Agile Satellite Mission Planning via Task Clustering and Double-Layer Tabu Algorithm

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Abstract: Satellite observation schedule is investigated in this paper. A mission planning algorithm of task clustering is proposed to improve the observation efficiency of agile satellite. The newly developed method can make the satellite observe more targets and therefore save observation resources. First, for the densely distributed target points, a pre-processing scheme based on task clustering is proposed. The target points are clustered according to the distance condition. Second, the local observation path is generated by Tabu algorithm in the inner layer of cluster regions. Third, considering the scatter and cluster sets, the global observation path is obtained by adopting Tabu algorithm in the outer layer. Simulation results show that the algorithm can effectively reduce the task planning time of large-scale point targets while ensuring the optimal solution quality.

Keywords: Mission planning, agile satellite, task clustering, Tabu algorithm.

1 Introduction

In Earth observation missions, the target area should be pointed by on-board cameras to collect image data. Based on the target characteristics, the targets can generally be divided into point targets and regional targets. The characteristic of the target plays an important role during the mission planning and scheduling operation. However, the characteristic of the target has been rarely addressed in current research since the state-of-the-art research mainly focused on single point target even for area coverage problems. As the number of tasks increases, the number of solutions increases exponentially. Therefore, the current optimization model can no longer handle the complex mission planning problems due to the limited computing capacity. To solve this problem, the fact that the observation strip on the ground with a certain width can be generated during observation is addressed. The reason lies in the fact that the on-board camera has a certain angle of Field of View (FoV). Therefore, if the constraints of observation angle and observation window are met for several targets, the pointing direction of camera can be adjusted so that multiple targets can be considered within the same observation strip. Thus, multiple observation tasks can be clustered into one single task and thus be handled within one observation strip. The proposed pre-processing scheme based on task

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clustering can effectively reduce the task allocation burden of the system, shorten the optimization time, and improve the observation efficiency.

Various constraints should be taken into consideration during the mission planning process, and a lot of works have been presented in this area [Darnopykh and Malyshev (2012); Neeck, Magner and Paules (2005); Li, Sheng and Liu (2017)]. Bensana et al. [Bensana, Lamaitre and Verfaillie (1999); Bensana and Verfaillie (1996)] investigated the agile satellite schedule problem and considered the single-satellite scheduling problem as a value constraint satisfaction problem. Multiple approaches, including exact methods like a depth-first Branching and Bounding Algorithm, Russian Doll searches and the Tabu Search (TS) were adopted to solve the Systeme Probatoire d'Observation de la Terre 5 (SPOT5) satellite scheduling problem [Baltié, Bensana and Fabiani (2008)]. Studies showed that the exact algorithm was only suitable for tackling small-size scheduling problems. Therefore, heuristic algorithms were widely used to solve large-scale problems. Lamaitre et al. [Lamaitre, Verfaillie and Jouhaud (2000); Lamaitre, Verfaillie and Bataille (1998)] carried out research on the task planning and scheduling problem of Pleiades agile satellite. Based on the construction of constrained programming model, four algorithms, including constrained programming, greedy, dynamic programming and local search, are compared. A simple yet effective heuristic method for mission planning is proposed [Mok, Jo, Bang et al. (2018)]. An additional degree of freedom in pitch axis is taken into account, which can significantly increase the number of images compared to the roll-only observations, and possibility of reverse order observation is considered with a simple objective function. Habet et al. [Habet and Vasquez (2003)] solved the problem of mission planning for agile satellite. The idea of consistent saturated neighborhood is adopted, and the Tabu algorithm is proposed to solve the problem. Habet et al. [Habet (2009); Habet, Vasquez and Vimont (2010)] also used the Tabu search algorithm to solve the single agile satellite scheduling problem and ensure the consistency of the neighborhood through constraint propagation. Xu et al. [Xu, Chen and Liang (2016)] established the satellite's resource scheduling model which conforms to constraint conditions and solved the problem by the ant colony algorithm.

The idea of task clustering was created during the research of computer science. Palis et al. [Palis, Liou and Wei (1996)] merged fine-grained tasks into a single, coarser task to minimize overall execution time, which can help reduce high communication overhead in existing parallel machines. By using the task clustering strategy, the efficiency of task planning can be improved effectively. Especially, when the satellite resources are limited, the scheduling algorithm can produce good results quickly. The task clustering algorithm is particularly suitable for observation problems of large amount of targets and closely distributed point target. Since the task clustering strategy can improve the efficiency of solving NP problems, the double-layer Tabu algorithm based on task clustering is compared with the simple Tabu algorithm to show its better performance [Aitsaadi, Achir, Boussetta et al. (2009); Abdelaziz and Mir (2016)]. Dewatripont et al. [Dewatripont, Jewitt and Tirole (2000)] introduced the task clustering into the planning domain to solve the optimal task clustering problem in multitasking agency theory. The factors such as task substitution, task conflicts, and task implicit incentives are properly considered in up-mentioned works. However, the research on task clustering for imaging satellite is still relatively rare. Bai et al. [Bai, He, Li et al. (2009)] proposed the concept of task synthesis, in which merging multiple targets into one target. This is basically equivalent to task clustering. Xu et al. [Xu, Xu, Wang et al. (2010)] created a task clustering method for imaging satellite, and proposed the coverage problem of multiple point targets by single observation sequence. The priority of the task after clustering is taken into consideration, and the corresponding adjustment strategy is also introduced. Guo et al. [Guo, Wu and Qiu (2012)] established a graph model of agile satellite imaging and designed a clustering algorithm based on the largest and smallest ant system. Hao [Hao (2013)] constructed a task clustering model based on the study of satellite attitude shift time and task-constrained analysis. The problem is solved by ant colony algorithm. Wu et al. [Wu, Ma and Wang (2011)] proposed a dynamic clustering model based on the task background of multi-satellites collaborative imaging, and optimized it by simulating annealing algorithm. Xu et al. [Xu, Wang and Xu (2012)] designed a heuristic clustering algorithm based on meta-task insertion. Cohen [Cohen (2002)] considered the problem of single strip which covers multiple targets, but the observation angle is fixed. Xu et al. investigated the parameter optimization problem of observation time and angle by considering multiple targets with the same side angle and time window [Xu, Gong, Huang et al. (2007)]. Wang [Wang (2007)] proposed the optimization algorithm which considers the synthesis of adjacent tasks with the same side angle on the time window. Peng et al. [Peng, Chen, Du et al. (2018)] developed a sequential decision-making model and proposed a deep learning-based planning method to solve the SOOTP. The sequential decision-making model enables the satellite to decide the observation task to execute in real-time. She et al. [She, Li and Zhao (2018)] investigated a new AEOS mission planning algorithm based on Modified Mixed-Integer Linear Programming approach. This algorithm performs better in calculation time and therefore is more suitable for onboard applications in engineering. Overall, the existing task clustering method mainly considers the influence of satellite imaging conditions and focuses on the aggregation of local tasks, but global optimization is not achieved. In this paper, a task clustering planning method based on target location relationship is proposed, in which clustering is conducted before planning. A pre-processing scheme based on task clustering for dense point is proposed in this paper. The target within camera width is synthesized and clustered, thus reducing the dimension of solution space. Besides, a double-layered Tabu algorithm is adopted, the local observation path is design in the inner layer clusters firstly, and the global target observation path is generated in the outer layer. The experimental results show that the proposed method can reduce the calculation cost and thus improve observation efficiency. Extensive experiments and analysis show that the double-layer Tabu algorithm based on task clustering can consume less cost to produce better results when solving the target task planning problem of the imaging point on the ground.

