Multi-round Bidding Strategy Based on Game Theory for Crowdsensing Task

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Abstract. Crowdsensing is a new activity form gathering a suitable set of users to collectively finish a sensing task. It has attracted great attention because it provides an easy-access sensing scheme and reduces the sensing cost compared with the traditional sensing method. Hence, several crowdsensing platforms have emerged at the right moment, where the requester can publish sensing tasks and the users compete for the winners of the tasks. Thus, there is a multi-round game among users, in which we consider a case that the users bid their available time for the specific sensing tasks, and the purpose of a user is to obtain as many tasks as possible within the available time budget. To this end, we propose a Multi-round Bidding strategy based on Game theory for Crowdsensing task (MBGC), where each user decides the bidding for the specific task according to its trade-off between the expected number of obtained tasks and remaining available time. Then, a user dynamically decides the probabilities to bid different kinds of biddings in the different rounds according to the Nash Equilibrium solution. We conduct extensive simulations to simulate the game process for the crowdsensing tasks. The results show that compared with other bidding strategies, MBGC always achieves the largest number of obtained tasks with an identical time budget.

Keywords: Crowdsensing · Bidding strategy · Game theory · Nash Equilibrium

1 Introduction

Recently, a noticeable phenomenon comes into our daily life: smartphones are widely used by almost everyone. The used devices are smart and powerful enough to sense the characteristics surrounding the environments, such as air quality, temperature as well as traffic congestion. Thanks to this, a novel sensing way called *Mobile Crowdsensing* (MCS) [1] has attracted a lot of attention because it could gather the power of many hand-hold devices to finish a common task.

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For example, the collection of moving cars' speeds could be used to draw a traffic map [2], while reports about available seatings in all the restaurants could be used to instruct the users to make smart dining choice [3].

By now, the works on MCS mainly focus on the following three aspects: task allocation [4], user recruitment [5] and incentive mechanism [6]. It is not difficult to find that, all the above works usually pay attention to the assignments among users and tasks. However, almost all the works assume that either the users prefer to assist in finishing the sensing tasks or they just play game with the requester and not the other users. Actually, this assumption is not suitable because a user may get a higher achievement (higher reward or lower cost) when they do a good trade-off by taking the other users' decisions into consideration. Hence, the problems turn out to be the optimization or game theory problems.

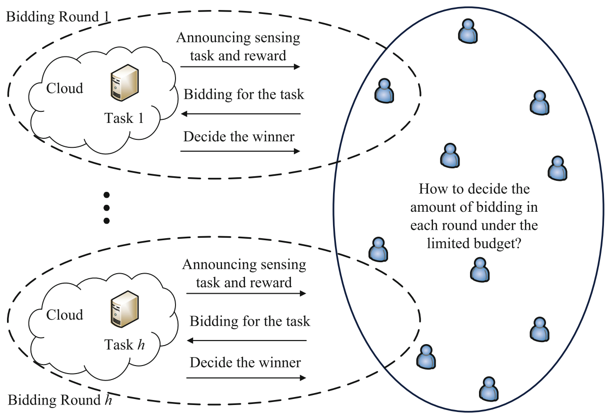

Fig. 1. The multi-round bidding problem description for crowdsensing task. In different bidding rounds, the users should determine the suitable bidding strategy according to the remaining available time.

In this paper, we focus on a multi-round bidding game in MCS. Multi-round means that there are many tasks that can be assigned to the users, and in each round there is only one task to be allocated. Obviously, there may be multi tasks to be allocated at the same time, while we assume that the tasks are independent with each other, and each user could only apply for finishing one time at the same time. Then, for each round the users compete to be the winner of the task. The user with the largest bidding (paying the longest time to the task) could win and get the reward. Generally speaking, people bid a price (money) for the task. However, the total money budget is usually different for different users. Hence, in this paper, we assume that they bid their available time quantum for the task in each round. Obviously, a game exists in the multi-round bidding process. If a user bids a long time quantum for a task, then it will have short remaining available time for the upcoming tasks. At the same time, if a user bids a short time quantum for a task, then it will have a low chance to get the reward of this task. Hence, we should decide a suitable bidding strategy in MCS.

