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Diversity-aware unmanned vehicle team arrangement in mobile crowdsourcing

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Abstract

With the continuous development of mobile edge computing and the improvement of unmanned vehicle technology, unmanned vehicle could handle ever-increasing demands. As a significant application of unmanned vehicle, spatial crowdsourcing will provide an important application scenario, which is about to organize a lot of unmanned vehicle to conduct the spatial tasks by physically moving to its locations, called task assignment. Previous works usually focus on assigning a spatial task to one single vehicle or a group of vehicles. Few of them consider that vehicle team diversity is essential to collaborative work. Collaborative work is benefits from organizing teams with various backgrounds vehicles. In this paper, we consider a spatial crowdsourcing scenario. Each vehicle has a set of skills and a property. The property denotes vehicle's special attribute (e.g., size, speed or weight). We introduce a concept of entropy to measure vehicle team diversity. Each spatial task (e.g., delivering the take-out, and carrying freight) is under the time and budget constraint, and required a set of skills. We need to assure that the assigned vehicle team is diverse. To address this issue, we first propose a practical problem, called team diversity spatial crowdsourcing (TD-SC) problem which finds an optimal team-and-task assignment strategy. Moreover, we design a framework which includes a greedy with diversity (GD) algorithm and a divide-and-conquer (D&C) algorithm to get team-and-task assignments. Finally, we demonstrate efficiency and effectiveness of the proposed methods through extensive experiments.

Keywords: Unmanned vehicle, Spatial crowdsourcing, Group task assignment, Team diversity

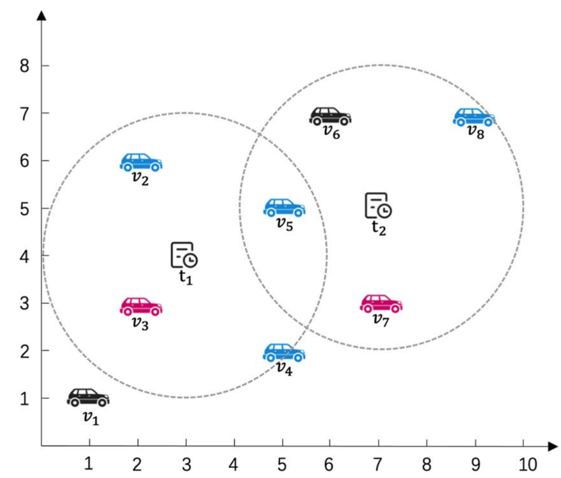
1 Introduction

With the rapid development of long-term evolution (LTE) network and the fifth-generation (5G) cellular network, unmanned vehicles have been widely used in real life. A unmanned vehicle can perceive its surroundings and navigate without human intervention. It uses a variety of technologies including radar, laser, ultrasonic, GPS, odometer, computer vision and other technologies to perceive its surrounding environment, through advanced computing and control systems, to identify obstacles and various signs and plan appropriate paths. [1, 2] There are many application fields for unmanned vehicles, and the demand is strong. For example, unmanned vehicles could conduct spatial crowdsourcing tasks instead of humans. Spatial crowdsourcing is about to organize a number of unmanned vehicles to conduct the spatial tasks by physically moving to its locations, called task assignment [3–6]. Some studies on spatial crowdsourcing usually concentrate on the problem of task assignment [7–11], which is to allocate tasks to unmanned vehicles, and they presume all tasks are simple and easy. Moreover, some studies consider the complicated spatial tasks, which usually need to be accomplished by a team of unmanned vehicles with different skills. However, in real scenarios, a simple team may not complete the spatial task well. We also need to concern about team diversity. Collaborative work is benefits from organizing teams with various backgrounds unmanned vehicles [12–15]. For instance, studies have suggested that diversity in a firm's knowledge background and its creativity are positively correlated [16]. Teams with diverse background members are usually regarded to be competitive, because teams like that are easier to get new thoughts [17]. Similarly, spatial crowdsourcing tasks completed by diverse fleet of autonomous vehicles are of higher quality

Example 1 To intuitively understand the significance of the team diversity, we could consider the effect of non-diverse teams. We can imagine a real scenario: There may be new and old versions of unmanned vehicles in industrial parks at the same time. The new version of the unmanned vehicle has more advanced sensors, so it will have an advantage when it comes to performing tasks. If some tasks are all assigned to the old version of the unmanned vehicle, the completion time of this task will be greatly increased and the quality of the task completion will be significantly reduced. But we want each task to use vehicle resources fairly, so it is best to have different versions of unmanned vehicles in a fleet at the same time. Therefore, we could form a diverse team which contains diverse unmanned vehicles. It can be seen that diversity is often necessary to the efficiency and quality.

In this paper, we will consider an essential problem in the spatial crowdsourcing, namely team diversity spatial crowdsourcing (TD-SC), which aims to effectively assign diverse unmanned vehicle fleets to complicated spatial tasks, under the task constraints of time, valid range, budgets and team diversity index, so that the required skill sets of tasks are completely covered by those unmanned vehicles, and the total value of the assignment (defined as the total traveling cost of unmanned vehicles) is minimized.

Example 2 In the next, we will illustrate the TD-SC problem by a motivation example. Figure 1 shows the information of unmanned vehicles/tasks. There exist eight unmanned vehicles (v_1, ..., v_8) and two tasks (t_1, t_2). Each task labeled with its required skills, current location and valid radius is required to be assigned to one or more unmanned vehicles. Each unmanned vehicle is associated with skills, current location and cluster. The cluster denotes unmanned vehicle's special attribute (e.g., size, speed or version) and used to measure the diversity of the fleet. The problem is to assign tasks to a fleet of unmanned vehicles so as to minimize the average task cost and optimal assigned team diversity. For task t_1, its available unmanned vehicles are v_2, v_3, v_4, v_5, respectively. We can choose unmanned vehicle v_2 and unmanned vehicle v_5 to from a team to complete this task. As can be seen, the skills union of unmanned vehicle v_2 and v_5 is $< s_1, s_2, s_3 >$ which can exactly cover task t_1 required skills set $< s_1, s_2, s_3 >$. Moreover, unmanned vehicle v_2 and v_5 cluster is 2 and 3, respectively. So we can make sure that the team is diverse.



