu, Y. Wang, Y. Wu, and L. Xu, "Time-sensitive and sybil-proof incentive mechanisms for mobile crowdsensing via social network," *IEEE Access*, vol. 6, pp. 48 156–48 168, 2018.
[27] X. Zhang, G. Xue, D. Yang, and R. Yu, "A sybil-proof and time-sensitive incentive tree mechanism for crowdsourcing," in *2015 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2015, pp. 1–6.
[28] M. Yokoo, "Characterization of strategy/false-name proof combinatorial auction protocols: price-oriented, rationing-free protocol," in *IJCAI*. Citeseer, 2003, pp. 733–742.
[29] R. Amici, M. Bonola, L. Bracciale, A. Rabuffi, P. Loreti, and G. Bianchi, "Performance assessment of an epidemic protocol in vanet using real traces." in *MoWNet*, 2014, pp. 92–99.