The rest of paper is organized as follows. Section 2 describes task clustering method in details. In Section 3, a clustering observation path planning based on the Tabu algorithm is designed. Computer simulation and analysis are presented in Section 4. Finally, Section 5 contains a conclusion.

2 Task clustering method

In the observation progress of tradition satellite, since the number of sway imaging is limited, the satellites need a lot of time to adjust the attitude for different targets. The emergence of agile satellites changed the situation. Agile satellites have high mobility and can perform observation missions quickly. Therefore, the agile satellite can adjust the camera angle of side-swing to contain multiple targets in the same observation strip. Task clustering can organize the satellite resources reasonably.

In the realistic observation task, the high-value targets are usually centralized. The traditional point target programming sorts all the observation targets, the solution set is too extremely large to select and the optimization efficiency is low. For this reason, the pre-processing scheme based on task clustering is developed. The point targets in close distances are effectively aggregated into one point set. The target in the point set is planned first, so that the secondary planning of the planned set can be realized with minimum calculation cost.

To carry out the target clustering operation, the following basic clustering assumptions are made in this paper:

- Each task is independent, and there is no time constraint between each sub-task.
- Conforming to the constraints, each sub-task can be well executed by the satellite.
- Supposing that there is the maximum maneuvering angle for camera.
- The differences on resolution caused by the side-swing of the camera are not considered.
- Each mission only needs to be observed once.

To decide if the tasks belong to clustering problem, the clustering criteria is defined. In this paper, the criteria is two or more tasks can be performed in one single satellite observation. The process of task clustering can be divided into the following steps.

1) Judging the clustering relationship between sub-tasks

Agile remote-sensing satellites are able to observe multiple targets in short time, which is consistent with task clustering. The distance between the point targets is first determined, and the points which meet the distance constraint are included in the task cluster set. After this process, all visible sub-task target points are classified into multiple cluster point sets. All targets are characterized by five parameters: number, latitude, longitude, benefit and observation duration. Benefits are used to represent the priority of the task. For instance, $Pot_1(\lambda_1, \phi_1)$ stands for the target of number 1, λ_1 means longitude and ϕ_1 represents latitude.

2) The observation model of sub-task set is established

By elaborate selection, the longest connecting line between targets is selected as the observation baseline. The relative distance from the remaining set points to the baseline is sequentially calculated, and the point whose distance is less than half of the camera width is added into the original task set to form the task clustering. Then, all feasible observation sequences are arranged, and the shortest sequence is selected as the observation path of the cluster point set.

3) Plan the overall observation path

To realize the overall observation path planning, several steps are needed. First, a clustering set and a non-cluster set are randomly combined to generate an initial observation sequence. Second, the observation direction of the clustering task set is changed, and the optimal observation direction is retained according to the variation of the overall revenue. Third, all feasible sequences are evaluated according to the indicators. The first indicator is the observation end time (early end time can reserve time for the subsequent tasks), the second indicator is the overall observation time. Taking the indicator as the objective function to select all feasible sequences, the optimal sequence is selected as the final observation sequence.

Take the center point Pot_x as an example, calculate the distance between Pot_x and Pot_i. If the distance $Dist(x,i)$ is less than the $Mdist$, Pot_i is put into $Cluster_x$ according to function (1).

$$Cluster_x = \{Pot_i \mid 1 \le i \le N, Dist(x,i) < Mdist\} \tag{1}$$

where N represents total number of task.

As shown in the Fig. 1, the distance is calculated between the point in $Cluster_x$ and Pot_j, which is around $Cluster_x$. If the distance is less than $Mdist$, the corresponding point is put into $Cluster_x$ according to function (2).

$$Cluster_{x\_\exp} = \{Pot_j \mid 1 \le j \le N, Pot_k \in Cluster_x, Dist(k,j) < Mdist\} \tag{2}$$

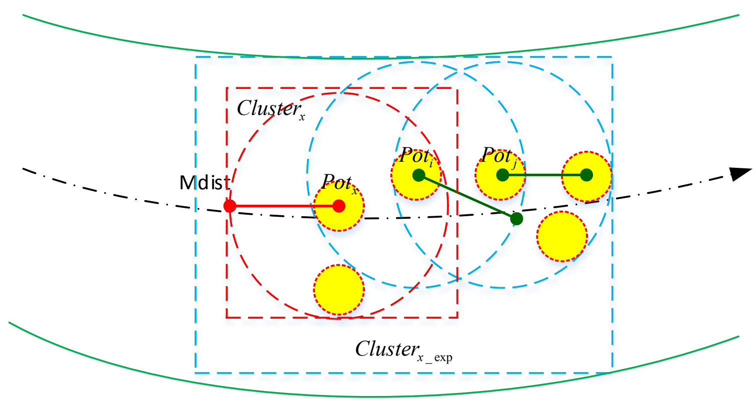


Figure 1: $Cluster_x$, $Cluster_{x\_\exp}$ schematic diagram in the view of satellite

After completing the above process, repeat the process of function (2) until the target set $Task_u = \{Pot_1, Pot_2, Pot_3, \ldots, Cluster_{x\_\exp}, Cluster_{y\_\exp}, \ldots, Cluster_{u\_\exp}\}$ which composed of target and cluster set is obtained. Where u represents the total number of points and cluster sets that need to be assigned.

