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Spatial crowdsourcing task allocation for heterogeneous multi-task hybrid scenarios: a model-embedded role division approach

Key words: Spatial crowdsourcing (SC); Heterogeneous task; Role division; Attraction–repulsion mechanism; Individual sorting

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Motivation

- Task allocation is a critical problem in spatial crowdsourcing. We study its new challenges under the trend of increasingly flexible services and diverse user needs.
- Address the impracticality of static-scenario assumptions by studying online allocation for dynamic environments with unpredictable tasks/workers.
- Move beyond homogeneous models to deal with heterogeneous multi-task allocation (HMTA) in hybrid environments where tasks and workers have diverse attributes.

Problem

In response to the described scenario of spatial crowdsourcing, we define a kind of HMTA problem.

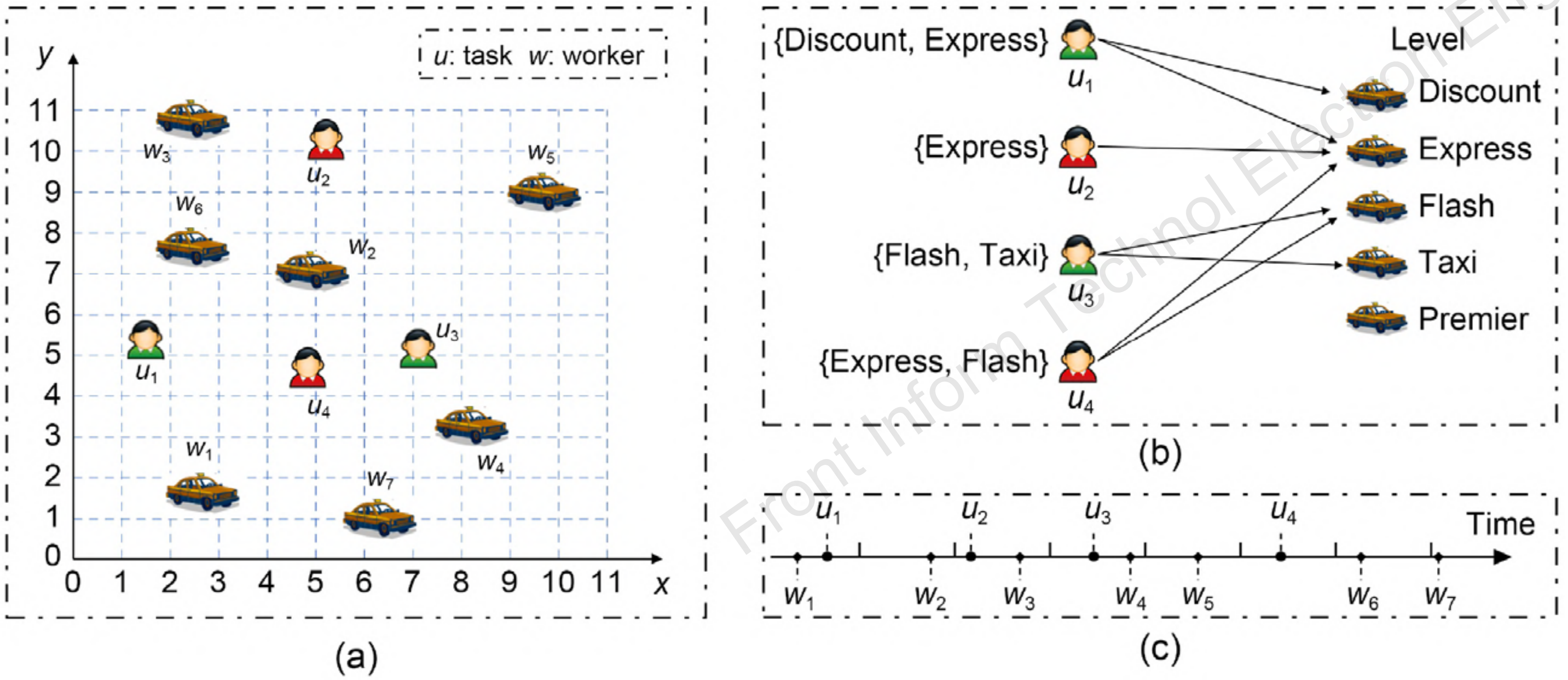

Fig. 1 Task allocation of a car-hailing scenario: (a) spatial distributions; (b) task requirements; (c) temporal distributions

