Multi-satellite Observation Scheduling for Large Area Disaster Emergency Response

X. N. Niu [1,2], H. Tang [1,2, *], L. X. Wu [3]

[1] Key Laboratory of Environment Change and Natural Disaster, Ministry of Education, Beijing Normal University, Beijing, 100875, China – niuxiaonan@mail.bnu.edu.cn, hongtang@bnu.edu.cn
[2] Beijing Key Laboratory of Environmental Remote Sensing and Digital Cities, Beijing Normal University, Beijing, 100875, China
[3] School of Geosciences and Info-Physics, Central South University, Changsha, 410083, China – awulixin@263.net

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ABSTRACT:

Timely acquiring remote sensing data is very important for rapid response to disasters. Satellite task scheduling aiming at making an optimal imaging plan, plays a key role in coordinating multiple satellites to monitor the disaster area. In the paper, to generate imaging plan dynamically according to the disaster relief, we propose a dynamic satellite task scheduling method for large area disaster response. First, an initial robust scheduling scheme is generated by a robust satellite scheduling model in which both the profit and the robustness of the schedule are simultaneously maximized. Then, we use a multi-objective optimization model to obtain a series of decomposing schemes. Based on the initial imaging plan, we propose a mixed optimizing algorithm named HA_NSGA-II to allocate the decomposing results thus to obtain an adjusted imaging schedule. A real disaster scenario, i.e., 2008 Wenchuan earthquake, is revisited in terms of rapid response using satellite resources and used to evaluate the performance of the proposed method with state-of-the-art approaches. We conclude that our satellite scheduling model can optimize the usage of satellite resources so as to obtain images in disaster response in a more timely and efficient manner.

1. INTRODUCTION

1.1 General Instructions

For disaster emergency response, the most critical information during the three days immediately following a disaster event are
the accurate and timely intelligence about the extent, scope and impact of the event (Liu and Hodgson, 2016). Based on the information, disaster management department and decision-makers can make advisable relief strategies. The earth observation satellite can be used to perform a wide range of observation activity to obtain the information of disaster formation, development and dynamic change, which can provide data of disaster monitoring timely.

Although much work has been done on information extraction for disaster reduction from satellite images, little attention has been paid to how to efficiently schedule multiple earth observation satellites to make an optimal imaging plan to meet requirements for disaster response. For remote sensing applications during the response phase, the first practical problem is satellite task scheduling. The scheduling can be primarily divided into static scheduling and dynamic scheduling. The static scheduling assumes that all imaging tasks have been submitted before scheduling, and once the scheduling scheme is produced, it is immutable until all tasks have been finished. Because natural disasters (earthquakes, landslides, debris flow, etc.) often happen unexpectedly, it is suggested to use dynamic scheduling methods to cope with these unexpected factors.

Dynamic scheduling has been defined under three categories (Ouelhadj and Petrovic, 2009): completely reactive scheduling, predictive–reactive scheduling, robust predictive–reactive scheduling and robust pro-active scheduling.

In completely reactive scheduling, all imaging tasks are dispatching in real-time, thus no initial schedule is generated in advance. Priority dispatching rules are frequently used. The literature (Qiu et al., 2013) proposed a rolling horizon strategy to deal with new arriving tasks. They designed various heuristic algorithms to schedule tasks. The heuristic algorithms are quick and easy to implement. However, the decisions are made locally and it is hard to predict system performance.

Predictive–reactive scheduling is the most common dynamic scheduling method used in satellite scheduling. An initial imaging plan is produced in advance and when emergent events occur unexpectedly, the initial scheme will be revised. Literature (Pemberton and Greenwald, 2002) developed the satellite scheduling problem and discussed contingency conditions under which the satellite scheduling problem becomes dynamic. The literature (Verfaillie et al., 1994) proposed an approach for reusing any previous schedule employing local adjustment. The literature (Sun et al., 2010) presented dynamic scheduling problem as a dynamic weighted maximal Constraint Satisfaction Problem and adopt genetic algorithm to obtain a satisfactory solution. In predictive–reactive scheduling, the new schedule may have large difference with the initial solution, which can seriously affect

* Corresponding author

other observing tasks in the initial schedule and may lead to poor performance of the schedule.

