Multi-objective Satellite Scheduling Approach for Very Large Areal Observation

Yingjie Xu, Xiaolu Liu, Renjie He, Yingguo Chen and Yuning Chen
College of System Engineering, National University of Defense Technology, China
xvyingjie1@163.com

Abstract. This paper presents a multi-objective satellite scheduling problem for very large areal observation in response to various requests. The objectives are to maximize the total profits of generated observation schedule and the high efficiency of the satellite utilization simultaneously. To address the satellite scheduling problem, we first demonstrate a detailed problem description and then transform the problem into set covering problem within several criteria and constraints. Based on that, a mathematical model is established. To solve the problem, a new three-phase solving framework is proposed. In the discretizing phase, an area discretization method is adopted to establish the evaluation system. In the target decomposing phase, area target is decomposed into strips and corresponding visible time windows are calculated. In the scheduling phase, a multi-objective genetic algorithm is introduced to generate an optimal observation schedule taking account of the distinct aspect of objectives. Through extensive computational experiments on realistically generated problems in various scenarios including real-world data from China’s satellite platform, the effectiveness and reliability of the proposed solving framework are verified.

1. Introduction

More and more attention is attached to environmental activities in recent years, such as territorial mapping, environmental monitoring, land desertification monitoring, tropical rain forest protection, Antarctic ice cover monitoring [1] etc. Earth observation satellites (EOSs) play an increasingly significant role in these activities. EOSs are space platforms which are able to acquire images of specified areas on the Earth’s surface in response to various observation requests from various customers such as government agencies and research institutes [2]. They can provide images of the observation targets in different time points and in different imaging angles. These images are essential and reliable foundation of analysis of the environmental condition and taking opportune measures in case of emergency [3]. Handling the scheduling problem for the observing process and acquiring adequate images will give impetus to the promotion and development of environmental activities. Nevertheless, traditional techniques and methods have failed to cope with the observation scheduling in these environmental activities which involve very large area targets and to generate a satisfactory observation schedule effectively and efficiently. Therefore, solving the satellite scheduling for very large area observation is in urgent need according to the realistic and practical circumstances and the multi-objective satellite scheduling problem for very large areal observation is researched in this paper.

2. Literature review
Generally, the observation targets for satellites can be classified into spot targets and polygon targets (i.e. area targets). Spot targets can be completely captured by one pass according to the observation scope of satellite sensor while polygon targets need to be captured by multiple passes of multiple satellites in a cooperative manner. To the best of our knowledge, most literature focused on spot targets or comparatively small polygon targets given the NP-hard nature. Several researches have been devoted to the multi-satellite scheduling problem for area targets. Bai et al. [4] regarded spot target as a special polygon and proposed an integrated model to deal with two kinds of targets and a multi-diversifications simulate annealing algorithm was applied for the satellite observation scheduling problem. Zhu et al. [5] found an approach to reasonably utilize the existing satellites to rapidly image the affected area during a short time period, taking two factors into consideration simultaneously in orbit design, i.e., the maximum observation coverage time and the minimum orbital transfer fuel cost. Wang et al. [6] further developed satellite scheduling problem of an earth observing satellite constellation and proposed a priority-based heuristic with conflict-avoided, limited backtracking and download-as-needed features to select and timetable the observation activities in a very short time. Additionally, Gao et al. [7] analysed advantages and disadvantages of traditional methods for area target scheduling of remote satellite and developed a fast dynamic algorithm for area target scheduling. For improving the reliability of multiple earth-observing satellites, especially in emergent scenarios such as obtaining photographs on battlefields or earthquake areas, Zhu et al. [8] proposed a novel dynamic fault-tolerant scheduling model for real-time tasks running on multiple observation satellites and developed a novel fault-tolerant satellite scheduling algorithm named FTSS. Taking into account the dynamic imaging requirement, N. Niu et al. [9] proposed a satellite scheduling model to address dynamic imaging tasks triggered by emergent disasters and designed a dynamic heuristic algorithm embedding in a greedy criterion to solve the scheduling problem for area targets. Considering dynamically occurring events, Skobelev et al. [10] developed a multi-agent planning system for a group of Earth remote sensing satellites with dynamic balancing of interests of satellites, data receiving points and observation area agents.