The multi-round bidding problem is described in Fig. 1. There are many users taking part in the bidding game. Also, there are some tasks assigned to the different bidding rounds, each round has only one sensing task. Then the users bid their available time quantum for each task. The task will select the user with the largest bidding as the winner. The purpose of the user is to win as many tasks as possible within the total available time budget in the multi-round game.

The multi-round bidding game is challenging for the following reasons: (1) the user could not know the bidding cases of the other users; (2) the bidding strategy is a dynamic decision-making process, and a user may dynamically change the strategy; (3) it is a game theory problem because there is an obvious trade-off among users' different choices. In order to overcome the above difficulties, we propose a multi-round bidding strategy based on game theory in MCS (MBGC). The main idea of MBGC is to find the Nash Equilibrium, which well solves the trade-off between expected number of obtained tasks and remaining available time. Then according to the Nash Equilibrium, we could dynamically decide the suitable bidding in each round to maximize the total number of obtained tasks.

The main contributions of this paper are briefly summarized as follows:

- We find the Nash Equilibrium in the multi-round bidding game in MCS, and under the condition that the user does not know the cases of other users' biddings.
- We propose a multi-round bidding strategy based on Game Theory in mobile crowdsensing (MBGC), where each user dynamically decides its suitable bidding according to the trade-off between the winning probability and remaining available time, in order to maximize the total reward within the available time budget.
- We conduct extensive simulations based on the actual bidding games. The results show that compared with other bidding strategies, MBGC achieves a larger number of obtained tasks.

The remainder of this paper is organized as follows: The problem description and formulation are introduced in Sect. 2. Section 3 analyzes the multi-round bidding problem and introduces game theory in MCS. The detailed bidding strategies are proposed in Sect. 4. In Sect. 5, we evaluate the performance of MBGC through extensive simulations. We review the related work in Sect. 6. We conclude the paper in Sect. 7.

2 Problem Description and Formulation

In this section, we first detailedly describe the problem to be addressed. Then we translate the problem into mathematical expressions. Finally, the problem is formulated as the game theory problem.

2.1 Problem Description

We first consider the following crowdsensing environment, a task requester publishes a series of tasks at different time. Each task is to sense some data in the specific area, hence it needs the users to spend time finishing the sensing tasks. There is a group of users $U = \{u_1, u_2, \cdots, u_n\}$ participating in the crowdsensing tasks. Then in each round, the users compete with each other to be the winner and obtain the task. In this way, a multi-round bidding problem is formulated. In other words, the users play a game with each other, they bid the available time quantum for each task, and the process to decide a task winner is called a round. We assume that, there is only one winner for each task.

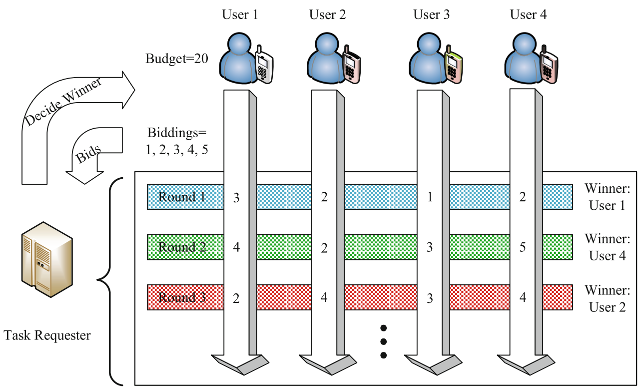

Fig. 2. The multi-round bidding framework including one requester and multiple users. Users should decide a bidding strategy in different bidding rounds in order to obtain as many tasks as possible.

