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Spatiotemporal distance embedded hybrid ant colony algorithm for a kind of vehicle routing problem with constraints

Key words: Vehicle routing problem with constraints (VRPC); Spatiotemporal distance function; Labor division strategy; Ant colony algorithm (ACO)

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Motivation

- Most of vehicle routing problem (VRP) variants are built on logistics networks. However, the demand for route planning is no longer limited to logistics and distribution, but reflected in aspects such as car-sharing traveling.
- Compared with VRP variants, the vehicle routing problem in the car-sharing environment has more stringent spatiotemporal constraints.
- Ant colony algorithm (ACO) is an effective method for solving VRPs, but it is easily trapped in local extremes and difficult to jump out.

Model

Based on the problem characteristics, we define a kind of vehicle routing problem with constraints (VRPC) model.

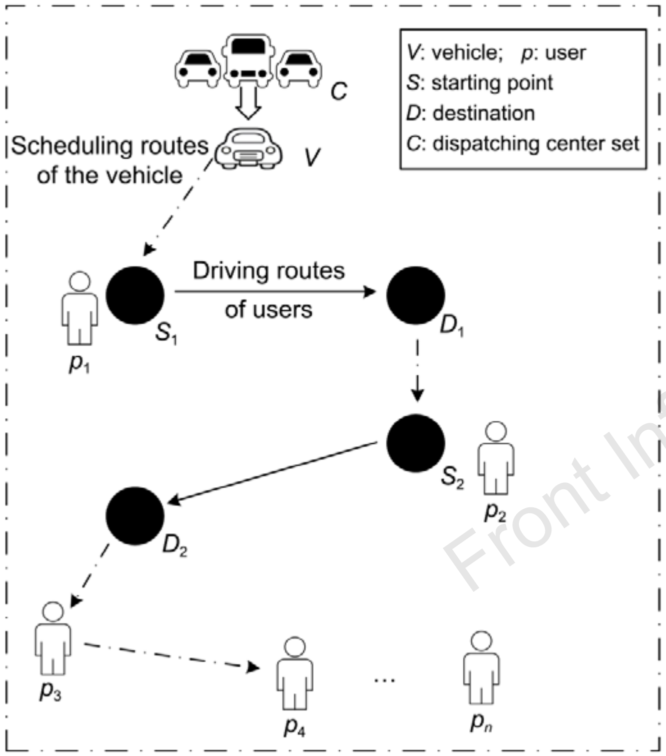

Fig. 1 Vehicle service process in the vehicle routing problem with constraints

$$\mathrm{Cost}_{\min} = C_{\mathrm{v}} + C_{\mathrm{s}} + C_{\mathrm{f}} + C_{\mathrm{t}},$$

$$C_{\mathrm{v}} = Z_1 K,$$

$$\begin{aligned} C_{\mathrm{s}} = Z_2 \Bigg[& \sum_{i\in P}\sum_{j\in P}\sum_{k\in[1,K]} \left(\mathrm{dist}\left(D_i, S_j\right) X_{ijk}\right) \\ & + \sum_{i\in P}\sum_{k\in[1,K]} \left(\mathrm{dist}\left(C, S_i\right) X_{cik}\right) \\ & + \sum_{i\in P}\sum_{k\in[1,K]} \left(\mathrm{dist}\left(D_i, C\right) X_{ick}\right) \Bigg], \end{aligned}$$

$$C_{\mathrm{f}} = Z_3 \sum_{i\in P} \mathrm{dist}\left(S_i, D_i\right),$$

$$C_{\mathrm{t}} = \sum_{i\in P} F_i, \quad \forall i \in P.$$

Method

First, the spatiotemporal distance function is established based on the spatiotemporal distribution characteristics of users.