3 Clustering observation path planning

After clustering points, the observation path of the cluster set can be planned according to the positional relationship between the points. This problem can be simplified as the

Traveling Salesman Problem (TSP) [Kruskal (1956); Lawler, Lenstra, Kan et al. (1986); Applegate, Bixby, Chvatál et al. (2011)]. It is believed that the traveling salesman problem can be considered as a Non-deterministic Polynomial Complete problem (NPC). An NP-complete decision problem is one belonging to both the NP and the NP-hard complexity classes. In this context, NP stands for "nondeterministic polynomial time". The set of NP-complete problems is often denoted by NP-C or NPC. At present, the methods for solving the NPC problem are mainly divided into two categories: The exact algorithm and the heuristic algorithm (approximation algorithm). When the exact algorithm is used to solve the small-scale problem, the optimal solution can be obtained, but as the scale of the problem increases, the solution time increases exponentially. Although the heuristic algorithm can only get an approximate solution, but the solution time is faster, which is more important than precision. Therefore, according to the characteristics of the NPC problem, this paper adopts the individual-based Tabu search algorithm in the meta-heuristic algorithm to plan the observation path of the clustering task.

1) Generating initial path

First, the two points with the largest distance in the set are chosen as the start and end nodes of the set. The node sequence $S_0 = \{Pot_1, Pot_2, Pot_3 ... Pot_N\}$ is added to the task combination. The initial path is got, then the return value of the initial path is evaluated.

2) Path exchanging

A_{ij} indicates number i and j tasks are exchanged in the task sequences S, and each round Nc determines the number of exchanges based on the number of candidate solutions. Only two elements are exchanged in path S. After the exchanging is completed, the benefit of the sequence is calculated by the evaluation function F. By exchanging the solution sequence, the elements of the solution are recombined and sorted, the swap operation is used repeatedly and the sequence with higher benefit value is retained.

3) Tabulation

Setting the length of the Tabu table to be Ncb. The length of the Tabu table does not exceed the number of candidate solutions. Generally, if the length of the Tabu table is small, the algorithm is easy to be local optimal. On the contrary, if the length of the Tabu table is large, the algorithm is difficult to converge. In order to exchange all candidate solutions A_{ij} for this round, the top Ncb is placed in the Tabu table. The initial number of contraindications is set as N_{cb-N}, and if the next round of random generation A_{ij} occurs in the Tabu table, the number of contraindications reduces 1 and A_{ij} regenerated randomly. Rows and columns represent node numbers to be contraindicated. The number in the table represents the tabooed times, which are shown in Fig. 2.

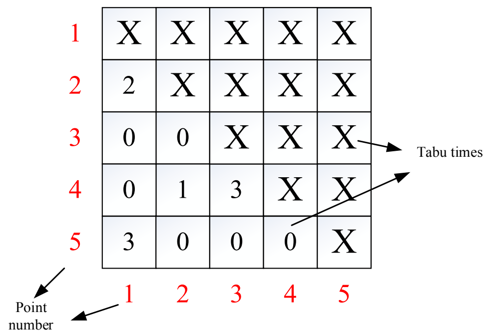


Figure 2: Tabu table schematic diagram

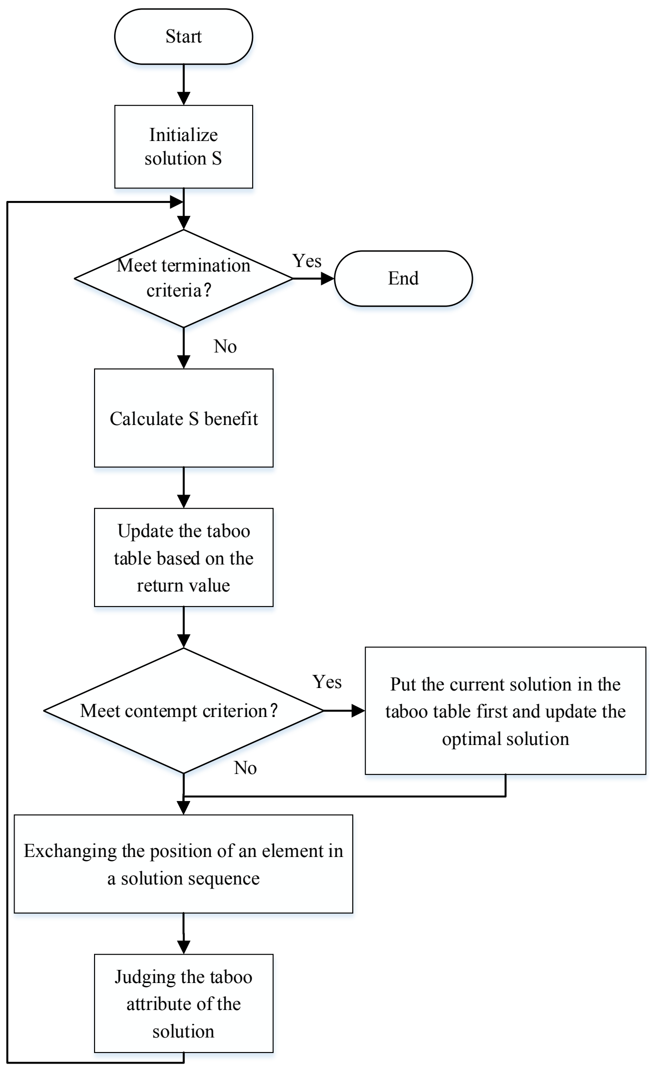


Figure 3: Flow chart: Tabu algorithm

4) Contempt criterion

Some solution sequences are obtained by the switching sequence, and the candidate solution group is generated from them. The candidate solution is renewed according to the benefit function, and the best solution is substituted for the current solution. The old object in the Tabu table are deleted, taking the current best solution as a new Tabu object, and replacing the current best state with the "best so far" state. If the path was contraindicated at last round, the benefit value is improved, and the benefit value of the candidate solution corresponding to the path is better than the current solution, then the Tabu solution is released.