As shown in Fig. 2, there are four users and a task requester. The whole time for completing all the sensing tasks is divided into several rounds, where each task is scheduled in only one round, and also one winner will be selected among the four users. In each round, the requester publishes a sensing task, and all the users bid for the task. The user with the largest bid could win the game. If there are two or more users bidding the same time quantum, which is the longest among all the biddings, then the requester will randomly select a user as the winner. The procedure continues until all the rounds are gone. In this paper, we assume that the total available time budget for all the users is uniform. The main notations are illustrated in Table 1.

2.2 Problem Formulation

We pay attention to the multi-round bidding strategy in MCS as previously described. In each round, the users could bid different kinds of biddings, we assume that there are m kinds of biddings: b_i, $(m \geq i \geq 1)$. So if a user bids a

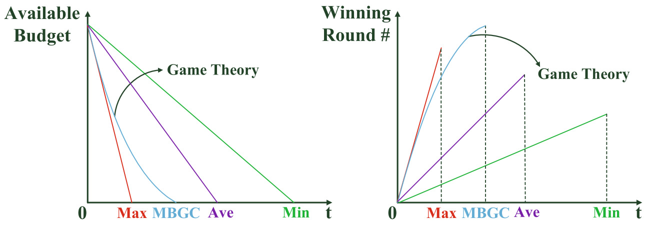

Fig. 3. The changing processes of the available time budget and the number of winning rounds for the four different bidding strategies.

time quantum for a task, then its available time budget is reduced. It is worth noting that the total available time budget for all the users is B. Obviously, all the users prefer to reasonably schedule their bidding strategy in order to win as many rounds as possible. The bidding strategy could be easily expressed as follows: for the player, how to divide his total available time budget into all the rounds in order to win as many as possible. It is not difficult to find that, there is a game among users, i.e., bidding a long time quantum when the others bid short ones is obviously a good choice. However, the user still takes the risk that the others may also bid a long time quantum.

We randomly select a user as the player, who will adopt the bidding strategy proposed in this paper. And the other ones are regarded as the competitors. In order to make the player win as many rounds as possible, some naive solutions could be easily proposed. For example, the first one is to always bid the shortest time quantum for all the rounds. The second one is to always bid the longest time quantum, in which the player may win many rounds in the beginning rounds and will not win any more in the last rounds. Hence, it is obviously not an optimal solution. The third one is to always bid the average time quantum (total time divided by the number of rounds). As shown in Fig. 3, neither constantly bidding max/min time quantum nor constantly bidding average time quantum can achieve the best winning reward. Based on game theory, we could dynamically schedule the biddings in different rounds more efficiently (game theory method in Fig. 3). In this paper, we propose a multi-round bidding strategy based on the game theory in mobile crowdsensing, through balancing the trade-off between winning probability and remaining available time.

3 Multi-round Bidding Game

3.1 Bidding Time Quantum

Here, bidding time quantum means the time that the user would like to take for finishing the sensing task. Obviously, a longer bidding time quantum leads to a higher probability to win in this round, while also leading to a shorter available time in the upcoming rounds. Suppose that, for the player, the total available time budget is B, and there are totally h rounds. For each round k, the bidding

Table 1. Main notations used throughout the paper

Symbol	Meaning
N	Total number of users
b_i	Different kinds of biddings, which is the arithmetic progression: $(b_1, b_2, \cdots, b_m)$
p_i	The probability for a user to bid b_i
$P_{max}(b_i)$	The probability that b_i is the maximal bidding among all the remaining users
B	The total available time budget
P_{win}	The winning probability of bidding the maximum time
γ	Euler's constant
B_r	The remaining available time
s_i	$(b_i - b_m)/B_r$, consumption ratio when bidding b_i
s	$(b_1 - b_m)/B_r$, consumption ratio when bidding b_1
$u(b_i)$	The benefit for bidding b_i

time quantum is $b(k)$, which is selected from a series of b_i, $m \geq i \geq 1$. Then we have $B = \sum_{k=1}^{h} b(k)$.