Task	Skills
t_1	$\{s_1, s_2, s_3\}$
t_2	$\{s_2, s_4, s_5\}$

Vehicle	Skills	property
v_1	$\{s_2\}$	1
v_2	$\{s_1, s_3\}$	2
v_3	$\{s_3\}$	3
v_4	$\{s_4, s_5\}$	3
v_5	$\{s_1, s_2\}$	3
v_6	$\{s_3, s_4\}$	1
v_7	$\{s_5\}$	2
v_8	$\{s_2\}$	3

Fig. 1 Information of unmanned vehicles/tasks

Table 1 Comparison of task between our paper and other papers

Paper ID	Task features					
	Location	Start time	Multi skills	Budget	Radius	Diversity
Our paper	✓	✓	✓	✓	✓	✓
Top-k	✓	✗	✓	✗	✓	✗
Task assign	✓	✓	✓	✓	✗	✗
Forming diverse	✗	✗	✗	✓	✗	✓

The contributions made by our paper can be summarized as follows:

- We formally define the team diversity spatial crowdsourcing (TD-SC) problem in Sect. 2, under the constraints of skills covering, timestamp, task's range, budget and team diversity index for tasks in the spatial crowdsourcing.
- We propose two effective approaches, namely greedy with diversity (GD) and divide-and-conquer with diversity (D&C) algorithms, to tackle the TD-SC problem in Sects. 3.3 and 3.4, respectively.
- As demonstrated by the experiments, our designed algorithms can effectively form diverse unmanned vehicle fleets for spatial tasks that can accomplish an optimal task assignment.

Section 2 reviews previous works on research on unmanned vehicles and spatial crowdsourcing. Section 3.2 introduces a general framework for our TD-SC problem in spatial crowdsourcing. Finally, Sect. 5 concludes this paper. Tables 1 and 2 show the comparison between our paper and other related papers.

Table 2 Comparison of vehicle between our paper and other papers

Paper ID	Vehicle features			
	Location	Multi skills	Multi teams	Cluster
Our paper	✓	✓	✓	✓
Top-k	✓	✗	✓	✗
Task assign	✓	✓	✓	✓
Forming diverse	✗	✗	✗	✓

2 Related works

2.1 Unmanned vehicle

In recent years, the rapid development of artificial intelligence, cognitive science, automatic control, ground mapping, sensor technology and other fields promotes the essential change of automobile industry [18]. Unmanned driving technology is a new direction for the development of the automotive industry, and its goal is to solve people high requirements for the safety, comfort and reliability of car driving [19]. The US National Highway Traffic Safety Administration released the regulations of traffic policies of intelligent driving cars in May, 2013. The regulations divided the automatic degree of cars into five levels: Level zero was no autonomous control, level one was intelligent driving with independent functions, level two was intelligent driving with cooperative control, level three was autonomous driving with limits, and level four was total autonomous driving [2]. Unmanned vehicles have made great progress in recent years, but there are still a series of problems and challenges in road traffic technology, cost ethics, laws and regulations, etc. As a result, structured environments such as office parks, technology parks and parks have become proving grounds for driverless vehicles. Moreover, industrial software is important in industrial systems. So it is critical to recommend suitable APIs from big APIs data to developers. [20] proposes a personalized recommendation framework which recommend suitable APIs to developers. Recent advances in computing are widely leveraged to design energy-efficient computing platforms for Internet of things. [21] proposes a method to reduce the amount of computation in the scanning process. Service composition is a key step in the complex business structure of the Internet of things, but it may lead to privacy leaks. [22] proposes an automatic method with the aim of formalizing timed privacy requirements for the Internet of things service composition. Besides, ethical issues remain a significant concern for future large-scale deployment of autonomous vehicles [23]. [24] provides a comprehensive review of the topic, covering the aspects of enabling wireless technologies and sensor fusion. [1] gives a detailed survey about the recent and state-of-the-art research methods in the field of human action recognition and discusses their advantages and limitations.

2.2 Spatial crowdsourcing

Crowdsourcing has been deeply studied in [25]. Previous works [25, 25, 26] often studied crowdsourcing problems. In these problems, workers do not need to move to the task's location, and they usually complete tasks online. On the contrary, the spatial crowdsourcing problems [26] requires the worker to move to a specific location of the task to perform the requested task. Spatial crowdsourcing problem can be classified into two kinds, namely server assigned tasks (SAT) and worker selected tasks (WST), based on the task publishing modes. Specifically, the SAT mode is that spatial crowdsourcing sever directly assigning spatial tasks to available workers. SAT mode needs sever to collect all the information of tasks and workers, such that it can maximize the number of assigned tasks [26]. The WST mode is that spatial tasks are published on server and all workers can get those information, so that workers can select a spatial task according to their personal preferences and behavior habit [27]. In our work, we study our TD-SC problem based on the SAT model, where workers are paid for conducting tasks. Our TD-SC problem targets at assigning vehicles to tasks by using our proposed algorithms, so that the needed skills of tasks can be covered.