These problems researched above are all involved with multiple satellites and area targets but are devoted to comparative small area targets and few to very large area targets. The original intention for our research is to solve the difficulties encountered in the satellite observation of environmental activities involving very large area. The proposed problem is much more sophisticated and hard to handle with more considerable enlargement of the search space and candidate solutions. Therefore, with the increasing number of requests from various customers, generating a feasible observation schedule for very large area with multiple satellites could be time-consuming and difficult. On this condition, current researches are not applicable for our problem whether in terms of mathematical models or proposed algorithms. Therefore, a new adequate solving method is essential for multiple satellite scheduling problem for large area observation.

3. Problem definition & formulation

3.1. Problem definition

Before addressing the proposed problem, several terms are defined:

- Visible time window (VTW): a period of time when the required area target is visible to the satellite.
- Strip: the projection on the surface of the earth of a single observation scope of a specific satellite when it flies over the target.
- Schedule: observation plan towards a specific area target. In an observation schedule, several elements are included: involved satellites, selected VTWs, attitudes of the involved satellites during selected VTWs, etc.

In this work, the problem is referred to the multi-satellite scheduling for very large area observation in response to various requests subject to constraints from both satellites and requirements. Earth observation scheduling employing multiple satellites involves optimization and coordination. The
scheduling process is aimed to optimally select which available targets the satellites will observe and determine when and how these will take place with multiple satellites in a cooperative manner. Consequently, the problem of satellite scheduling for very large area observation is a combinatorial optimization problem.

Moreover, the image of the required area target can only be acquired during a specific visible time window (VTW). On account of the maneuvering ability of a specific satellite, there could be more than one VTW when a satellite flies over the area target for one time, as depicted in Figure 1. Each VTW is corresponding to a specific strip with a certain roll angle within the field of view of a specific satellite. Field of view (FOV) refers to the spatial range that the remote sensor can observe.

![Figure 1. Multiple observation opportunities for targets.](image)

Each acquisition of each strip generates a different profit. The profit of a specific schedule is proportional to the percentage of the target area covered by the selected strips and the main objective of optimization is total profit maximization. Meanwhile, it is realistically necessary to maximize the utilization efficiency of the satellites, such as minimize the number of selected strips and the overlaps. Thus, the multiple satellites scheduling problem of very large area observation is consequently a VTW selecting problem. The scheduling process is aimed to select an optimal set of VTWs from candidate ones within the fields of view of multiple satellites maximizing the observing profit and efficiency in response to the requests of various customers.

### 3.2. Problem formulation

#### 3.2.1. Sets and Parameters

- $T = \{t_1, \ldots, t_T\}$, the ordered set of requests from various customers. For $t_q$, the following attributes are defined:
  - $q$ is the required observing large area target of request $t_q$.
  - $H_q$ is the required resolution of the images of request $t_q$.
  - $B_q$ is the required start time of the scheduling for request $t_q$.
  - $E_q$ is the required end time of the scheduling for request $t_q$.
- $S = \{s_1, \ldots, s_S\}$, the set of satellites. For $s_i$, the following attributes are defined:
  - $O_i$ is the set of orbits of satellite $s_i$.
  - $o_{ij}$ is the $j^{th}$ orbit of satellite $s_i$.
  - $M_i$ is maximal data storage capacity for satellite $s_i$.
  - $V_i$ is maximal reserved electrical power for satellite $s_i$.
  - $G_i$ is maximal maneuvering capacity for satellite $s_i$.
- $W_i = \{w_{i1}, \ldots, w_{i|W_i|}\}$ is the set of VTWs of satellite $s_i$ and $w_{ijk}$ is the $k^{th}$ VTW on orbit $o_{ij}$ of satellite $s_i$. For $w_{ijk}$, the following attributes are defined:
  - $b_{ijk}$, $e_{ijk}$ are the start and end times of $w_{ijk}$.
  - $m_{ijk}$ is the occupied data storage for the image corresponding with $w_{ijk}$.
\( v_{ijk} \) is the consumed electrical power for acquiring the image corresponding with \( w_{ijk} \).