If a user chooses to bid a long time quantum in a round, then the available time will be consumed a lot. In contrast, if a user chooses to bid a short time quantum, the available time will not be influenced that much. We attempt to measure the different influences when the user bids different kinds of biddings. We use s_i to define the time consumption when a user bids b_i, the set b_i are arithmetic progression and b_m is the shortest bidding time quantum. Let B_r be the remaining available time, then we have $s_i = \frac{b_i - b_m}{B_r}$, $i = 1, 2, \cdots, m$. According to the value of B_r, the above expression could be represented as the following two cases:

$$s_i = \begin{cases} \frac{b_i - b_m}{B_r} & B_r \geq b_i - b_m \\ 1 & B_r < b_i - b_m \end{cases} \tag{1}$$

3.2 Winning Probability

In this section, we try to compute the winning probability for a user. It is not difficult to find that, a user could win only when his bidding time quantum is the longest among all the users (may be the same length as others). If a user bids the longest time quantum b_1, and all the other users bid the shorter time quantum than him, then he should win 100%. If there are k users bidding b_1 in the others, then the winning probability should be $\frac{1}{k+1}$. Hence, the following two questions are important for measuring the winning probability.

Here, we use symbol $P_{max}(b_i)$ to present the probability that b_i is the maximal bidding among all the remaining users. Obviously, we have $\sum_{i=1}^{n} P_{max}(b_i) = 1$.

Then, the probability (p_i) of bidding b_i in a round also influences the result of winning probability. Then we have $\sum_{i=1}^{n} p_i = 1$. In the following sections, the above two terms are used to calculate the winning probability.

3.3 Game Theory

Game theory studies the interactions among players, who take actions to influence each other, and usually have conflicting or common benefits. Recently, game theory is widely used in balancing the resources sharing among multiple mobile devices, which are called players. These players decide to do the actions by themselves and compete for non-shared resources [7]. In this paper, the purpose of a player is to win as many rounds as possible during the multiple rounds.

Consider the following game process, an action done by a player $n_i \in \mathbf{N}$ in round $e_i \in \mathbf{E}$ is called a strategy $g_i \in \mathbf{G}$. In this paper, we assume that the strategy set is the same for all users, and selected from a series of b_i. Then $\mathbf{G} = \mathbf{G}_1 \times \mathbf{G}_2 \times \cdots \times \mathbf{G}_N$ is the set of the players' strategies. For user n_i, the payoff of action g_i is denoted by $u_i \in \mathbf{U}$ which is the expected payoff after considering the action done by n_i as well as the actions of the other players. Hence, a game is determined by quadruple form $\langle \mathbf{N}, \mathbf{E}, \mathbf{G}, \mathbf{U} \rangle$.

Obviously, the above game is a symmetric finite game because the strategy set $\mathbf{G}$ and round set $\mathbf{E}$ for all the users are the same. Moreover, the number of rounds and the number of their strategies are finite. These characteristics are very important in the following discussions.

Dominant Strategies and Nash Equilibrium. Nash Equilibrium (NE) is an important concept in game theory, each user chooses a strategy to maximize its expected individual payoff, and for all the users they form an equilibrium state, where all the users do not want to change its strategy because they could achieve the maximum expected payoff. In other words, in an NE state, if a user changes its action, it will achieve a lower expected payoff. When entering an NE state, the strategy adopted by a user is called a dominant strategy. A dominant strategy equilibrium is a strategy set including all the dominant strategies of all players. Hence, NE is commonly a classical state, where a player does not have the incentive to change its strategy so that the other players also will not change theirs.

Pure and Mixed Strategies. A pure strategy means that a user clearly decides its action, which includes 'do' or 'not do', while a mixed strategy means that a user could make a probabilistic decision about the actions. Actually, the main difference between pure strategy and mixed strategy is that pure strategies assign a probability of 1 to a specific action and probability of 0 to the remaining of the available actions. In the following parts, NE in pure (mixed) strategy is called pure (mixed) strategy NE.