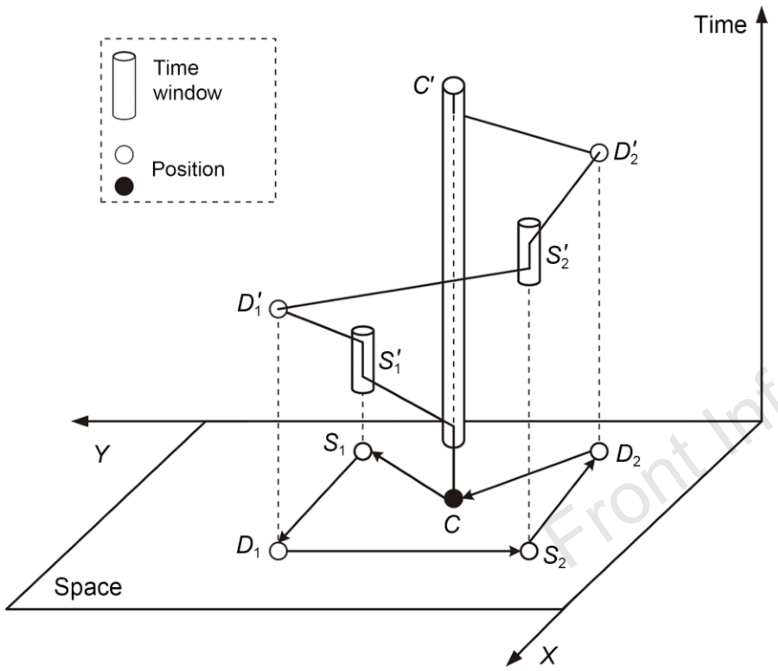

Fig. 2 Vehicle trajectory and user services of the vehicle routing problem with constraints

$$\text{dist}T_{ij} = \begin{cases} K_{t1}\left(e_j - T_{Sj}\right), & T_{Sj} < e_j, \\ 0, & e_j \le T_{Sj} \le l_j, \\ K_{t2}\left(T_{Sj} - l_j\right), & T_{Sj} > l_j, \end{cases}$$

$$\forall i, j \in P \text{ and } e_i < e_j,$$

$$\text{dist}S_{ij} = \begin{cases} \text{dist}\left(D_i, S_j\right), & e_i \le e_j, \\ \text{dist}\left(D_j, S_i\right), & e_i > e_j, \end{cases}$$

$$\forall i, j \in P,$$

$$\text{dist}\,\text{ST}_{ij} = K_T T \text{dist} T_{ij} + K_S T \,\text{dist}\, S_{ij}, \quad \forall i, j \in P.$$

Method

Second, a clustering method based on the spatiotemporal distance is designed, called the spatiotemporal clustering algorithm (STCA). Subsequently, the initial solutions are constructed according to the clustering results.

Algorithm 1 Spatiotemporal clustering algorithm (STCA)

Input: datasets P, S, and D, time window $[e, l]$, cluster number z, and maximum clustering number $\mathrm{Clu}_{\max}$

Output: set of clusters $C_{\mathrm{I}}=\{C_{11}, C_{12}, \cdots, C_{1z}\}$

1 Data$=\{P_1, S_1, D_1, [e_1, l_1]; P_2, S_2, D_2, [e_2, l_2]; \cdots; P_n, S_n, D_n, [e_n, l_n]\}$

2 Randomly select data of z users from Data as cluster center Ct

3 **repeat**

4 $C_{1i}=\phi$ $(1\le i \le z)$ // Cluster C_{1i}

5 **for** $j=1, 2, \cdots, n$ **do**

6 Calculate the spatiotemporal distance distST_{ji} between user P_j and each clustering center Ct_i

7 Determine the cluster label of P_i based on the closest

… …

Algorithm 2 Heuristic semi-random strategy

Input: clustering results $C_{\mathrm{I}}=\{C_{11}, C_{12}, \cdots, C_{1z}\}$, and the number of initial solutions N

Output: initial solution set $S_{\mathrm{I}}=\{S_{\mathrm{I}1}, S_{\mathrm{I}2}, \cdots, S_{\mathrm{I}N}\}$

1 Set count=0

2 **while** count $<N$ **do**

3 **for** $i=1, 2, \cdots, z$ **do**

4 Cluster C_{1i} randomly selected to become a sequentially ranked object or a randomly ranked object

5 **if** $C_{1i}\in$Sequentially ranked object

6 Sort the users of C_{1i} according to the time window order and obtain Part_i=sort$\{C_{1i}\}$

7 **else**

… …

Method

Finally, we propose an improved ant colony algorithm (IMFACO) for routing optimization of VRPC, which can be divided into four parts.