\( g_{ijk} \) is the attitude of satellite \( s_i \) during the \( w_{ijk} \).

\( GSD_{ijk} \) is the resolution of the acquired image during the \( w_{ijk} \).

\( q_{ijk} \) is the observing target during the \( w_{ijk} \).

- Function applied in the modeling process is defined as follows:
  \( f \) is a piecewise linear profit function defined by points (0, 0), (0.4, 0.1), (0.7, 0.4), (1, 1). And this function is associated with the summed contribution area of all scheduled strips for the target area (deducting the overlapped area among all the strips). The more contribution the strips make to the coverage for the target area, the more profit is generated.

\( p \) is a profit function intended for evaluating the contribution area for a specific strip that is corresponding to a VTW.

\( l \) is a function for calculating the proportion of observation overlaps in an observation schedule.

- Decision variable:
  \[
  x_{ijk} = \begin{cases} 
  1 & \text{if } w_{ijk} \text{ is selected in the observation schedule} \\
  0 & \text{otherwise}
  \end{cases}
  \]  

\[ (1) \]

3.2.2. Assumptions. Based on the practical applications in reality, some assumptions are adopted.

- The satellites mentioned in this paper are referred to the imaging satellites.

- In this paper, the downloading process of the acquired images falls outside the scope of our study.

- Once a visible time window is scheduled, the acquisition process cannot be interrupted or cancelled until it is finished. At any time, there is at most one task being processed on a satellite.

- The satellite scheduling problem for large area is over-constrained, and not all the requests can be fully satisfied. Thus, the circumstance that some tasks are not assigned or partially observed is acceptable.

3.2.3. Mathematical formulations

\[
\max \sum_{i=1}^{l|S|} \sum_{j=1}^{l|O|} \sum_{k=1}^{l|W_o|} f(x_{ijk} \Delta p) \quad \min \sum_{i=1}^{l|S|} \sum_{j=1}^{l|O|} \sum_{k=1}^{l|W_o|} x_{ijk} \quad \min \sum_{i=1}^{l|S|} \sum_{j=1}^{l|O|} \sum_{k=1}^{l|W_o|} l(x_{ijk})
\]

\[ (2) \]

s.t.

\[
\sum_{k=1}^{l|O|} x_{ijk} \leq l, \forall i \in [l|S|], \forall j \in [l|O|] \]

\[ (3) \]

\[
\sum_{j=1}^{l|O|} \sum_{k=1}^{l|W_o|} (m_{ijk} \Delta x_{ijk}) \leq M_i, \forall i \in [l|S|]
\]

\[ (4) \]

\[
\sum_{j=1}^{l|O|} \sum_{k=1}^{l|W_o|} (v_{ijk} \Delta x_{ijk}) \leq V_i, \forall i \in [l|S|]
\]

\[ (5) \]

\[
\sum_{j=1}^{l|O|} \sum_{k=1}^{l|W_o|} (e_{ijk} \Delta b_{ijk}) \leq \delta
\]

\[ (6) \]

\[
b_{ijk} \geq B_{iqj}, \forall i \in [l|S|], \forall j \in [l|O_i|], \forall k \in [l|W_{ij}|]
\]

\[ (7) \]

\[
e_{ijk} \geq E_{iqj}, \forall i \in [l|S|], \forall j \in [l|O_i|], \forall k \in [l|W_{ij}|]
\]

\[ (8) \]