Existence of Equilibrium. In order to prove that the multi-round bidding problem proposed in this paper has a Nash Equilibrium, we give the following theorems [8,9]:

Theorem 1 (Nash Theorem). *Any finite game has either a pure or a mixed strategy NE.*

Theorem 2 (Nash Theorem for symmetric games). *A finite symmetric game has a symmetric mixed strategy NE.*

Table 2. Payoffs of n_i in the 3-strategies bidding game

N users	Longest $b_1 = 3$ with $P_{max}(b_1)$	Longest $b_2 = 2$ with $P_{max}(b_2)$	Longest $b_3 = 1$ with $P_{max}(b_3)$
n_i bids b_1	$(1 - s) \cdot P_{win}$	$(1 - s) \cdot 1$	$(1 - s) \cdot 1$
n_i bids b_2	0	$(1 - \frac{1}{2}s) \cdot P_{win}$	$(1 - \frac{1}{2}s) \cdot 1$
n_i bids b_3	0	0	$\frac{1}{N}$

4 Multi-round Bidding Strategy Based on Game Theory

As previously stated, the game in this paper is a non-cooperative, multi-round, multi-strategy, symmetric game.

The *N*-Player Three-Strategy Bidding Game. Here, 'multi' means the number is larger than two or at least three. Hence we consider a simple case, where N users play the bidding game with the three strategies to be selected. In this paper, we do not consider the simplest case: two strategies, because the similar case has been discussed in the previous research work [10].

Consider the N-player three-strategy bidding game. Table 2 shows the payoffs of the users considering both the improvement on winning probability and also the consumption in remaining available time. s_i as shown in Eq. 1, is the normalized time consumption when the user bids b_i. As shown in Table 2, when the player decides to bid b_1 (the longest time quantum), then the following three cases are considered: (1) the longest bidding time quantum of the other users is b_1; (2) the longest bidding time quantum of the other users is b_2; (3) the longest bidding time quantum of the other users is b_3. For case 1, the time consumption is $s = \frac{b_1 - b_m}{B_r}$, while the winning probability is P_{win}, which represents the expected probability of obtaining the task when the user bids the longest time quantum. However, for cases 2 and 3, the time consumptions are still s, while the chance of winning is 1, because the player bidding b_1 must win the task.

Next, when the user bids b_2, there are also the same three cases being considered. For case 1, because the longest bid of the others is b_1, hence the player bidding b_2 has no chance to win, so the probability is 0. For case 2, the time consumption is $\frac{1}{2}s$ because $s_2 = \frac{b_2 - b_3}{b_1 - b_3}s$ and the set b_i forms arithmetic progression, hence $s_2 = \frac{1}{2}s$. We omit the descriptions for bidding b_3, as the procedure is similar to the above cases. Then we focus on whether there is a pure or mixed strategy NE for the above N player three-strategy game.

Table 3. Payoffs of n_i in the multi-strategy bidding game

N users	Longest $b_1 = 6$ with $P_{max}(b_1)$	Longest $b_2 = 5$ with $P_{max}(b_2)$	Longest $b_3 = 4$ with $P_{max}(b_3)$	Longest $b_4 = 3$ with $P_{max}(b_4)$	Longest $b_5 = 2$ with $P_{max}(b_5)$	Longest $b_6 = 1$ with $P_{max}(b_6)$
n_i bids b_1	$(1-s) \cdot P_{win}$	$(1-s) \cdot 1$	$(1-s) \cdot 1$	$(1-s) \cdot 1$	$(1-s) \cdot 1$	$(1-s) \cdot 1$
n_i bids b_2	0	$(1-\frac{4}{5}s) \cdot P_{win}$	$(1-\frac{4}{5}s) \cdot 1$	$(1-\frac{4}{5}s) \cdot 1$	$(1-\frac{4}{5}s) \cdot 1$	$(1-\frac{4}{5}s) \cdot 1$
n_i bids b_3	0	0	$(1-\frac{3}{5}s) \cdot P_{win}$	$(1-\frac{3}{5}s) \cdot 1$	$(1-\frac{3}{5}s) \cdot 1$	$(1-\frac{3}{5}s) \cdot 1$
n_i bids b_4	0	0	0	$(1-\frac{2}{5}s) \cdot P_{win}$	$(1-\frac{2}{5}s) \cdot 1$	$(1-\frac{2}{5}s) \cdot 1$
n_i bids b_5	0	0	0	0	$(1-\frac{1}{5}s) \cdot P_{win}$	$(1-\frac{1}{5}s) \cdot 1$
n_i bids b_6	0	0	0	0	0	$\frac{1}{5}$