Robust predictive–reactive scheduling aims at developing predictive–reactive schedules to minimize the perturbation to the previous schedule. Considering the tradeoff between the performance and the degree of the adjustment, the literature (Wang et al., 2007) proposed a robust scheduling model and adopted a rule-based heuristic algorithm to solve the dynamic scheduling problem.
The literatures (Niu et al., 2015, Zhai et al., 2015) propose a robust multi-objective scheduling model to generate robust initial solutions so as to minimize the difference between the adjusted schedule and the initial schedule.

Robust pro-active scheduling strategy focus on obtaining predictive schedules which satisfy performance requirements predictably in a dynamic environment (Ouelhadj and Petrovic, 2009). However, the environment is very difficult to predict and the determination of the predictability measures is also hard.

To sum up, the robust predictive–reactive scheduling approach is appropriate to generate stable imaging plans for response to practical emergent tasks. During the disaster relief process, the disaster information obtained changes dynamically, which accordingly leads to new imaging requirement. In the paper, we focus on the dynamic emergent imaging requirements. A robust multi-satellite dynamic scheduling model is proposed to address the area emergent tasks. A multi-objective genetic algorithm is used to decompose the area task into a series of adjacent strips. Then we present the multi-objective genetic algorithm embedding in a heuristic rule to obtain the dynamic scheduling plans.

The remainder of the paper is organized as follows. In section 2, we describe the dynamic scheduling model. Then we present the satellite scheduling of area tasks algorithm in section 3. In section 4, we conduct experimental simulations. We conclude the paper with a summary in section 5.

2. DYNAMIC SCHEUDLING MODEL

To deal with the new emergent tasks, we use a robust predict-reactive scheduling strategy. Based on a robust initial schedule obtained by a robust scheduling model (Zhai et al., 2015), we build a dynamic satellite scheduling model to adjust the current imaging plan so as to arrange the new coming emergent tasks. The model includes five parts.

2.1 Tasks

The paper mainly focuses on emergent area tasks which cannot be image in one shot. The area task must be decomposed into several strips and each strip is allocated to a satellite within a time window. Considering the disaster events usually occur unexpectedly, with uncertainties of occurrence time and number. So the emergency task number and arrival times are not known a priori. Moreover, the emergent tasks need to be completed in time, because rapid information acquisition during the three days after a disaster event is crucial.

Let $T^E = \left\{T^{E_1}, T^{E_2}, \cdots, T^{E_n}\right\}$ be the emergency area task set. T^{E_i} denotes the emergent task for the *i-th* phase. Each task is associated with the weight p_i, the indispensable duration of task execution d_i.

Considering that many tasks are commonly submitted together, thus we assume in this paper the new tasks arrive in batch style. Let $TS = \left\{T_S^1, T_S^2, \cdots, T_S^n\right\}$ be the dynamic scheduling time set where T_S^i is the *i*-th dynamic scheduling time.

2.2 Satellites

Multiple satellites is used to acquire images of these tasks, which are denoted as $S = \{s^1, \cdots s^J\}$. For each satellite $s^j \in S$, its key parameters used in the model include the field of view $\Delta\theta^j$, the longest duration allowed for a continuous observation Δd^j, slewing rate, sl^j, attitude stability time st^j, the maximum swing angle msg^j, the flight time in each orbit orb^j, the start-up time of sensor su^j, the retention time of shutdown sd^j, and the longest imaging time $duty^j$ in each orbit, respectively.

2.3 Time windows

Satellites' observing activities must performed within the available time windows between tasks and satellites. For a task t_i, its corresponding the time window is $tw_i^j = \left[ws_i^j, we_i^j\right]$ with the observation angle θ_i^j. We define the time windows of t_i as a set $TW_i = \bigcup_{j=1}^{J}\bigcup_{k=1}^{K_{ij}} tw_{ik}^j$, K_{ij} is the number of time windows between task t_i and satellite s^j.