Most of the former works in spatial crowdsourcing concentrate on assigning spatial tasks to a single worker. Nevertheless, some papers also focus on collaborative task assignment in spatial crowdsourcing [28–31], which is assigning tasks to a team of workers. Cheng et al. [28] propose an algorithm called Cooperation-Aware Spatial Crowdsourcing to tackle team task assignment problem so that the spatial tasks can be completed with high cooperation quality scores. [32] focuses on the trust node management of vehicular ad hoc networks, which aims to quantify node credibility as an assessment method and avoid assigning malicious nodes. An increasing number of applications have been deployed to the cloud. [33] proposes a scheme to schedule workflows dynamically with minimum cost under different deadline constraints. Besides, [34] proposes an allocation scheme for optimization based on user requirements in a cloud data center. Our proposed TD-SC problem not only focuses on the team collaboration but also team diversity. Collaborative work is benefits from organizing teams with diverse unmanned vehicle fleets.

2.3 Team formation problem

Team formation problem is also closely related. The problem of team formation is about finding the minimum cost of unmanned vehicle fleets according to their skills. Anagnostopoulos et al. [35, 36] study the workload balance problem in the team formation problem. Majumder et al. [37] consider the capacity constraint of experts issue in team formation problem.

Moreover, the problem of forming diverse team in crowdsourcing is also studied. Sara et al. [38] study the diverse team formation problem. Faez et al. [39] present a method to form diverse teams from people arriving sequentially over time in a firm. However, none of those papers consider the team diversity problem in spatial crowdsourcing. In our paper, we introduce a monotone function which can measure the team diversity in spatial crowdsourcing.

3 Methods

3.1 Problem statement

In this section, we first introduce the essential concepts and present the formal definition of the team diversity spatial crowdsourcing (TD-SC) problem, in which we assign diverse team to complicated spatial tasks. Table 3 summarizes the key notations used in the rest of our paper.

Table 3 Summary of notations

Notations	Description
p	Timestamp
V_p	A set of unmanned vehicles at timestamp p
v_i	A unmanned vehicle $v_i \in V_p$
l_i	Location of the unmanned vehicle v_i
o_i	Online time of the unmanned vehicle v_i
S_i	A skill set of the unmanned vehicle v_i
$c_{i,j}$	Cost of the unmanned vehicle v_i to complete the task t_j
p_i	Property of the unmanned vehicle v_i
T_p	A set of tasks at timestamp p
t_j	A spatial task t_j
l_j	Location of the task t_j
o_j	Online time of the task t_j
S_j	A skill set of the task t_j
b_j	Budget of the task t_j
r_j	Radius of the task t_j
d_j	Diversity of the task t_j

We first define the multi-skilled unmanned vehicles in spatial crowdsourcing platform, in which we assign those unmanned vehicles to complicated spatial tasks. We assume that $S = \{s_1, s_2, \ldots, s_l\}$ is a set of L skills. Each unmanned vehicle has one or more skills in S and can carry out some spatial tasks which require some skills in S. We also assume that $P = \{p_1, p_2, \ldots, p_k\}$ is a set of K properties. Each unmanned vehicle has one property. A property denotes unmanned vehicle's special attribute (e.g., size, speed or version) (Table 3).

Definition 1 (Unmanned vehicles) Let $V_p = \{v_1, v_2, \ldots, v_m\}$ be a set of m unmanned vehicles at timestamp p. Each unmanned vehicle is denoted by $v_i =< l_i, o_i, S_i, c_{i,j}, p_i > (1 \leq i \leq m)$, where l_i is the location of the unmanned vehicle in a 2D space, o_i is the online time of the unmanned vehicle, $S_i \subseteq S$ is the skill set possessed by the unmanned vehicle, c_i is the cost for the unmanned vehicle to complete a task, and p_i is the property of the unmanned vehicle.

3.1.1 Complex spatial tasks

Now, we define complicated spatial tasks in the spatial crowdsourcing platform, which are constrained by range, budgets and diversity index.

Definition 2 (Tasks) Let $T_p = \{t_1, t_2, \ldots, t_n\}$ be a set of complex spatial tasks at a timestamp p. Each task is denoted by $t_j =< l_j, o_j, S_j, b_j, r_j, d_j >$, where l_j is the location of the task in a 2D space, o_j is the online time of the task, $S_j \subseteq S$ is the set of skills needed by the task, b_j is the budget of the task, r_j is the valid range of the task, only those unmanned vehicles which are located in the circular range with the radius r_j around l_j can conduct the task t_j, and d_j is the diversity index of the team measured by monotone function. Later, we will discuss it again. The team contains those unmanned vehicles which can complete the task t_j.

3.1.2 Team diversity spatial crowdsourcing problem

In this subsection, we will formally define the team diversity spatial crowdsourcing (TD-SC) problem, which assigns a diverse team of unmanned vehicles to spatial tasks so that all unmanned vehicles can cover the skills required by tasks and the assignment can obtain high team diversity and low traveling cost.

Before we present the TD-SC problem, we first introduce the concept of task assignment instance.

Definition 3 (Task Assignment Instance) At timestamp p, given a unmanned vehicle set V_p and a task T_p, a *task assignment instance* is a form $< v_1, v_2, \ldots, v_n, t_j >$, where each unmanned vehicle $v_i \subseteq V_p$ is assigned to one spatial task $t_j \subseteq T_p$.

Intuitively, the task assignment instance,$< v_1, v_2, \ldots, v_n, t_j >$, is one valid assignment. Each assignment instance must satisfy all constraints of task t_j, with regard to task range (i.e., r_j), online time (i.e., o_j), budget (i.e., b_j), skills (i.e., S_j) and diversity index (i.e., d_j). The *task assignment instance* means that all unmanned vehicles skills can cover the spatial task' skills S_j and no redundant unmanned vehicles.