Theorem 3. *There is no pure strategy NE for the above N-player three-strategy bidding game.*

Proof. As shown in Table 2, if there is a pure strategy NE for the N-player three-strategy bidding game, then no matter in which case, the payoff to bid b_1 is always higher or lower than that of bidding b_2 or b_3. However, this is not true in Table 2. When the longest bidding time quantum for the others is b_1, then the player will bid b_1 to achieve a higher payoff $(1-s)P_{win} > 0$. However, when the longest bidding time quantum for the others is b_3, then the player will bid b_2 to achieve a higher payoff $(1 - \frac{1}{2}s)1 > (1 - s)1$. Hence, there is no pure strategy NE for the above N-player three-strategy bidding game. Theorem 3 is proved.

Theorem 4. *Mixed strategy NE exists for the N-player three-strategy bidding game.*

Proof. We assume that each user has a probability of p_i to bid b_i. And for the above three cases, we use $P_{max}(b_i)$ to present the probability that b_i is the maximal bidding among the remaining users. Then, we achieve the following three equations:

$$P_{max}(b_1) = \sum_{k=1}^{N-1} \binom{N-1}{k} \cdot {p_1}^k \cdot (1-p_1)^{N-1-k} = 1 - (1-p_1)^{N-1} \tag{2}$$

$$P_{max}(b_2) = (1-p_1)^{N-1} - (1-p_1-p_2)^{N-1} \tag{3}$$

$$P_{max}(b_3) = p_3^{N-1} \tag{4}$$

Then, the expected payoff of the player when it bids b_1 is shown as follows:

$$u(b_1) = (1-s)P_{win}P_{max}(b_1) + (1-s)P_{max}(b_2) + (1-s)P_{max}(b_3) \tag{5}$$

where P_{win} is shown as follows:

$$P_{win} = \frac{\sum_{k=1}^{N-1} \frac{1}{k+1}}{N-1} = \frac{\ln(N) + \gamma + 1}{N-1}, \quad \gamma = 0.577215 \tag{6}$$

Here k ($N > k > 1$) is the number of users bidding the longest time quantum among all the other users, and γ is the Euler's constant. We use property of nth harmonic number[1] to get the above equation. It is not difficult to find that, Eq. 6 is still useful for calculating the P_{win} in multi-user multi-round and multi-strategy case, which is discussed in the following section.

Similarly, we could achieve $u(b_2)$ and $u(b_3)$. Combining $u(b_1) = u(b_3)$ and $u(b_2) = u(b_3)$, we could get the solution of p_i. So the mixed strategy NE actually exists because we can get the solution of p_i in the above equations, and p_i satisfies $0 \leq p_i \leq 1$. The detail calculation process is shown in the N-player multi-round multi-strategy case.

The *N*-Player Multi-round Multi-strategy Game. The game is that a player plays with the other $N-1$ users. Without loss of generality, we show a six-round six-strategy case in Table 3. First of all, we consider the normalized time consumption $s_i = \frac{n-1}{n-i}s$, which represents the case that the player bids b_i in this round. Then, we consider the payoffs if a user bids b_i. Suppose that the longest bidding time quantum of the others is also b_i, and there are k users bidding b_i among the other users. Then the winning probability is $\frac{1}{k+1}$. The payoffs in terms of available time is $1 - s_i$. Hence, we have the expected payoffs $u(b_i) = (1 - \frac{n-1}{n-i}s)\frac{1}{k+1}$. Similarly, if the longest bidding time quantum of the others is shorter than b_i, the player must win the game, hence $u(b_i) = 1 - s_i$. Finally, if the longest bidding time quantum of the others is longer than b_i, then $u(b_i) = 0$.