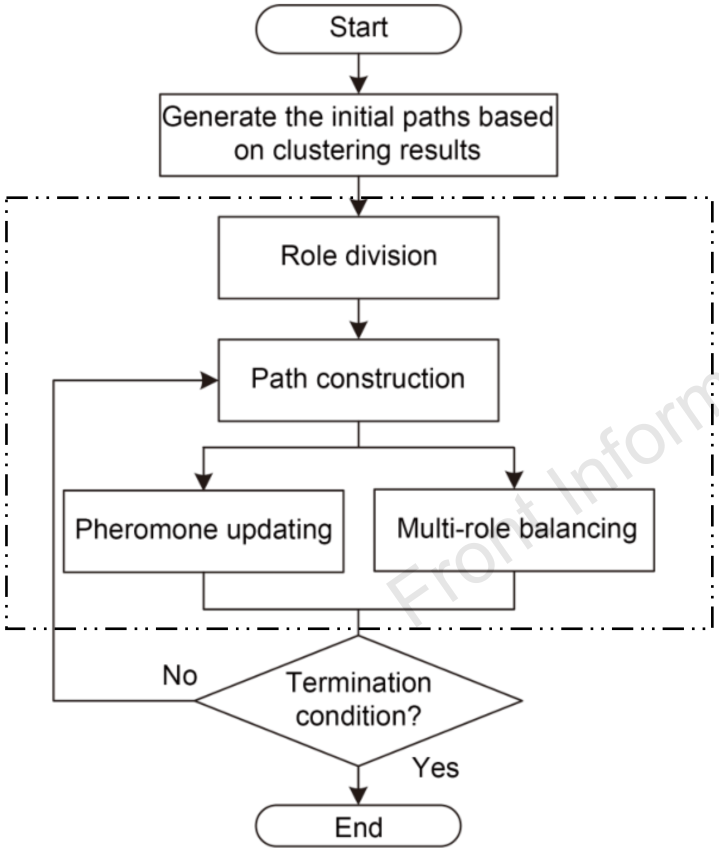

Fig. 5 Framework of the improved ant colony algorithm based on the mixed feedback mechanism

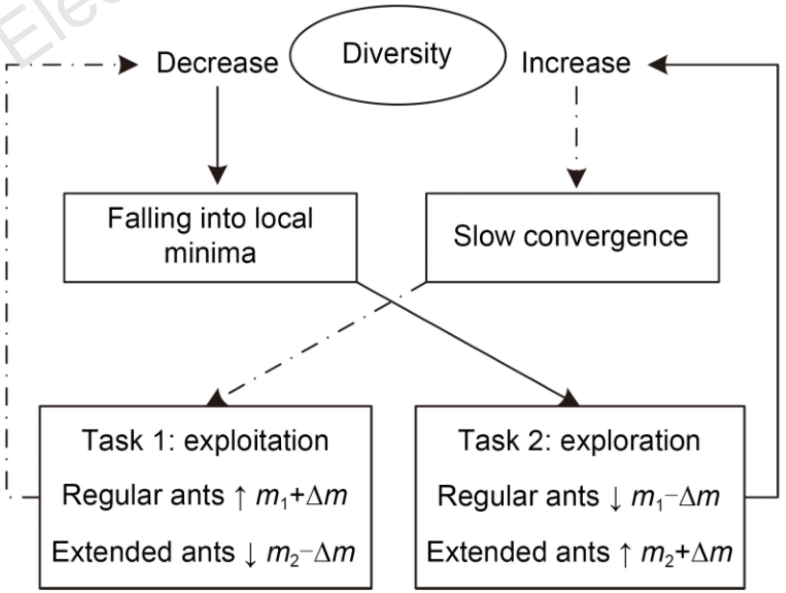

Fig. 8 Multi-role balancing mechanism

Major results

To assess the quality of the proposed algorithm, we first use the test instances for testing. Concerning the combined cost, our proposed algorithm has competitive cost compared to existing algorithms.

Table 4 Comparison results of VRPC test instances

Instance	Algorithm	Minimum	Average	Dev (%)	Instance	Algorithm	Minimum	Average	Dev (%)
C1 n=30	ACO	1074.7	1176.6	9.48	C5 n=60	ACO	2232.4	2516.6	12.73
	AADC	922.4	1050.9	13.94		AADC	2182.5	2441.4	11.86
	IWPA	891.5	983.9	10.36		IWPA	2201.8	2509.4	13.97
	IGA	947.4	1068.3	12.76		IGA	2182.5	2431.6	11.41
	HACA-ST	879.4	897.2	2.02		HACA-ST	2087.2	2170.5	3.99
C2 n=30	ACO	1097.3	1279.1	16.57	C6 n=60	ACO	1999.6	2306.8	15.36
	AADC	921.0	1026.3	11.44		AADC	1950.2	2217.2	13.69
	IWPA	1004.3	1127.7	12.29		IWPA	1903.4	2138.8	12.37
	IGA	988.6	1135.8	14.89		IGA	2067.2	2402.6	16.22
	HACA-ST	900.9	920.1	2.13		HACA-ST	1854.8	1929.5	4.03
C3 n=30	ACO	868.1	970.5	11.80	C7 n=100	ACO	3564.0	4205.9	18.01
	AADC	740.8	820.2	10.72		AADC	3434.4	3909.0	13.82
	IWPA	718.7	785.3	9.26		IWPA	3500.4	4072.8	16.35
	IGA	791.2	868.9	9.82		IGA	3564.0	4126.8	15.79
	HACA-ST	697.1	723.1	3.73		HACA-ST	3341.3	3553.8	6.34