Definition 4 (TD-SC Problem) Given a time interval P, a spatial crowdsourced task t_j, a set of unmanned vehicle V_p, the problem of team diversity spatial crowdsourcing problem is to assign the available team with diverse unmanned vehicles to a spatial task $t_j \subseteq T_p$, at each timestamp $p \subseteq P$, such that the following constrains are satisfied:

1) Range constraint: each unmanned vehicle $v_i \subseteq V_p$ must be within the range of the task t_j.
2) Time constraint: the unmanned vehicle $v_i \subseteq V_p$ and task t_j assigned to v_i must have same time interval P.
3) Budget constraint: the sum cost of all unmanned vehicles, $< v_1, v_2, \ldots, v_n >$ in task assignment instance, must be lower than spatial task t_j budget.
4) Skill constraint: all unmanned vehicles, $< v_1, v_2, \ldots, v_n >$ in task assignment instance, must cover the spatial task skill S_j.
5) Diversity constraint: the diversity of all unmanned vehicles, $< v_1, v_2, \ldots, v_n >$ in task assignment instance, must be more than specific value, such that the team, $< v_1, v_2, \ldots, v_n >$ in task assignment instance, is diverse.

3.2 Framework of our approach

In this section, we present a general framework, namely TD-SC_Framework, in Algorithm 1 for solving the TD-SC problem, which assigns a diverse team of unmanned vehicles to spatial tasks for many rounds. S denotes the assignment strategy of vehicles and tasks in all time interval P. For each round within time interval P, we first retrieve a set, V_p, of all the available unmanned vehicles, and a set, T_p, of all the available spatial tasks (lines 3-4). The set V_p includes those unmanned vehicles which newly arrive at the system and have completed the previously assigned tasks. Thus, they are available to conduct new tasks in the current round. Moreover, the available task set T_p contains existing spatial tasks that have not been assigned to unmanned vehicles, and the ones that newly arrive at the system.

After we obtain the available spatial tasks T_p and unmanned vehicles V_p, we can apply our approach obtain a good vehicles and tasks assignment strategy S_p, which is a subset of S (lines 5-6).

Finally, for each unmanned vehicles in task assignment strategy S_p, we will notify unmanned vehicle v_i to conduct task t_j (lines 7-9).

Algorithm 1: TD-SC Framework

```
  Input: a time interval P, V = {v_1, v_2, ..., v_|V|} and our approach(,...,)
  Output: unmanned vehicle and task assignment strategy S with in the time interval P
1 S ← φ for each time interval P in all time do
2     retrieve all available spatial tasks to Tp ;
3     retrieve all available unmanned vehicles to Vp ;
4     use our approach to obtain a good assignment instance set Sp ;
5     S ← S ∪ S_p
6 for each Sp in S do
7     for each unmanned vehicle vi in Sp do
8         Inform unmanned vehicle vi to conduct task tj ;
```

3.3 TD-SC greedy with diversity approach

In this section, we will propose a greedy algorithm. Algorithm 2 shows the pseudocode of our task assignment with team diversity algorithm. Initially, we set I_p to be empty, since no tasks are assigned to any unmanned vehicles (line 1). Next, for each task t_j in T_p, we find out all valid unmanned vehicles $t_j\,Vehicles$ in the crowdsourcing system within time interval P(line 3). Here, the valid unmanned vehicles $t_j\,Vehicles$ satisfy those conditions: (1) Each unmanned vehicle $v_i \subseteq V_p$ must locate in restricted range of the task t_j; (2) each unmanned vehicle $v_i \subseteq V_p$ and task t_j assigned to v_i must have same time interval P; and (3)unmanned vehicle v_i has skills that task t_j requires.

Then, for each unmanned vehicle $v_i \in t_j\,Vehicles$, we would select one best unmanned vehicle with the highest score increase and add it to $Team_j$ (lines 5-6). If $Team_j$ could complete the task t_j, we continue to compute the diversity index of $Team_j$, denoted by D_j (line 8). If the diversity index of $Team_j$ is more than lower bound of diversity index, we remove all unmanned vehicle in $t_j\,Vehicles$ from the available unmanned vehicles V_p and add the valid pairs $< t\_j, Team\_j >$ into unmanned vehicles and task assignment strategy S_p (lines 9-11). If the diversity index of $Team_j$ is lower than lower bound of diversity index, we replace each unmanned vehicle in $Team_j$ to form a new team, until the new team diversity index could be more than the lower bound of diversity index (lines 13-14). If $Team_j$ could not complete the task t_j, we forgo this task (lines 15-16).

Algorithm 2: The Greedy with Diversity Algorithm

Input: The available spatial tasks T_p, The available unmanned vehicles V_p
Output: Task assignment instance set S_p

1 $S_p \leftarrow \phi$
2 **for** *each task* $t_j \in T_p$ **do**
3   $t_j Vehicles \leftarrow$ get valid unmannedvehicles of task $\mathrm{t_j}$;
4   **for** *each unmanned vehicles* $v_i \in t_j Vehicles$ **do**
5     $v_{best} \leftarrow argmax_{v_i}\left(\frac{MAXITEM(Team_j \cup v) - MAXITEM(v)}{c}\right)$;
6     $Team_j \leftarrow Team_j \cup v_{best}$;
7   **if** $Team_j$ *could complete task* t_j **then**
8       $D_j \leftarrow$ *use monotone function obtain* $Team_j$ *diversity* ;
9   **if** $D_j >$ *lowerBound of Diversity* **then**
10         $V_p \leftarrow V_p - Team_j$;
11         $S_p \leftarrow S_p \cup < t_j, Team_j >$;
12   **else**
13   retrieve new unmanned vehicle from $t_j Vehicles$ to form new $Team_j$;
14   go to line7;
15   **else**
16   forgo this task;