$$u(b_i) = \begin{cases} (1-\frac{n-1}{n-i}s)\frac{1}{k+1} & \text{the longest bidding} = b_i \\ (1-\frac{n-1}{n-i}s)1 & \text{the longest bidding} < b_i \\ 0 & \text{the longest bidding} > b_i \end{cases} \tag{7}$$

We also assume that each user has a probability of p_i to bid b_i. Then, similar to N-player three-strategy bidding game, we get $P_{max}(b_1) \sim P_{max}(b_6)$ and $\sum_{k=1}^{6} P_{max}(b_k) = 1$. Then the payoff of the player when it bids b_1 is shown as follows:

$$u(b_1) = (1-s)P_{win}P_{max}(b_1) + \sum_{i=2}^{6}(1-s)P_{max}(b_i) \tag{8}$$

[1] https://en.wikipedia.org/wiki/Harmonic_number.

In a similar way, $u(b_i)$ could be achieved, and we find the NE solution for p_i through solving a group of equations: $u(b_i) = u(b_j),\ i \neq j$.

Here, we use the fsolve function in Matlab to solve the nonlinear equations [11]. In this way, the player could dynamically calculate the p_i in NE according to the current remaining available time. Finally, the player decides the probability of bidding different time quantums for the specific sensing task in the different rounds.

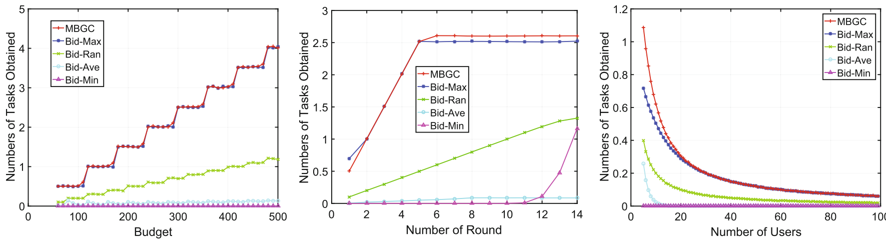

Fig. 4. Performance comparisons along with the changes of budget & number of rounds & number of users, when users could choose 6 different biddings.

5 Performance Evaluation

5.1 Settings

We test the proposed strategy through simulations. A group of users compete for a series of tasks, and in each round they have some biddings to select. We consider that the following elements will influence the final number of winning rounds: the number of different kinds of biddings, total available time budget, the number of users and the number of rounds. The detailed simulation parameters are set as follows: the number of different kinds of biddings is 6, the budget changes from 60 to 500, number of rounds changes from 1 to 14 and the range of number of users is [5, 10].

5.2 Methods and Performances in Comparison

The compared methods include: bid-max (always bidding the longest time quantum), bid-ran (always bidding a random time quantum), bid-ave (always bidding average time quantum, which is calculated through the budget divided by the number of rounds) and bid-min (always bidding the shortest time quantum).

While a range of data is gathered from the simulations, we take the following main performance metric into consideration: numbers of tasks obtained, which is the number of winning rounds in the bidding game.

5.3 Simulation Results

We focus on three groups of simulations: 6 different kinds of biddings. For the first group of simulations, we test the number of tasks obtained along with the increase in budget, number of rounds and number of users. The simulation results are shown in Fig. 4. Along with the growth of budget, the number of tasks obtained also increases, because a large budget leads to a long total available time, and the number of tasks obtained also rises. Moreover, along with the increase in the number of rounds, the number of tasks obtained is also increasing, because a large number of rounds lead to a large number of tasks. Finally, along with the growth of the number of users, the number of tasks obtained goes down, which means that more competitors lead to a less number of tasks obtained by the player.