$$u_i = \langle \mathbf{lu}_i, \mathrm{Rl}_i, h_i, s_i, e_i \rangle$$

$$w_j = \langle \mathbf{lw}_j, r_j, p_j, c_j, b_j, d_j \rangle$$

$$\mathrm{Rf}\left(u_i, w_j\right) = \left[p_j \cdot h_i - C_\mathrm{d} \cdot \mathrm{dist}\left(\mathbf{lw}_j, \mathbf{lu}_i\right)\right] \cdot X_{ij}$$

$$\mathrm{UT} = \sum\nolimits_{u_i \in U', w_j \in W'} \mathrm{Rf}\left(u_i, w_j\right) - \eta \sum\nolimits_{u_i \in \mathrm{Uf}} h_i$$

Method

We propose the role division approach embedded with individual sorting model (RD-ISM) to address the problem. The method begins with data processing of perceived information, where we collect tuples of objects to be matched using batch-based mode (BBM).

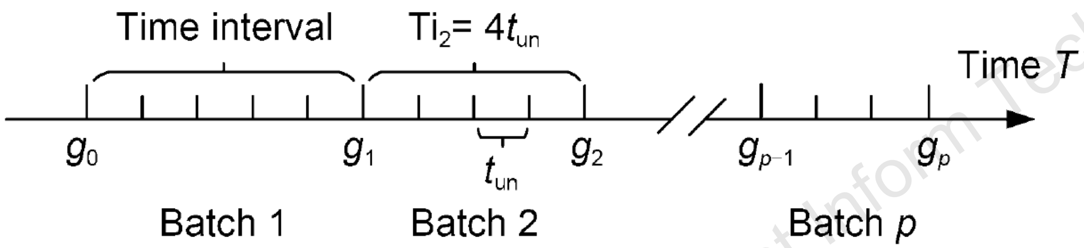

Fig. 2 Timeline diagram of the BBM

Algorithm 1 Batch-based mode

Input: Total time T and time interval Ti

Output: Task–worker matching results M within T

1 Set $M \leftarrow \varnothing$

2 After every time interval Ti, a batch p is obtained

3 **for** each batch $p \in T$ **do**

4 Collect a set of tasks U_p

5 Collect a set of workers W_p

6 Prioritize all objects according to the individual sorting model to obtain a task sequence

7 Based on the task sequence, perform matching based on the role division model and obtain a feasible matching $M_p \subseteq U_p \times W_p$

8 Let the matching result M_p be a feasible matching of batch p and output it

… …

Method

During the allocation process, the individual sorting model is first introduced to determine the sequence of tasks and workers. Then, a role division model based on attraction–repulsion mechanism is designed to match tasks and workers.

Table 1 Mapping relationship between attraction–repulsion mechanism and task allocation

Attraction–repulsion mechanism	Task allocation
Agent	Worker
Role	Task
Environment	Task attributes
Role diversion	Task–worker matching
Overall role distribution	Matching results $M \subseteq U \times W$