\[
g_{ijk} \geq G_{iqj}, \forall i \in [l|S|], \forall j \in [l|O_i|], \forall k \in [l|W_{ij}|]
\]

\[ (9) \]

\[
GSD_{ijk} \geq H_{iqj}, \forall i \in [l|S|], \forall j \in [l|O_i|], \forall k \in [l|W_{ij}|]
\]

\[ (10) \]
The objective function (2) is to maximize the summed reward, to minimize the number of selected VTWs and to minimize the overlaps of the observation schedule for a specific target area respectively. Constraint (3) regulates that for each target area, at most one visible time window can be selected on its every satellites orbit owing to the long-strip imaging mode. Constraint (4) restricts that the satellite memory storage is always within its safe range. Constraint (5) insures that the satellite is charged with adequate power to support the process of image acquisition. Constraints (6) reveals the duration for each image acquisition must be restricted to the maximal working duration for each image acquisition for the sake of normal operation according the long-strip imaging mode. Constraints (7) and (8) ensure that the selected visible time window must be included in a given schedule horizon. Constraint (9) points out the restriction of maneuvering capability for a specific satellite. Constraint (10) reveals that the resolution of the images is supposed to satisfy the requirements from customers.

4. Multi-objective satellite scheduling method for very large areal observation
The main solving process for multi-satellite scheduling problem for very large area observation can be divided into three phases: the discretizing phase, target decomposing phase and the scheduling phase, as illustrated in Figure 2.

4.1. The discretizing phase
As illustrated above, the objective of the multiple satellite scheduling problem for large area observation is to maximize the summed coverage of the strips in a generated observation schedule. Thus, the area calculation of the strips in a specific observation schedule is essential. Since our problem is involved with multiple satellites and very large areas, applying the geometric methods will lead to considerable computational time and the loss of accuracy.

Hence, we develop a discretization-based area calculation method to reduce the time and space complexity in the calculation process. The area target is discretized equidistantly with spots, and the set of interpolated spots represents the whole area target, as depicted in Figure 3. Meanwhile, the visible time window is represented as a strip. As one strip can cover a portion of the area target, each strip can cover some interpolated spots. Consequently, the evaluation system can be established. The profit of a specific observation schedule can be measured by the number of the interpolated points of the strips located in the whole area target. Despite the circumstance that different strips may cover several points repeatedly, the discretization-based calculation method largely simplifies profit measurement of observation schedules.

4.2. Target decomposing phase
Considering the area target is far much larger than single observation scope for the satellites, it is a common measure to decompose the area into strips. Accordingly, a visible capacity based area target decomposition method is proposed. The concrete decomposition method is depicted below.
STEP 1. For each satellite $i$, compute $FOV$ for each area target $r$ and the bounding rectangle of the overlapping region of the $FOV$ and target.

The bounding rectangle is associated with the intersection points $e$ between the $FOV$ and the area target. The satellite observes the two intersection points on the length in the earliest time $t^e$ and the latest time $t^l$. The satellite observes the two intersection points on the width with the smallest roll angle $r^-$ and the largest roll angle $r^+$. 

STEP 2. Set the excursion parameter $\Delta \lambda$.

Decompose the bounding rectangle of each area target into strips with $\Delta \lambda$. The excursion parameter can adjust the extent to which the strips overlap considering the requirement and preference of the customers. In terms of the satellites equipped with optical cameras, $\Delta \lambda$ is represented by a specific roll angle which can be changed.

STEP 3. Cut the strips.

After STEP 3, strips of equal length are obtained. They are supposed to be cut according to target boundary in order to improve the effective coverage.

STEP 4. Compute the $VTWs$ of the corresponding strips.

$VTWs$ are calculated by judging the visibility between the satellites and the area target in a specific time span $[T_{begin}, T_{end}]$ and search the visible time spans as the visible time window $[TW_{begin}, TW_{end}]$.

After the 5 steps, strips of a specific target area are obtained, as depicted in Figure 4.