As shown in Fig. 5, we test the number of tasks obtained along with the increase in the number of different biddings. The results show that the proposed MBGC achieves a better performance when the bidding number is large enough. This is because large number of biddings leave us a lot of space to dynamically decide the bidding time quantum. Hence, the performance gets better. Then, in Fig. 6, we test some specific methods related to MBGC, where "bid 3" means a method of always bidding the third shortest time quantum. We find that MBGC always achieves the best performance. It is worth noting that, when the bidding round gets large enough, 'bid 1' gets better, which makes sense because bidding a short time quantum will save the time cost for the last rounds. Finally, we test the changes of p_i along with number of round, the results in Fig. 7 show their changing processes are not monotonous and have crossed with each other.

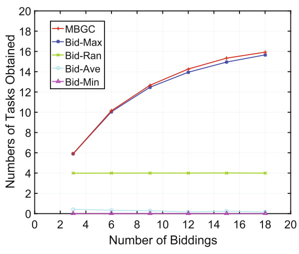

Fig. 5. The performance changing process along with the growth of number of biddings for different bidding strategies.

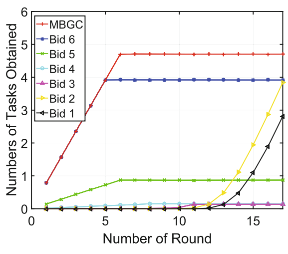

Fig. 6. The performance changing process along with the number of round for different bidding strategies.

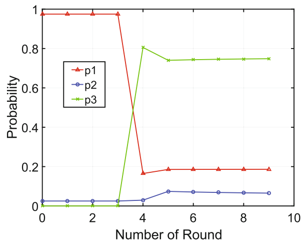

Fig. 7. The probability change processes along with the increase of bidding rounds in MBGC.

6 Related Work

6.1 Task Allocation

In order to address the free crowdsensing market where multiple task initiators and users want to maximize their profits, He [12] studied the exchange economy theory and adopted the Walrasian Equilibrium which is proven to exist within each supply-demand pattern. Xiong *et al.* [13] proposed a task allocation framework called iCrowd based on Piggyback task model, iCrowd utilizes historical data to forecast mobility of users and employs suitable set of users to optimize task allocation. Wang *et al.* [14] researched a spatial crowdsourcing situation under limited task probability coverage and budget, then they present the prediction model of worker mobility behavior to obtain the optimal solution of task allocation. The above researches discuss the task allocation methods in MCS. However, the users in the above works were selected by the requester according to the users' attributes. The users could only passively accept tasks.

6.2 Game Theory

Chakeri *et al.* [15] regarded incentive mechanism as a non-cooperative game and presented a discrete time dynamic called elite strategy dynamics based on best response dynamic to compute a Nash Equilibrium and get the maximization utilities. Yang *et al.* [16] combined quality evaluation and money incentive, then they presented a truth evaluation based quality and remaining share method. Focusing on user diversity and social effect in mobile crowdsensing, Cheung *et al.* [17] analyzed a payment scheme for provider to utilize users' social relationship to achieve diversity, and then proposed a two-round decision strategy where provider optimizes its utility as a leader, after that the users decide their contribution level according to providers' scheme as a follower in the game process. Alsheikh *et al.* [18] focused on privacy management and optimal pricing in mobile crowdsensing, and analyzed the negative correlation of sensing quality and privacy level, then combined the utility maximization models with profit sharing models from game theory. Jiang *et al.* [19] considered high operational cost such as storage resources, and presented a scalability P2P-based MCS architecture, focusing on user behavior in the context of game theory and presenting a quality-aware data sharing market. The above works focused on proposing incentive mechanisms, while they did not consider the multi-round bidding case among users.

7 Conclusion

In this paper, the multi-round bidding game is formulated in mobile crowdsensing. In each round, the users compete for a sensing task. They bid a long enough time quantum for winning the task while taking a risk of failure and wasting the bidding time quantum. We propose a multi-round bidding strategy based on the game theory in mobile crowdsensing (MBGC), where users dynamically determine the bidding time quantum through the trade-off between the winning probability and remaining available time. Then, a Nash Equilibrium is achieved to instruct the users to reasonably schedule their bidding strategies. We conduct simulations to test the number of tasks obtained. The results show that, compared with the other bidding strategies, MBGC achieves a better performance.

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