Algorithm 2 RD-ISM

Input: Total time T and initial time interval Ti

Output: Matching results M

1 Set $M \leftarrow \varnothing$

2 Let $v \leftarrow \text{floor}(\ln(\text{Rf}_{\text{Max}}))$

3 Set $\omega_z=1$, where $z=0, 1, \cdots, v$

4 Calculate the probability $\boldsymbol{P}=(P_0, P_1, \cdots, P_v)$ according to Eq. (25)

5 After every time interval Ti, a batch p is obtained

6 **for** each $p \in T$ **do**

7 Collect the task set U_p and the worker set W_p

8 Calculate the priority Pr(·) of objects and EU and EW according to the individual sorting model

… …

Method

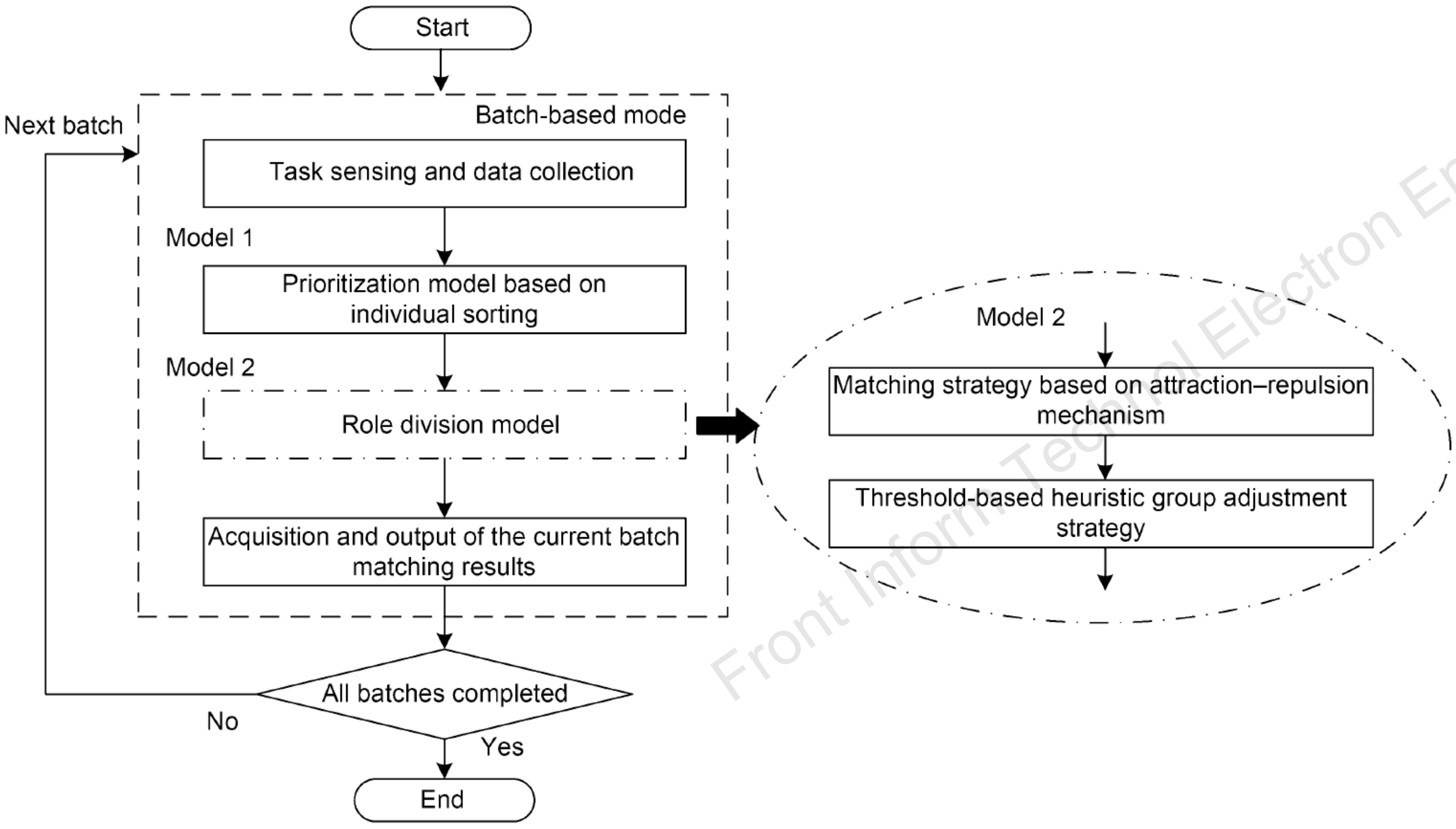

Fig. 3 Overall framework of RD-ISM

After individual sorting and role division, the current batch matching results are obtained. In the real-time task allocation process, the algorithm can achieve the final matching results of all objects following multiple batches of iteration.

Major results

To evaluate the performance of RD-ISM, we design two distinct sets of test cases: synthetic dataset instances and real-world dataset instances.