2.4 Objectives

The model is to produce an imaging plan to maximize the revenue of the emergent tasks as well as to minimize the difference between the new schedule and the initial schedule. So the model include two objectives: accumulated revenue of the allocated emergency tasks and the disturbance of the schedule made by the previous phase. We assume that T_S^k is the current scheduling time.

In the model, all the emergent tasks have large scope and a satellite often cannot acquire the entire area in a single pass. The area targets must be partitioned into a set of contiguous strips based on the different characteristics of the satellites and disaster emergent imaging requirements. Therefore, before satellite scheduling, we use a multi-objective optimizing model (Niu et al., 2018) to segment the emergent area tasks so as to obtaining a group of decomposing results, which are the inputs of the scheduling model.

The first objective is to maximize the profit of the observed area of emergency tasks.

$$\max: PRO(SS^k) = \sum_{i=1}^{|T_k^E|} \max(\bigcup\nolimits_{m=1}^{M_i} COV(m) \times p_i) \quad (1)$$

where M_i denotes the number of decomposing results of the area task i and $COV(m)$is the proportion of area of the target covered by all selected strips of the decomposing solution m.

The second objective is to minimize the difference between the adjusted schedule SS^k and the initial schedule SS^{k-1}. Generally, the scheduled emergent tasks may have two types of variances in dynamic scheduling: (1) change of finish time and (2) rejection (Wang et al., 2015).

$$\min: PER(SS^k) = \sum_{i=1}^{|SS^{k1}|}\sum_{q=1}^{2} disturb(i,q) \times w_q \qquad (2)$$

where *disturb(i,q)* is the count of variance 1 on task t_i in the whole scheduling. ω_q , q =1, 2 represents the influence degree of type q variance, and generally $\omega_1 < \omega_2$.

2.5 Constraints

In our model, regardless of the satellite measurement and control requirements and the data transmission with ground station requirements, there are four constraints that must be satisfied in the model.

2.5.1 Time window constraint

Any meta-tasks must be observed within its time windows:

$$\begin{cases} x_{ikv}^{j}\left(ts_{ikv}^{j} - we_{ikv}^{j}\right) \geq 0 \\ x_{ikv}^{j}\left(ts_{ikv}^{j} + d_{ikv}^{j} - we_{ikv}^{j}\right) \leq 0 \\ at_i \leq T_S^k \leq ts_{ikv}^{j} \leq dt_i \end{cases} \qquad (3)$$

where ts_{ikv}^{j} presents the start time of the meta-task ro_{ikv}^{j} .

2.5.2 Switch time constraint

The transition time between any two successive tasks for the same satellite j should be enough for sensor to execute a series activities including shutting down, pointing to the target, stabilizing gesture and start-up.

$$te_m^j + sd^j + tr_{m,n}^j + su^j \leq ts_n^j \qquad (4)$$

where te_m^j is the end time of the previous task t_m , $tr_{m,n}^j$ denotes the transition time between task t_m and the next task t_n .

2.5.3 Imaging time constraint

The total imaging time of any satellite s^j should be less than the allowable longest imaging time for one orbit.

$$\sum_{i \in SS_b^j} d_i \leq duty^j \qquad (5)$$

where SS_b^j denotes a sequence of scheduled tasks on satellite j *on* orbit b.

2.5.4 Storage constraint

The storage capacity of a satellite is limited, so only limited number of tasks can be scheduled.

$$\sum_{l=1}^{L^j} d_l^j \times m \leq M^j \qquad (6)$$

where M^j is the maximum storage capacity of satellite j. L^j is the number of tasks allocated to satellite j.

3. ALGORITHM

Since the impact area caused by major natural disasters is generally large which cannot be imaged in one shot by a single satellite. Therefore, the area target must be decomposed into several contiguous strips which is called meta-tasks. Considering multiple emergency imaging requirements, we use a multi-objective optimization model to obtain a group of decomposing results. Based on the decomposing results, we use a mixed algorithm HA-NSGA2 to insert the meta-tasks into the current scheduling scheme. The process to solve the model is shown in Figure 1.