5) Termination criterion

The termination criterion is as follows: when the number of iteration of the algorithm is greater than the threshold, the algorithm is terminated.

The algorithm flow is shown in Fig. 3.

An external nested Tabu algorithm is used to centrally plan the clustered sets and scattered point targets, and finally generate a total observation path. This section includes following parts:

1) Initialization

Initial solution includes $Cluster$ and point Pot. There are two directions of observation for the cluster set. After generating an initial solution, a screening judgment is needed. A high quality initial solution is also an important factor in ensuring the efficiency of the Tabu algorithm. Therefore, the process of generating the initial population in the Tabu algorithm in this paper is as follows:

Step 1: Decrease the $Task$ in the middle according to the size of the priority.

Step 2: The largest weight of J in the $Task$ is chosen, and a new solution S' is generated by changing the neighborhood structure from the current local solution S. If S' is better than S, then, accept S' as the current partial solution, otherwise, S keep updating. J will be removed from $Task$.

Step 3: Repeat Step 2 until all the $Task$ have been executed.

2) Objective function

When the satellite passes over the targets, only a certain amount of targets can be observed. In order to observe as many high weight targets as possible. The weight of the task and the time of the gesture transfer should be included in the objective function.

$$Maximize \sum_{i \in N_{allowed}} w \cdot x_i \tag{3}$$

$$Minimize \sum_{i,j \in N_{allowed}} Shift(i,j) \tag{4}$$

$$F = \sum_{i \in N_{allowed}} w \cdot x_i + 1 / \sum_{i,j \in N_{allowed}} Shift(i,j) \tag{5}$$

In function (3) w stands for the task weight. The weight of a clustering task is the sum of the task weights in its collection, and F means benefit function in function (5). In order to maximize the benefits of the task, it is necessary to shorten the posture transfer time as much as possible on the basis of maximizing the weight gain, so as to free save time for the remaining tasks. The paths that meet the indicator are filtered out through continuous iterative calculation. The purpose of finding the optimal solution is achieved through round-by-round screening.

3) Same strip observations

The calculation of the time window and the sensor side swing angle needs to be completed before the task clustering constraint since they have considerable impact on the task clustering constraint. If multiple meta-tasks can be performed by the same sensor using similar side-swing angles within the same orbital circle, multiple meta-tasks can be defined as one observation strip, i.e., the available side of the multi-task is required. There is an intersection in the range of the pendulum angle. Let the points in the $Task$ set contain $\{J_1, J_2, ..., J_n\}$ and set of side swing angles $\{\boldsymbol{\beta}_{J1}, \boldsymbol{\beta}_{J2}, ..., \boldsymbol{\beta}_{Jn}\}$.

$$\boldsymbol{\beta}_{J1} \cap \boldsymbol{\beta}_{J2} \cap, ..., \cap \boldsymbol{\beta}_{Jn} \neq \varnothing \tag{6}$$

4) Cluster target observation time

st_i represents the start time and et_i denotes the end time, which constitutes visible time window $TW_i = [st_i, et_i]$. After clustering multiple meta-tasks, a time window for the new clustering task should be determined. In this paper, a method is proposed to superimpose the time windows of multiple meta-tasks as the time window of the clustering task. Assuming that $TW_j = [st_j, et_j]$ is overlap with the meta-task, the time window $[st_i, et_j]$ of the clustering task is set.

5) Observation condition judgment

In order to determine the observation time of the task sequence, it is necessary to calculate the timeline. The start time of the first node is selected as the start of the timeline, and the observation time l is added on the timeline. The attitude transition time $Shift(i,j)$ is then computed, and the attitude transition time $Shift(i,j)$ is added to the timeline. The relationship between the time t_1 after the gesture transition and the start time st, et is determined. If $t_1 < st$, the start time of the next node $t_2 = st$. If $st < t_1 < et$, t_1 is the start time of the next node. If $t_1 > et$, the current node is skipped and the relationship between the current time and the next node is judged. The up-mentioned judgment for the entire sequence and the actual observable node sequences are obtained as output along with benefit F.

6) Neighborhood swapping

The diversity of solutions is an important factor for improving the performance of algorithms. The diversity of neighborhood structures can produce new solutions in different ways, resulting in more diverse solutions and producing an optimal one potentially. In order to enhance the diversity of solutions, we generate more observation paths in a random way and then paths that do not meet the constraint are removed. This neighborhood structure attempts to move the scheduled task from the current location to others. Unscheduled tasks may be inserted into the scheduled task sequence as the resources are released during task replacement. The conflict scheduling task will be removed from the scheduling sequence.

4 Simulation and analysis

Three sets of scatter points are used to measure algorithm performance in this paper. The first sets of scatter points consist of 9 points, with a trend distribution perpendicular to the trajectory of the stars. An example is used as a brief introduction to the clustering process to test the performance of the task clustering algorithm in the face of horizontally distributed observation targets. This set of targets has the characteristics of a shorter visible time window for the whole point targets. The second sets of scatter points consist of 13 points, distributed in a trend parallel to the trajectory of the sub-satellite points. This group of targets is larger than the previous one because the visible time window of the target points is more dispersed, so the observation period of the entire task is longer. The third group consists of 40 points, mainly to test the computational performance of the algorithm under large-scale targets. The orbit elements of the satellite are shown Tab. 1.

Table 1: Orbital element of remote sensing satellites

Number	Semimajor axis (km)	Eccentricity	Inclination (degree)	Right ascension of ascending node (degree)	Argument of perigee (degree)	True anomaly (degree)
748 km	0.02	90°	51°	0°	25°	20°

The simulation start time is: 2007-06-30 T 01:20:00 (UTCG). The attitude maneuverability of the satellite around either axis is 0.8 °/s.

4.1 Case 1

In case 1, the 9-point target plan is taken as an example to introduce the entire planning process in its entirety. The relevant information of the target is shown in Tab. 2.