Figure 3. Area target discretization. Figure 4. The set of generated strips.

4.3. The scheduling phase

Based on the two preconditioning phases, the multi-satellite scheduling problem for very large area observation can be transformed into a multi-objective set covering problem subject to several constraints. The definition of the complex set covering problem is presented as follows.

Given a set of points $I_q = \{i_{q1}, ..., i_{qn}\}$ and a set of $m$ subsets of $I_q$, $A = \{I_{q1}, I_{q2}, ..., I_{qm}\}$, find an optimal collection $C$ of the sets from $A$ such that $C$ covers the elements in $I_q$ to the maximal extent and contains the minimal number of elements and overlapping portions. $I_q$ is the set of points representing the area target $q$, and $I_{qj}$ is the set of points that a specific strip can cover in the area target $q$. $I_{qj}$ is relative exclusively to each $VTW$. $I_q$ and $I_{qj}$ are generated in the front phases.

Much interest and effort has been devoted to the set covering problem; the proposed algorithms up to now can be categorized into two classes: heuristic and exact approaches. Considering the considerable strips yielded by the large area target and the high combinatorial nature of the scheduling problem, heuristic solving approach is more appropriate for our problem. In order to generate an observation plan taking count of the efficiency and accuracy simultaneously, in view of the characteristics of the multiple satellite scheduling problem that the problem is virtually a $VTW$ selecting problem, a multi-objective genetic algorithm is developed based on NSGA-II. Applying fast
non-dominated sorting operator, crowded-comparison operator and elite strategy selection operator in our approach, we further develop the encoding and fitness evaluation formulations.

Note that due to the maneuver constraints, satellites are in a long-strip imaging mode while observing a very large area target. It means that one visible time window can be selected into the schedule when the satellite passes over the target once. Accordingly, the encoding of individuals is constructed by the number of the satellite orbits $Q_{\text{num}}$ in a given schedule horizon. The structure of each chromosome in the population is illustrated as Figure 5. Each chromosome reaches a length of the $Q_{\text{num}}$ and each gene on the chromosome represents a $VTW$ on a specific orbit. Sequence of the genes on a chromosome represents the order of the observation.

![Figure 5. The encoding of chromosome in the proposed algorithm.](image)

As depicted above, each target area is represented by a set of interpolated points and the visible time window is represented as a strip. The coverage rate of the obtained observation schedule and overlaps can be measured by the quantity of points both inside the target area and the visible time windows in the observation plan. The fitness evaluation formulations of our algorithm are presented as follows.

\[
F_1(\text{schedule}) = \frac{N(\bigcup_{\ell_1} U_{\ell_1} \cup \cdots \cup U_{\ell_{Q_{\text{num}}}} \cap U_{\ell_0})}{N(\ell_0)} \tag{11}
\]

\[
F_2(\text{schedule}) = N(\text{schedule}) \tag{12}
\]

\[
F_3(\text{schedule}) = \frac{\bigcup_{\ell_{Q_{\text{num}}}} \bigcup_{\ell_{Q_{\text{num}}+1}} U_{\ell_0} \cap U_{\ell_0}}{N(\ell_0)} \tag{13}
\]

In the formula above, $F_1$ defines the optimization objective to maximize the total profit. $F_2$ defines the objective to minimize the number of selected $VTWs$. $F_3$ defines the objective to minimize the overlaps in an observation schedule. And $N$ is a number calculating function.