As shown in Figure 1, the solving method begins with producing a set of decomposing schemes for the area task using multi-genetic algorithm. This process is to search for the combinations of meta-tasks covering the area target considering multiple emergent imaging requirements such as the extent of coverage over the stricken area, timeliness, and the spatial resolution. Each decomposition result contains a series of specific time windows within which the associated satellite can observe a part of the target area. Based on the partitioning solutions, using the HA_NSGA-II algorithm, we insert all the meta-tasks belonging to a decomposition scheme into the current imaging plan. As a result, a group of adjusted scheduling schemes is obtained. The scheduling scheme with maximum profit and minimum perturbation is selected as the final solution.

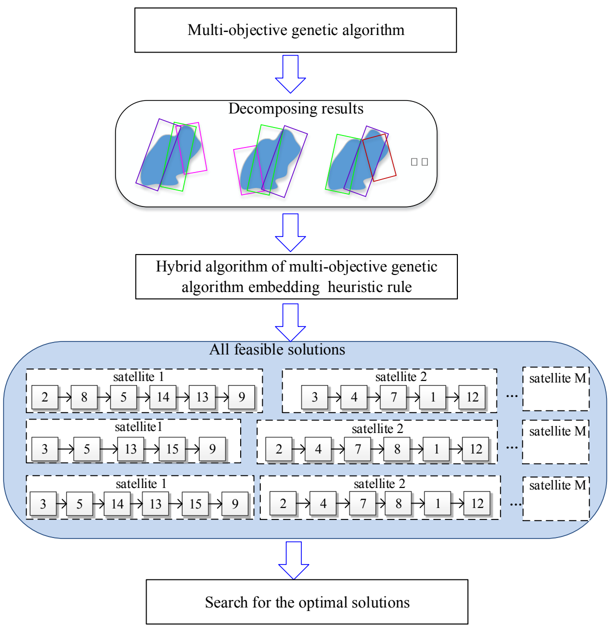

Figure 1. The flowchart of solving method

4. EXPERIMENT

We take Wenchuan Earthquake as the emergent event. After the earthquake occur, users will summit the imaging requirements. Based on the situation of disaster relief at that time, we simulate three batches of emergent tasks. As shown in Table 1, we describe the experimental scenarios. The location and scope of the area tasks are presented in Figure 2 the scheduling period is set as three days.

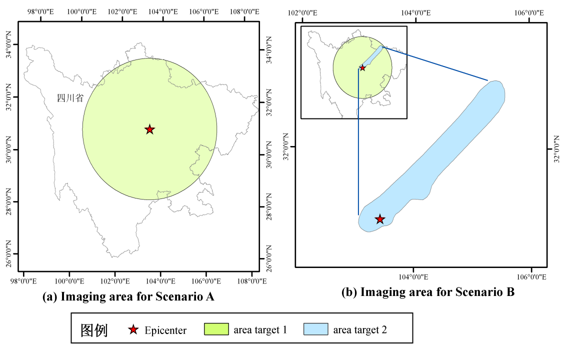

Figure 2. The target area

Scenarios	Purpose	Target area	Imaging requirements
Scenario A	roughly grasping the extent of damage area	A buffer zone with a radius of 300 km centered on the epicenter	Spatial resolution: 1-10m.
Scenario B	Evaluating the damage of the worst-hit area	Ninth-degree seismic intensity region	Spatial resolution: 0-5m.
Scenario C	Seeking data sharing from international satellites of CHARTER	Ninth-degree seismic intensity region	Spatial resolution: 0-1m.

Table 1. The information about emergent tasks

When the earthquake breaks out, there is an urgent need to acquire the information about stricken area as soon as possible. The first imaging requirement is to acquire the information to grasp the extent of impact area. We use the HA_NSGA-II algorithm to obtain the imaging plans for this scenario, as shown in Figure 4. It can be found that the area task is decomposed into multiple strips which are assigned to satellites and time windows. The target area is entirely covered by observation strips. In the scenario B, the worst-hit area of earthquake is set as the observing target, namely T_2^E . Hence, the new imaging requirement triggers the second dynamic scheduling. Based on the previous scheduling scheme (solution#1), we schedule new emergent tasks to and the adjusted scheduling schemes are produced, as depicted in Figure 5. The result indicates that a subset of meta-tasks are adjusted to satisfy new imaging requirement. To obtain very-high resolution images, we seek for data sharing from international satellites of CHARTER. The scheduling results are as shown in Figure 6. There are different imaging plans and those solutions with maximum profit and minimum perturbation should be selected as the final imaging plan, as shown in Figure 3.