Table 2: The 9 point targets information

Number	Latitude (degree)	Longitude (degree)	Benefits	Duration(s)
1	104.07	30.00	1	5
2	103.00	34.00	1	5
3	113.40	32.94	1	5
4	116.50	33.60	1	5
5	111.02	30.70	1	5
6	114.74	34.42	1	5
7	115.03	38.57	1	5
8	120.00	40.00	1	5
9	121.00	41.00	1	5

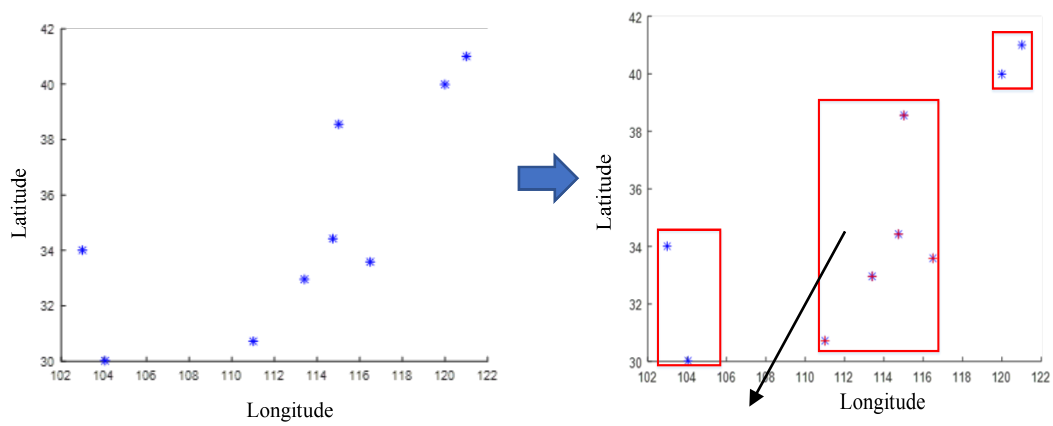
Table 3: The output of the tasks clustering algorithm

Number	1	2	3
Tasks	(1,2)	(5,3,6,4,7)	(8,9)

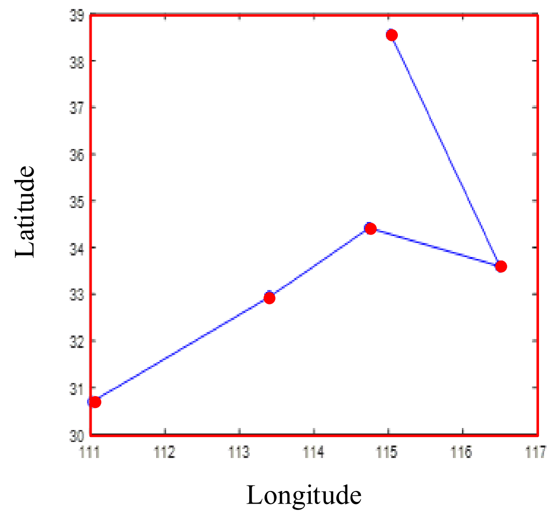
The target is distributed in the northern hemisphere of the satellite, while the satellite moves longitudinally. The point targets are divided into three groups of clusters, of which the second group of clusters contains the most. As shown in Tab. 3, when there are more than 3 internal point sets in the cluster, an inner layer Tabu algorithm is needed to make a path plan for the cluster internal point set. The result of the output is a set including multiple point targets. The cluster result is shown in Fig. 4. In Fig. 4(A), target points are distributed in the latitude and longitude coordinate systems. Points are clustered into point sets by task clustering in Fig. 4(B). Then, the observation path of each point is planned in the point set through the inner layer Tabu algorithm in Fig. 4(C). The inner Tabu algorithm does not consider the imaging constraints of the satellite and only plans the shortest observation path according to the distance of the target point in the latitude and longitude coordinate system. The result is adopted as a part of the planning of the outer global Tabu algorithm.

Table 4: The points targets' time window

Number	1	2	3	4	5	6	7	8	9
Start time/s	256	329	248	281	209	279	347	462	0
End time/s	394	454	478	465	447	496	566	501	0



A. Target distribution B. Task clustering result



C. Observation path

Figure 4: The clustering result and observation path of the nine-point target

Table 5: Tabu algorithm parameters

Parameter	Value	Parameter	Value
Iterations	100	Tabu length	16
Number of candidate solutions	32	Tabu number	3

Tab. 4 shows the visible time window of the target relative to the satellite. From the table it can be seen that the observation window of the 9th point target is 0, indicating that the target of the node is not visible during the imaging process. Tab. 5 indicates Tabu algorithm parameters. Tab. 6 and Fig. 5 show schedule results. Generally speaking, the observation path from bottom to top contains the visible eight point targets. Benefit is calculated by function (5).

Table 6: The 9 point targets observation sequence and time

Number	Observation sequence	Start time	End time	Benefit
1	1,2,5,3,6,4,7,8	1:24:21	1:28:37	8.0062

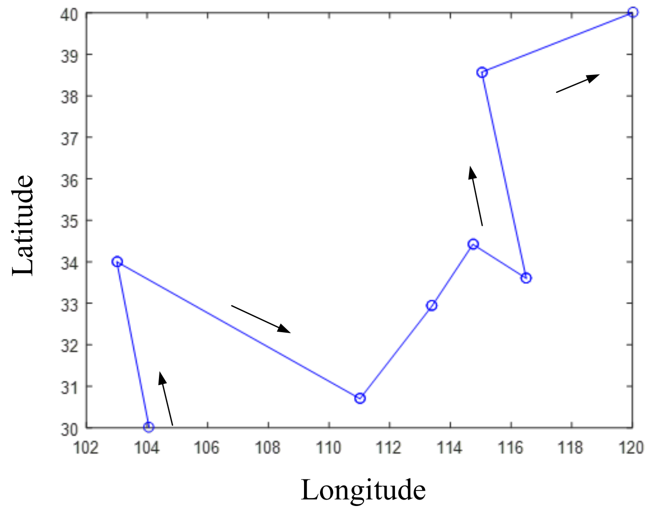


Figure 5: Global observation path of 9 points targets

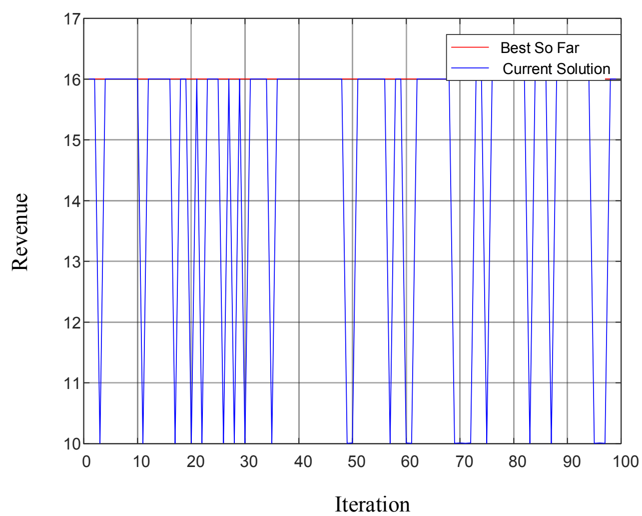


Figure 6: Iterative process of 9 point targets

Fig. 6 shows the variation of the optimal candidate solutions obtained through the iterative search process. It can be seen that the optimal solution can be found in the early stage of the search, and the profit value of the optimal solution for each round is distributed between 5 and 8.