Specifically, we use monotone function to obtain $team_j$ diversity index (line 8). In Sect. 2.1, we assume that $P = \{p_1, p_2, \ldots, p_k\}$ is a set of K properties. Each unmanned vehicle has one property. Now, we assume vehicles belong to K clusters, and $p_k \subseteq P$ is a partition of all vehicles properties P. We also define $r_{i,j}$ as the quality of unmanned vehicle v_i to do task t_j. In our context, for a specific task t_j, we define an objective function $f_j : E \rightarrow \mathbb{R}$ which rewards diversity as follows:

$$f\left(Teamj\right) = \sum_{k=1}^{K} \sqrt{\sum_{v_i \in Team_j} r_{i,j}} \tag{1}$$

Example 3 Back to our running example in Example 2. The running process of the greedy algorithm is as follows. For task t_1, we retrieve its valid unmanned vehicles $\{v_2, v_3, v_4, v_5\}$. Every unmanned vehicle's value is shown in Table 4, so that we choose v_2 with the biggest value in the first round. Since v_2 cannot complete this task by itself, we continue to choose v_5 with the biggest value. According to function 1, task t_1 diversity value is 0.69, so that it is a good team which meets the team diversity requirements. For the task t_2, we retrieve its valid unmanned vehicles $\{v_6, v_7, v_8\}$. Similarly, we can form a team with three unmanned vehicles $\{v_6, v_7, v_8\}$ to conduct this task. The team diversity value is 1.09 which also meets the team diversity requirements.

Table 4 Running process of greedy with diversity algorithm

Round	v_2	v_3	v_4	v_5
1	$\sqrt{2}*$	$\frac{1}{\sqrt{2}}$	0	$\frac{2}{\sqrt{5}}$
2	–	0	0	$\frac{1}{\sqrt{5}}*$

3.4 TD-SC divide-and-conquer approach

The greedy algorithm could solve this problem. But it may incur that we can only accomplish local optimality. Consequently, in this section, we present a divide-and-conquer algorithm (D&C), which first divides the TD-SC problem into smaller subproblems, such that each subproblem includes a subset of all spatial tasks and then conquers the subproblems recursively until the final set size is 1.

Specially, for each subproblem, we will process this problem by recursion. We should note that we can solve the problem by the greedy algorithm 2 when the subproblem includes only one task. During the recursive process, we will merge assignment results from subproblems and obtain the assignment results by reconciling the conflictive assignment instance. Finally, we can return the task assignment instance set I_p.

3.4.1 TD-SC problem decompositions

In this subsection, we decompose a TD-SC problem into subproblems. Given n unmanned vehicles and m spatial tasks, we part those spatial tasks into k subgroups, and each subgroup contains $\lceil m/g \rceil$ tasks. Algorithm 3 presents the pseudocode of our decomposition algorithm, namely TD-SC_Decomposition, which returns TD-SC subproblems, P_s, after decomposing the original TD-SC problem.

Specially, we could set g with different number according to the spatial task's number. In our case, we let g be 5 (line 1). Then, we initialize empty subproblems P_s (lines 2-3). Next, we obtain one subproblem P_s at a time (lines 4-8). In particular, for each round, we retrieve a task t_j and its top-$\lceil m/g \rceil$ nearest tasks (line 5). Then, for each task t_j, we obtain its valid unmanned vehicles which can meet the task t_j requirement (such as: time interval constraint, range constraint, skills constraint.) (lines 6-7). Finally, we return all the decomposed subproblems P_s.

Algorithm 3: TD-SC_decomposition

Input: m available spatial tasks in T_p
Output: decomposed TD-SC sub-problems, $P_s(1 \leq s \leq g)$
1 estimate the best number of groups, g, for V_p
2 **for** $s = 1$ *to* g **do**
3     $P_s \leftarrow \phi$
4 **for** $s = 1$ *to* g **do**
5   let set T_p^j contain the next task t_j and its top-($\lceil m/g \rceil$ - 1) nearest tasks **for** *each task* $t_j \in T_p^j$ **do**
6   obtain all valid unmanned vehicle for task t_j
7   add $T_p^{(j)}$ to P_s
8 return $P_s(1 \leq s \leq g)$

3.4.2 TD-SC problem divide-and-conquer

In this subsection, we propose a divide-and-conquer algorithm, namely TD-SC_D&C, which recursively parts the initial TD-SC problem into subproblems, recursively solves every subproblem and merges assignment results of subproblems by resolving the conflicts. Specifically, in Algorithm 4 (TD-SC_DC), we first initialize empty task assignment instance set S_p (line 1). Then, we call the TD-SC_Decomposition approach (as mentioned in Algorithm 3) to get subproblems P_s (line 2). For each subproblem P_s, if

P_s includes more than 1 task, we will recursively call Algorithm 4 (TD-SC_DC) itself to divide the subproblem P_s (lines 4-5). Or, when subproblem P_s includes only one task, we can apply algorithm 2 (the greedy algorithm) to solve this subproblem T_p^s and get assignment results I_p^s (lines 6-7). Afterward, we can get an assignment instance set I_p^s for each subproblem P_s and merge them into one task assignment instance set I_p, by reconciling the conflict unmanned vehicles (lines 8-10). Specifically, I_p is merged with an assignment set I_p^s from subproblem P_s at each time (lines 9–10). We call algorithm 5 (TD-SC_Conflict_Reconcile) to solve the conflict. Eventually, we return the final result of merged task assignment instance set I_p (line 11).