Table 2 Dataset statistics and parameter settings

Parameter	Settings and statistics	
	Real-world dataset	Synthetic dataset
N=4|U|=|W|	2500, **5000**, 10 000, 20 000	5000, 10 000, **20 000**, 40 000, 80 000
Time range (min)	[0, 300]	[0, 500]
Spatial range	Latitude and longitude to coordinates	Randomly distributed within 30 km×30 km area
Task requirements and worker levels R	{1, 2, 3, 4}	{1, 2, 3, 4}
Unit service price pr (CNY)	{1, 2, 3, 4}	{1, 2, 3, 4}
Worker service radius c (km)	10	5, **10**, 15, 20
Unit distance cost C_d (CNY/km)	0.8	0.8
Dissatisfaction coefficient η	0.1	0.1
Expected value μ of task service cost h	20, **25**, 30, 35, 40	20, **25**, 30, 35, 40

Bold entries represent the default settings used during the experiment

Major results

In the above instances, the effectiveness of RD-ISM in solving the HMTA problem was verified through comparisons with other algorithms. Additionally, we investigated the impact of different parameter values on performance and validated the scalability of the method.

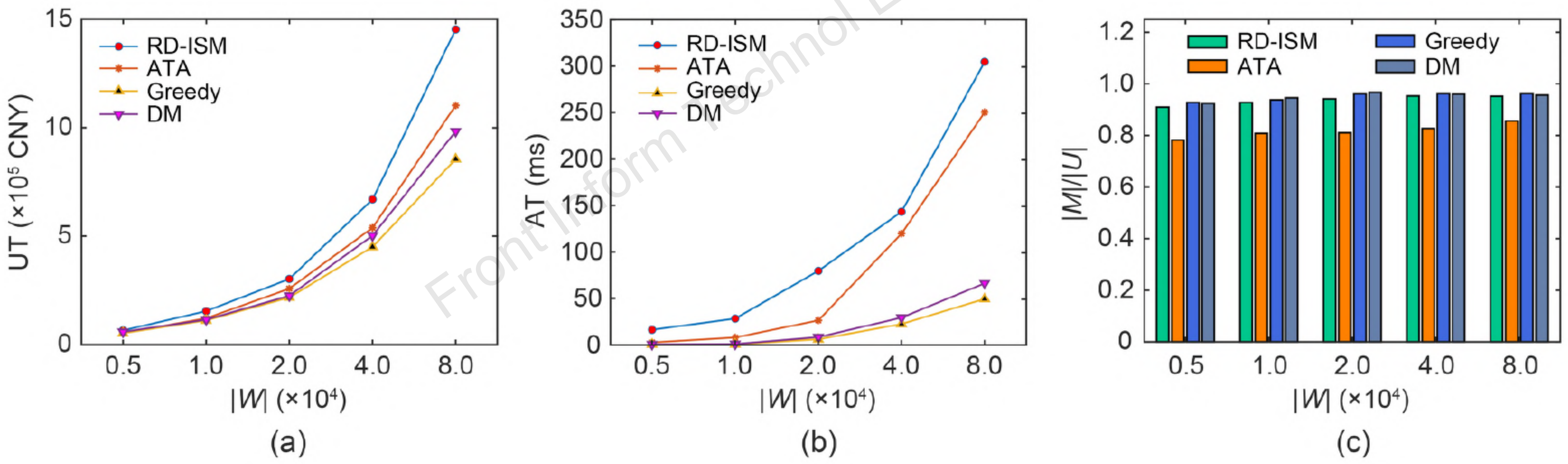

Fig. 4 Comparison of results from varying $|W|$: (a) UT; (b) AT; (c) $|M|/|U|$

Conclusions

- Define and formalize HMTA for hybrid heterogeneous scenarios, optimizing both direct allocation benefits and user satisfaction metrics.
- Design a role-division approach with individual sorting and attraction–repulsion mechanisms for spatiotemporal priority-based worker–task matching via iterative batch processing.
- Validate the method’s performance and scalability through comparative experiments on real-world/synthetic datasets and parameter sensitivity analysis.

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