4.2 Case 2

In case 2, 13 point targets were selected and clustering result in Fig. 7. This example sets up a control experiment without clustering method to compare the influence of clustering method on the planning results in Tab. 7 and Fig. 8.

Table 7: The 13 point targets information

Number	Latitude (degree)	Longitude (degree)	Benefits	Duration(s)
1	109.48	22.22	3	5
2	105.94	50.57	1	5
3	114.00	41.20	3	5
4	112.09	20.96	3	5
5	116.15	9.41	1	5
6	117.46	8.33	1	5
7	105.40	30.44	2	5
8	107.45	50.80	1	5
9	114.89	54.62	3	5
10	111.30	41.20	1	5
11	106.00	31.50	1	5
12	108.00	52.10	2	5
13	104.00	29.00	2	5

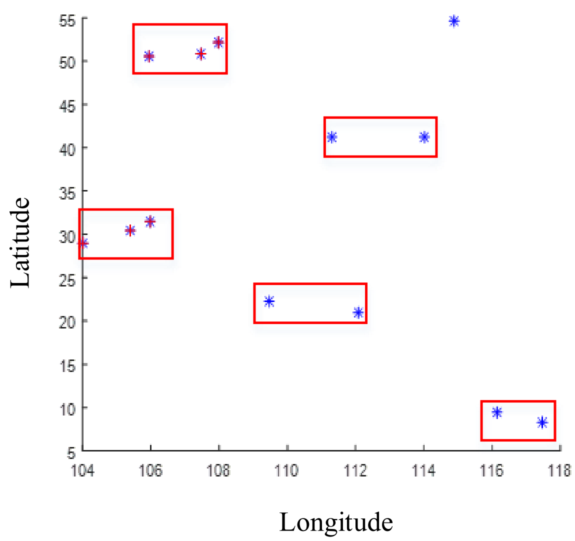


Figure 7: The clustering result 13 point targets

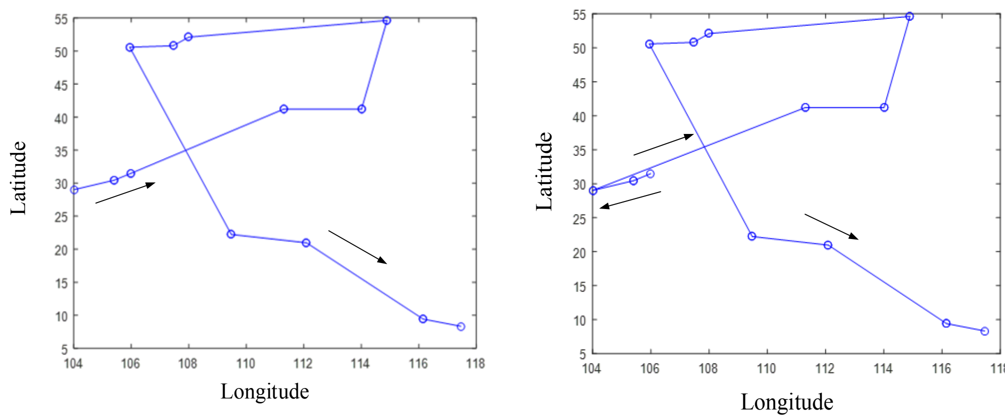
Table 8: The 13 point targets clustering results

Number	1	2	3	4	5	6
Task	(1,4)	(3,10)	(5,6)	(12,8,2)	(11,7,13)	9

Table 9: The 13 point targets observation sequence and time

	Observation sequence	Start time/s	End time/s	Benefit	Simulation time
Experiment group	13,7,11,10,3,9,12, 8,2,1,4,5,6	1:24:9	1:33:38	24.0052	27.61
Control group	11,7,13,10,3,9,12, 8,2,1,4,5,6	1:24:9	1:32:48	24.0043	85.29

The observation path for scatter and cluster sets is planned through the outer Tabu algorithm, and the results of the planning process are shown in Fig. 9 and Tabs. 8 and 9:



A experiment group B control group

Figure 8: The global observation path of the 13 point targets

From the simulation result, it can be noticed that the planned observation path only has one intersection, and the overall path is smooth without more inflection points. The observation time window is reasonable, and generally meets the user's observation requirement.

From Fig. 8, the latter half of the observation path is approved to be the same as the experimental group. However, there is an unnecessary turning in the first half, and the posture adjustment time is longer, and the transit time of the satellite is not effectively utilized.

There is little difference in the benefits between the two groups. However, the calculation time between two groups shows a huge difference, as shown in Fig. 10. The method proposed in this paper takes 27.61 seconds, and the control group takes 85.29 seconds without the task clustering method. This part of the difference comes from the increase of the number of calculations. After task clustering, only 6 sets need to be sorted and exchange, and 5 clustering sets need to be reversed sorting. The simple Tabu algorithm requires 13 nodes to be ranked, which greatly increases the space of the candidate solution and the frequency of calculation. Therefore, the 13 point targets take more time in the calculation. This fully demonstrates the significant role played by task clustering in reducing the calculation cost.