Algorithm 4: TD-SC_D&C

Input: The available spatial tasks T_p, The available unmanned vehicle V_p
Output: Task assignment instance set I_p

1 $I_p \leftarrow \phi$
2 invoke TD-SC_Decomposition(V_p, T_p), and obtain subproblems T_p^s
3 **for** s = *1 to* g **do**
4   **if** *the number of tasks in subproblem* T_p^s *is more than 1* **then**
5         $I_p^{(s)}$ = TD-SC_&D&C(V_p, T_p)
6   **else**
7   invoke algorithm 2 (The Greedy Algorithm) to solve sub-problem T_p^s, and obtain assignment results $I_p^{(s)}$
8 **for** i = *1 to* g **do**
9   get the next subproblem T_p^s;
10     $I_p = TD - SC\_Conflict\_Reconcile(I_p, I_p^s)$
11 return I_p

3.4.3 TD-SC problem conflict reconciliation

In this subsection, we propose the conflict reconciliation algorithm, which solves the conflicts while merging assignment results of subproblems. We presume that I_p is the merged assignment instance set. There is a new subproblem P_s with assignment set $I_p^{(s)}$. Algorithm 5 (TD-SC_Conflict_Reconcile) presents the merging algorithm, namely TD-SC_Conflict_Reconcile, which incorporates two assignment sets I_p and $I_p^{(s)}$ by resolving conflicts. Figure 2 shows the process of reconciling conflict.

Specifically, the same unmanned vehicle v_i could be assigned to two different tasks from two subproblems. But a unmanned vehicle can only conduct one task at the same time. So we must avoid this case. Our algorithm needs to find a set, V_c, of all conflicting unmanned vehicles between I_p and $I_p^{(s)}$ (line 1). After that, we get conflicting unmanned vehicle v_i and its k corresponding spatial tasks. For each task, we calculate the value that the unmanned vehicle v_i can bring to this task. We assign the unmanned vehicle v_i to the task with highest value (lines 4-9). Then, we let conflicting unmanned vehicle v_i assign to the task with higher value and substitute the conflicting unmanned vehicle v_i with another available unmanned vehicle for task with lower value (lines 9-10). It is worth noting that if no other unmanned vehicles are available for replacing v_i , we may need to sacrifice the task with lower value. After resolving all conflicts, we merge assignment instance set I_p with $I_p^{(s)}$ (line 12) and return the merged result I_p (line 13).

Algorithm 5: TD-SC_Conflict_Reconcile

Input: the current assignment instance set, I_p, of subproblem P have been merged, and the assignment instance set, $I_p^{(s)}$, of subproblem P_s

Output: a merged task assignment instance set, I_p

$V_c \leftarrow find$;
all;
conflicting;
unmanned vehicles;
between;
I_p and I_p^s
while $V_c \neq \phi$ **do**
  get a unmanned vehicle $v_i \in V_c$ with the highest traveling cost in Ip(s), and its k corresponding spatial tasks;
  $bestValue_{t_j} = 0$;
  for i = *0 to* k **do**
    $value_{t_j} \leftarrow argmax_{v_i}\left(\frac{MAXITEM(Team_j \cup w)}{c}\right)$;
    if $value_{t_j} < bestValue_{t_j}$ **then**
      $bestValue_{t_j} = value_{t_j}$
  let the conflicting unmanned vehicle v_i stay in the best task's team;;
  find another unmanned vehicle v_j for the task which lost the the conflicting unmanned vehicle v_i;;
  $V_c = V_c - \{v\_i\}$;
$I_p = I_p \cup I_p^s$;
return I_p

Example 4 Back to our running example in Example 2. The running process of the divide-and-conquer algorithm is as follows. First, we invoke TD-SC_Decomposition(V_p, T_p) and obtain subproblems T_p^s. In this case, we get two subproblems. T_p^1 contains task t_1. T_p^2 contains task t_2. For each subproblem, we invoke algorithm 2 (the greedy with diversity algorithm) to solve subproblem T_p^s and obtain assignment results $I_p^{(s)}$. For subproblems T_p^1, we retrieve task t_1 valid unmanned vehicles $\{v_2, v_3, v_4, v_5\}$. Similarly, we choose unmanned vehicle v_2 and unmanned vehicle v_5 to conduct this task, and its team diversity is 0.69. For subproblems T_p^2, we retrieve task t_2 valid unmanned vehicles $\{v_5, v_6, v_7, v_8\}$. Every unmanned vehicle's value is shown in Table 5. Similarly, we can form a team with three unmanned vehicles $\{v_5, v_6, v_7\}$ to conduct this task. However,

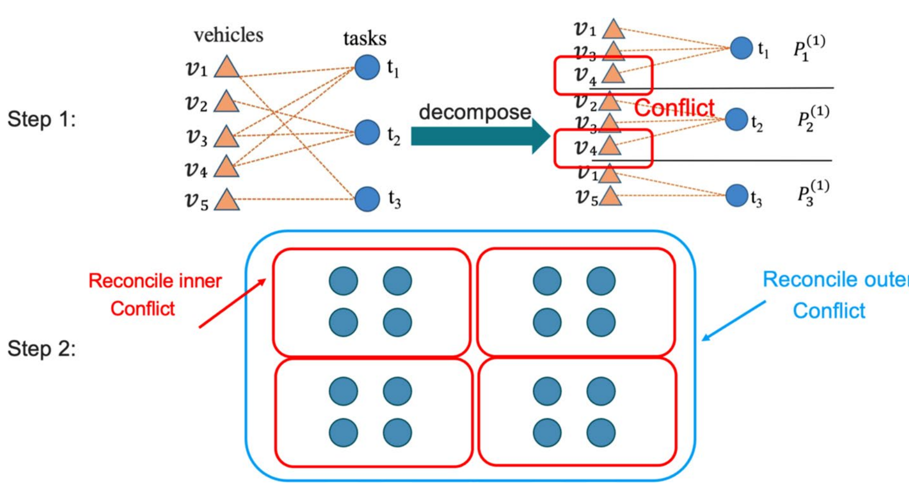


Fig. 2 Conflict reconcile

unmanned vehicle v_5 is assigned to two different tasks which is not acceptable. So we reconcile this conflict by Algorithm 5. We calculate the value of unmanned vehicle v_5 which can bring to those tasks, respectively. Task t_1 value is $\frac{2}{\sqrt{5}}$, and t_2 value is $\frac{1}{2}$, so that we let v_5 stay in task t_1 team. Then, we will find another unmanned vehicle for task t_2. As can be seen, we find that v_8 can perfectly substitute v_5. Finally, task t_1 team is $\{v_2, v_5\}$ and team diversity is 0.69. Task t_2 team is $\{v_6, v_7, v_8\}$ and team diversity is 1.09.