… …   … …

Major results

In addition, to further assess the solution performance of the algorithm in a realistic environment, two scenarios instances are designed based on the real city.

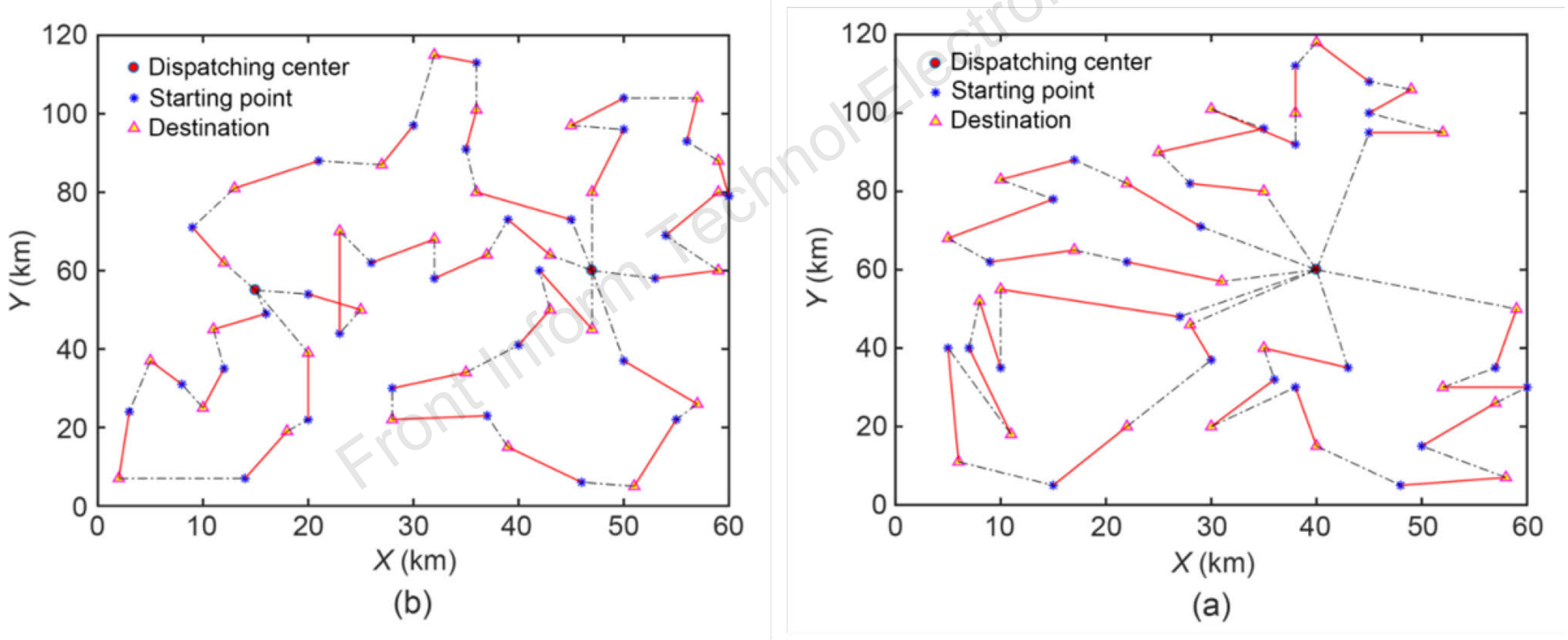

Fig. 11 Optimal routes of the scenario instances: (a) route of case 1; (b) route of case 2

Conclusions

- We investigate a kind of VRPC in the car-sharing mobility environment.
- We define a spatiotemporal distance function based on the temporal and spatial properties of users.
- We propose a spatiotemporal distance embedded hybrid ant colony algorithm (HACA-ST) to solve VRPC.

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