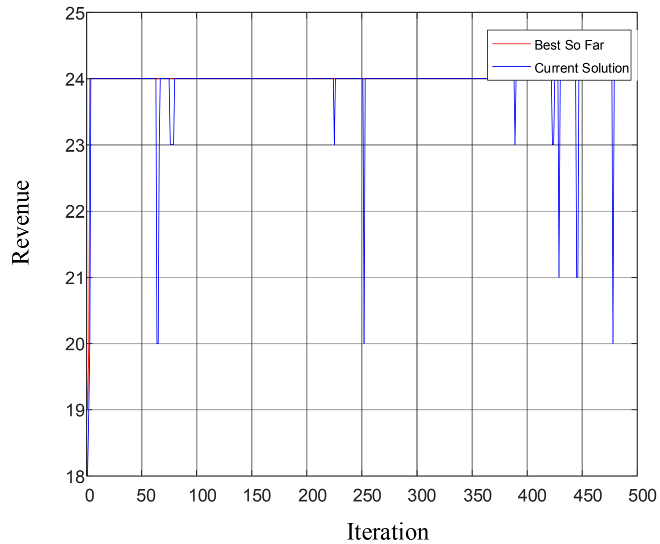


Figure 9: Iterative process of 13 point targets

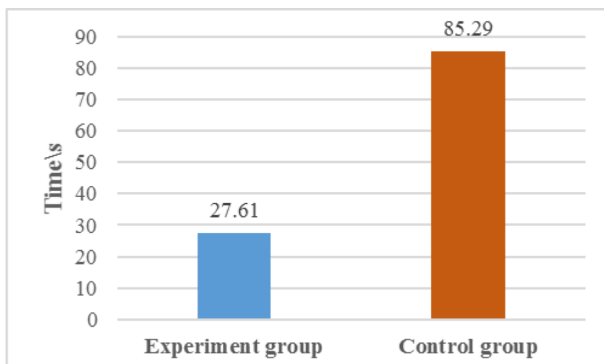


Figure 10: The 13 targets simulation time comparison between clustering group and non-clustering group

4.3 Case 3

In order to test the efficiency of the algorithm on large-scale target planning, this paper sets up a task clustering scenario with 40 dense point targets. The group has a larger target and a wider distribution. The target point information is shown in Tab. 10 and cluster sets and inner observation path show in Fig. 11. Comparing the difference between the experimental group and the non-cluster in the relatively large-scale case, the observation path of the cluster group is shorter than that of the non-cluster group in Fig. 12.

Table 10: The 40 point targets information

Number	Latitude (degree)	Longitude (degree)	Benefits	Duration (s)
1	124.94	53.75	2	5
2	125.33	49.14	2	5
3	107.77	47.01	2	5
4	105.34	49.17	2	5
5	110.72	45.10	2	5
6	109.91	45.62	3	5
7	133.12	18.34	3	5
8	132.96	17.66	2	5
9	130.70	19.39	3	5
10	133.04	16.99	1	5
11	94.99	30.94	1	5
12	96.97	30.21	2	5
13	92.71	33.64	2	5
14	95.25	32.47	1	5
15	132.30	21.68	1	5
16	134.42	20.75	1	5
17	119.81	30.85	1	5
18	117.92	30.50	3	5
19	130.42	31.84	1	5
20	130.61	33.10	1	5
21	136.59	40.14	3	5
22	137.50	41.00	3	5
23	109.25	38.16	3	5
24	110.33	39.60	3	5
25	89.88	29.31	1	5
26	88.59	31.58	2	5
27	119.70	41.93	3	5
28	118.18	42.40	3	5
29	102.88	49.53	2	5
30	99.47	47.51	2	5
31	130.09	20.54	1	5
32	129.09	19.94	2	5
33	111.72	60.07	1	5
34	112.42	55.48	1	5
35	137.88	23.24	3	5
36	137.04	22.13	2	5
37	116.28	54.06	3	5
38	117.05	52.77	1	5
39	107.09	18.23	3	5
40	107.69	18.06	3	5

Table 11: The 40 point targets cluster set and number

Number	1	2	3	4	5	6
Task	(1,2)	(12,11,14,13, 25,26)	(32,31,9, 10,8,7,15,16, 36,35)	(17,18)	(19,20)	(21,22)
Cluster number	7	8	9	10	11	12
Cluster task	(23,24,5, 6,3,4,29)	(27,28)	(33,34)	(37,38)	(39,40)	30

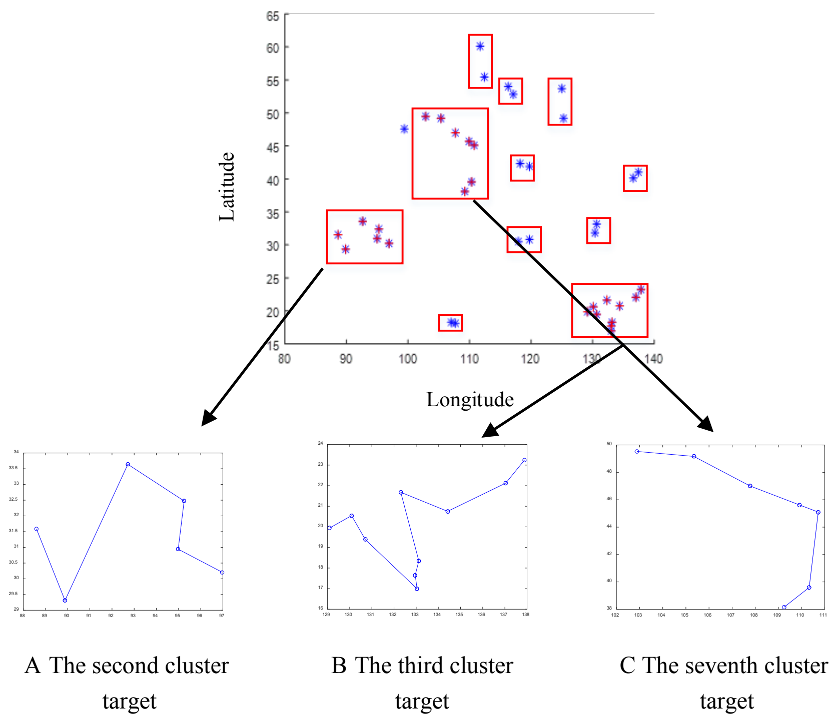
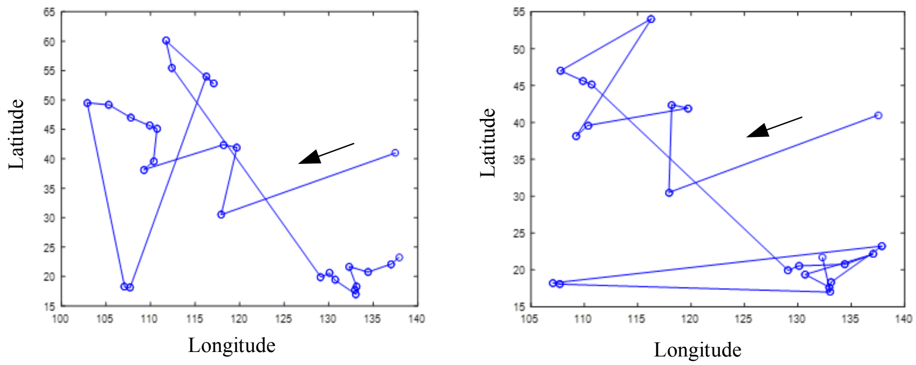