4 Results and discussion

4.1 Performance metrics

We measure the performance of team diversity with two elements—how much team diversity it increases to the team and how much efficiency it loses. In order to measure advancement on team diversity, we measure the Shannon entropy of a team of diverse unmanned vehicles with and without using our approach. Shannon entropy of a team is given by: $-\sum_{i=1}^{K}\left(p_k \log p_k\right)$, where p_k is the proportion of people on that team from cluster k. Therefore, the impact of team diversity can be measured as advancement in average entropy for all teams. We define the *entropy gain* (EG) as:

$$\mathrm{EG} = \frac{\text{Average entropy based on team diversity}}{\text{Average entropy without team diversity}} \tag{2}$$

If a team of unmanned vehicles are evenly come from different clusters, entropy for a team is maximized. In the same way, if a team of unmanned vehicle are all come from same cluster, entropy for a team is minimized.

To measure the loss of efficiency owing to diverse matching, we use the *cost of diversity* ($C\ o\ D$) metric which measures the trade-off in completed task's number under a team diverse matching objective. In particularly, we define the metric to measure the completed task's number loss.

$$\mathrm{CoD} = \frac{\text{Number of completed tasks based on diversity algorithm}}{\text{Number of completed tasks based on greedy algorithm}} \tag{3}$$

For instance, at timestamp p, we first retrieve a set, V_p, of all the available unmanned vehicles, and a set, T_p, of all the available spatial tasks. If diversity approach can match up to 120 tasks, greedy without diversity approach can only match up to 100 tasks. Then, *CoD* will be 1.2, suggesting that this diversity algorithm does not reduce the number of tasks matched.

Table 5 Running process of divide-and-conquer algorithm

Round	v_5	v_6	v_7	v_8
1	$\frac{1}{2}*$	$\frac{1}{\sqrt{5}}$	$\frac{1}{2}$	$\frac{1}{\sqrt{8}}$
2	–	$\frac{1}{\sqrt{5}}*$	$\frac{1}{3}$	
3	–	–	$\frac{1}{3}*$	0

Table 6 Data of vehicle parameter

Parameters	Description	Example
vehicle_id	A unmanned vehicle has a unique id	00345
(Lat, Long)	The position coordinates of the unmanned vehicle are expressed in latitude and longitude	(121.747619, 31.115913)
Timestamp	It indicates when the vehicle went online	1615910406
Skills set	The set of skills the vehicle has	{2, 4}
Property	It denotes unmanned vehicle special attribute	3

Table 7 Data of task parameter

Parameters	Description	Example
task_id	A task has a unique id	0235
(Lat, Long)	The position coordinates of the task are expressed in latitude and longitude	(121.540184, 31.21628)
Timestamp	It indicates when the task went online	1615911829
Skills set	The set of skills the task need	{1, 3}
Budget	Maximum budget for the task	2840

Table 8 Experimental setting

Parameters	Values
The range of task radius	2000, 2500, 3000, 4000
The number of task budget	1600, 2000, 2400, 3000

4.2 Experimental study

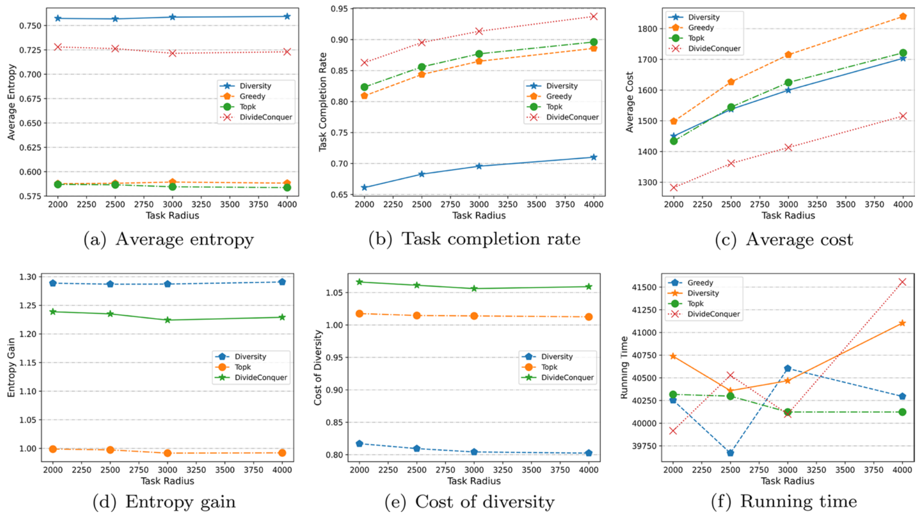
In this section, we conduct experiments to demonstrate the effectiveness and efficiency of our proposed algorithms. All the experiments were run on a MacOS with Intel Core i5 @ 3.1 GHz and 16 GB memory, and all the algorithms were implemented in Java with JDK 11.

4.2.1 Experimental setup

Data Sets We use a real data set collected from DiDi, which is a Chinese vehicle for hire company. We collected the taxi-calling data sampled from October 2016 in XiAn by a large-scale online taxi-calling platform in China. In the DiDi data set, every order has a ID, a matched driver ID, a start timestamp, a end timestamp, a start location, a end location (Table 6).

We use synthetic data based on the DiDi's real data set to test our approaches. Specifically, each unmanned vehicle has a ID, a start location, a online timestamp, one or two skills and a property. Each task has a ID, a start location, a online timestamp, one or more needed skills and the budget. In this paper, our synthetic data set includes the information of 10,536 unmanned vehicles and 3,512 spatial tasks (Tables 7, 8).