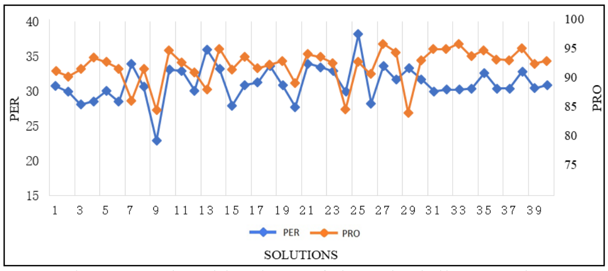

Figure 3. The objectives of the scheduling results

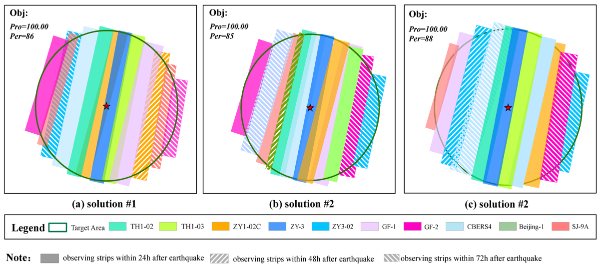

Figure 4. The scheduling schemes for Scenario A

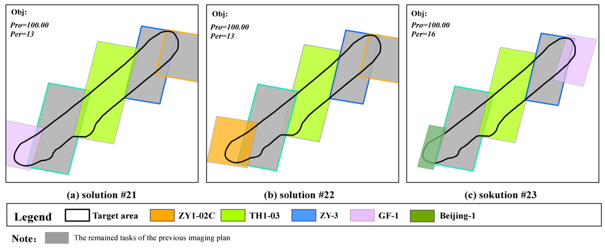

Figure 5. The scheduling schemes for Scenario B

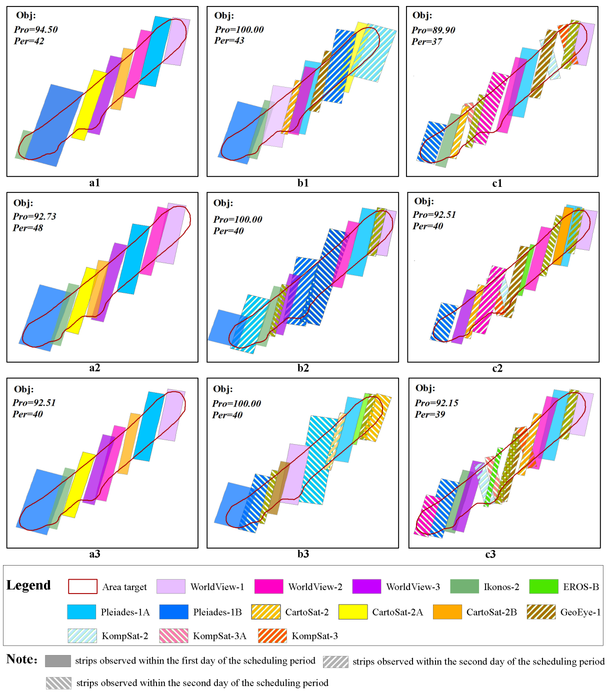

Figure 6. The scheduling schemes for Scenario C

5. CONCLOSION

To address the scheduling problem oriented to the dynamic area tasks triggered by emergent disasters, we build a dynamic scheduling model in which the profit of the emergent tasks is maximized and the perturbation to the initial schedule is minimized. The multi-objective genetic algorithm is used to generate decomposing schemes of the area tasks. Then we employ the HA_NSGA-II algorithm to obtain the dynamic scheduling result. To evaluate our model, we conduct experimental simulations in the scene of Wenchuan Earthquake. The simulated imaging plan can schedule satellites to observe a wide scope of target area. We conclude that our satellite scheduling method can deal with the emergent imaging requirements of large area target.

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