Figure 11: The cluster set and observation path in subset

In Fig. 11, when there are more than 3 points in the cluster set, the inner layer tabu algorithm needs to be used to plan the points of the cluster set. In Figs. 4(A), 4(B), 4(C) include three multi-element clusters. First, the inner layer Tabu algorithm is used to plan the shortest set observation path for the multi-element clustering set in Tab. 12. Then, all the cluster sets are put into the outer Tabu algorithm to calculate the global optimal observation path.



A. experiment group B. control group

Figure 12: The 40 point targets observation path

Table 12: The 40 point targets observation sequence and time

	Observation sequence	Start time/s	End time/s	Benefit
Experiment group	22,18,27,28,23,24,5,6,3,4,29,30,39,40,37,38,33,34,32,31,9,10,8,7,15,16,36,35	1:20:05	1:39:57	62.0026
Control group	22,18,28,27,24,23,37,3,6,5,32,31,16,36,9,8,7,35,39,40,10,15	1:20:05	1:40:04	53.0045

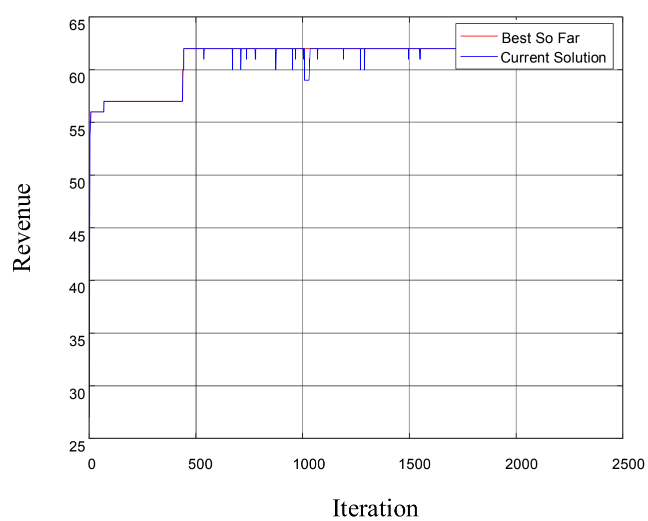


Figure 13: Search iterative process of 40 point targets

In Tab. 12, it can be seen that in large-scale examples, the calculation speed of the algorithm is still very fast. In Fig. 12, the obtained solution contains cross-over phenomena, it is likely that the path is not a global optimal solution. The local optimal solution has the potential for further optimization. In Fig. 13, in the process of algorithm iterative calculation, the optimal solution is generated in the first 500 iterations, and the subsequent solution has little change. After 500 steps, it becomes difficult to find a new optimal solution.

From the experimental results of the different groups in Fig. 12 and Tab. 11, it can be seen that the optimal solution no longer changes after a certain iteration step by the Tabu algorithm, and the calculation time increases exponentially with the scale of the problem. Meanwhile, the benefit of the optimal solution is lower than that of the cluster group and the observation path of the control group is irregular. In Fig. 14, task clustering reduces planning times, so the calculation efficiency of the non-cluster group is lower than that of the cluster group which can save plenty of time. Therefore, the double-layer Tabu algorithm based on task clustering can effectively solve the task planning problem of dense point targets, improve the efficiency of task planning. It implies that the proposed algorithm has a good application prospect in engineering.

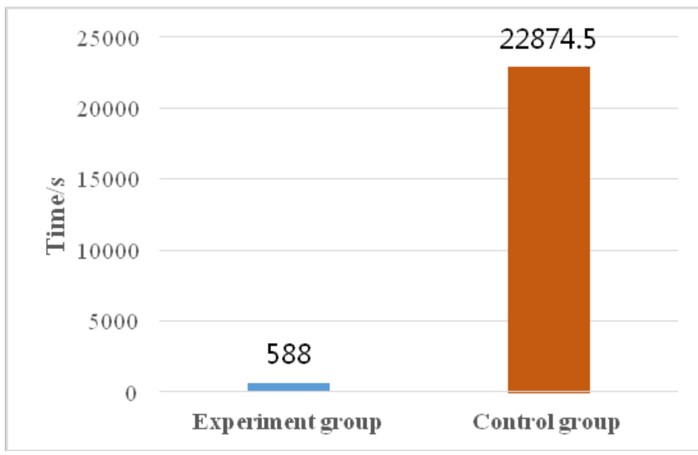


Figure 14: The 40 targets simulation time comparison between clustering group and non-clustering group

5 Conclusions

In this paper, the engineering constraints in the planning process are clarified, and the clustering model of agile satellite missions is established by mathematical modeling. A task clustering strategy is proposed to improve the efficiency of solving NP problems. The double-layer Tabu algorithm based on task clustering is compared with the simple Tabu algorithm, showing better performance. It has been proved that the efficiency of task planning can be great improved by task clustering strategy, especially when the satellite resources are limited, and the scheduling algorithm is faster to produce better results. The task clustering algorithm is particularly suitable for inclusion of a large number of targets or closely distributed point target observation problems. Consequently, the rationality and feasibility of the model are verified by numerical simulation. The task planning method proposed in this paper can circumvent the resource waste issue caused by planning and design reasons in the observation process. The entire observation process is optimized from the planning level, which provides a strong guarantee for the engineering application of agile satellites.

Data Availability: The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare that there is no conflict of interest regarding the publication of this paper.

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