Evaluation We compare and evaluate the performance of following methods:



(a) Average entropy (b) Task completion rate (c) Average cost

(d) Entropy gain (e) Cost of diversity (f) Running time

Fig. 3 Effect of the range of task radius

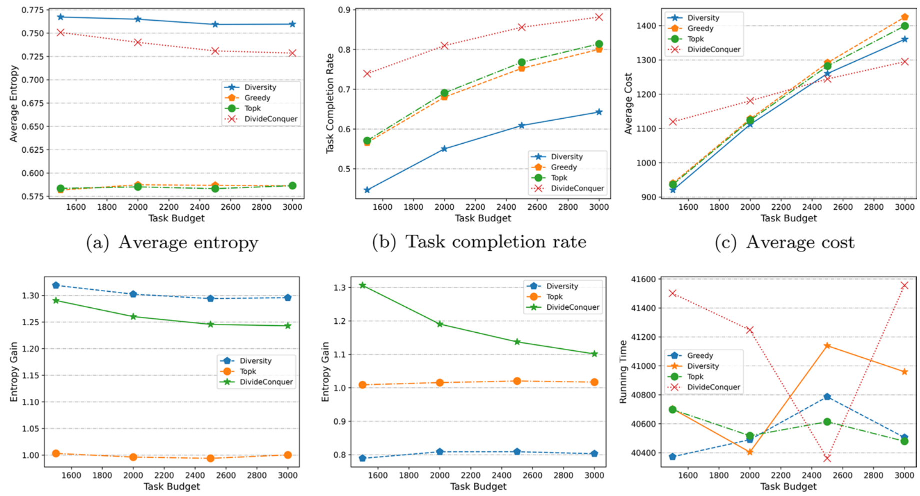
1 Greedy: a approach without diversity. We introduce this method because we want to calculate entropy gain and cost of diversity. We mentioned it in Sect. 4.1.
2 GD: Greedy diversity algorithm. This is our baseline.
3 Top-k: This method from paper [40].
4 DC: Divide-and-conquer algorithm

4.2.2 Experimental results

In this subsection, we show the effects of the range of task budgets and the range of task radius.

Effect of the Range of Task Radius Figure 3 illustrates the experimental results on different task's radius of task B_j from 2000 to 4000. In Fig. 3a, when the value of task's radius increases, the task's team average entropy of baseline and Top-k increases slightly, and the task's team average entropy of GD and DC decreases. However, our proposed two algorithms can obtain a high value. It suggests that our algorithms can make the team diverse in task assignment. In Fig. 3b, when the value of task's radius increases, the task completion rate of four approaches all increases. The reason is that the more task radius, the more available unmanned vehicles for tasks. In Fig. 3c, when the value of task's radius increases, the task completion rate of four approaches all increases. The reason is that task cost is positively correlated with the task radius. Although our GD algorithm average cost is highest, our DC algorithm can decrease the task cost largely. In Fig. 4d, e, except for method DC, the entropy gain and cost of diversity are basically the same. Our proposed method DC has good results. This suggests that method DC increases team diversity without reducing the number of task matches. In Fig. 4e, the running time of the program varies widely, and the running time of the different methods is not very different.

Effect of the Task Budgets Figure 4a–c illustrates the experimental results on different values of task B_j from 1500 to 3000. In Fig. 4a, the task's team average entropy of



(a) Average entropy (b) Task completion rate (c) Average cost

(d) Entropy gain (e) Cost of diversity (f) Running time

Fig. 4 Effect of the task budgets

baseline and Top-k increases, when the value of task budgets gets larger. In contrast, the task's team average entropy of GD and DC decreases, when the value of task budgets gets larger. GD and DC can achieve higher value than baseline and Top-k. It shows that our proposed two approaches are more better. As shown in Fig. 4b, the task completion rate of all the four algorithms increases, when the value of task budgets gets larger. GD and DC can achieve task completion rate than baseline and Top-k. It shows that our proposed two approaches are more effective. As shown in Fig. 4c, the task's average cost of all the four algorithms increases, when the value of task budgets gets larger. Task's average cost of GD is highest in those four approaches. Task's average cost of DC is generally lowest. It shows that our proposed DC approaches are effective. In Fig. 4d, e, the entropy gain and cost of diversity are basically the same. Our proposed method DC has good results. This suggests that method DC increases team diversity without reducing the number of task matches. In Fig. 4e, the running time of the program varies widely, and the running time of the different methods is not very different.

5 Conclusions

In this paper, we study a novel spatial crowdsourcing problem, called the team diversity in spatial crowdsourcing, which assigns a team of diverse unmanned vehicles to the multi-skill-required spatial tasks, so that the needed skills of spatial tasks can be contented by a team of unmanned vehicles. To address the TD-SC problem, we design a general framework, which not only includes a greedy algorithm but also divide-and-conquer algorithm, which can effectively retrieve TD-SC answers. Finally, we conduct a lot of experiments which verify the efficiency and effectiveness of our proposed algorithms.

Abbreviations

TD-SC	Team diversity spatial crowdsourcing
GD	Greedy algorithm with diversity
D & C	Divide-and-conquer algorithm
LTE	Long-term evolution network
5G	The fifth-generation cellular network

SAT	Server assigned tasks
WST	Worker selected tasks
EG	Entropy gain for all teams
CoD	Cost of diversity for a team
Top-k	Top-k team recommendation and its variants in spatial crowdsourcing

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Author contributions
YL and HF designed the problem and proposed the experimental algorithms. HF and ZP simulated the method and tested it; besides, they drafted the manuscript. YL and LZ revised and improved the manuscript. JW provided technical support. All authors read and approved the final manuscript.

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Availability of data and materials
The data sets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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