5. Computational experiments

5.1. Design of the test scenarios

To the best of our knowledge, little concentration and effort has been devoted to the multiple satellite scheduling problem for large area observation. Besides, different satellites in different countries are designed for different missions, which leads to their capabilities, adopted technologies and management differ significantly. It is accordingly unreasonable to test a satellite scheduling algorithm by a common benchmark designed for a specific satellite. There is no competing algorithm and instances exiting for our problem. Hence, it is extremely hard to compute the optimal solutions due to the high combinatorial nature. Additionally, the greedy-based heuristic algorithm is widely accepted in the practical circumstances for our problem because it can guarantee the efficiency of the scheduling process and a generated feasible solution. We therefore conducted various scenarios to evaluate the performance of the greedy-based heuristic algorithm and our algorithm. And this computational experiment was coded in C# and executed on a PC with Intel (R) Core (TM) i5-3317U2.99 GHz CPU speed and 4 GB RAM. The configurations of the scenarios are depicted as follows.

| Target          | Latitude & Longitude                        | Size (km$^2$) |
|-----------------|--------------------------------------------|---------------|
| African Savannah| (5.33,30.26), (5.33,9.32), (5.17,9.32), (-5.17,30.26) | 123210        |
| Amazon Forest   | (0.53,50.50), (0.53,75.26), (9.06,75.26), (-9.06,-50.50) | 106154        |
| Southern China  | (32.58,114.91), (32.58,105.09), (22.09,105.09), (22.09,114.91) | 109780        |
Given that nowadays EOSs play an increasingly important role in the environment protection and the forests in the world are precious presents from the nature that are supposed to be supervised on end in case of emergency, high vegetation covered areas are selected to be the observation targets. Three high vegetation covered areas are selected from African Savannah, Amazon Forest and Southern China respectively. And the geographical location and basic information of the three target are illustrated as Table 1. For each target area, the scheduling is conducted in 5 independent one-day horizons, from 2018-5-22 0:00:00 to 2018-5-27 0:00:00. And 14 optical satellites from Chinas satellite platform are involved.

Based on several tests on the impact of different parameters of the GA, the values for some parameters are fixed as follows: population size equals to 100, maximal iteration equals to 500, mutation probability equals to 0.1, crossover probability equals to 0.9, maximal working duration for each image acquisition equals to 10 min and excursion parameter equals to 1.8. Figure 6 illustrates the distinct results of the proposed algorithm performance in different mutation probability($p_m$) and crossover probability($p_c$) settings.

5.2. Experimental results

Table 2. Comparison between the proposed algorithm and greedy based heuristic algorithm

| Performance | Scenario_African Savannah | Scenario_Amazon Forest | Scenario_Southern China |
|-------------|----------------------------|------------------------|-------------------------|
| $DT_{10}$   | 190                        | 192                    | 194                     |
| $CR_{10}$   | 17.7                       | 22.2                   | 19.6                    |
| Sec(s)      | 88.8                       | 109.3                  | 76.2                    |
| $DT_{20}$   | 189                        | 178                    | 189                     |
| $CR_{20}$   | 4.2                        | 17.1                   | 13                      |
| Sec(s)      | 31                         | 80                     | 82                      |

Table 2 presents the results of the proposed multi-objective genetic algorithm and the greedy search algorithm for 3 different scenarios in aspect of coverage(the main objective). The result of each scenario is the average of twenty runs. The column Performance indicates that these two algorithms are evaluated in three main aspects, $DT$, $CR$ and Sec. $DT$ refers to duration time of the observation
process of the generated optimal schedule, indicating the efficiency of the image acquisition for a requested large area target. CR points out the maximal coverage rate of the target areas in a specific schedule horizon, indicating the completion of the requests from various customers. Here we use 0 as the minimal possible reward of each observation schedule and 100% as the maximal. The fractions occur in the rewards are because of the partially imaged area targets. Due to the constrained capacity of the involved satellites from Chinas satellite platform, low completion of the tasks is acceptable. Sec reports the computational time in seconds. DT1, CR1, Sec1 evaluate the performance of the proposed genetic algorithm while DT2, CR2, Sec2 evaluate the performance of the heuristic greedy search. Different scenarios are denoted in accordance with the location of the requested areas, which are Africa, Amazon and China. The column D1, D2, D3, D4 and D5 describe the 5 independent one-day schedule horizons, from 2018-5-22 0:00:00 to 2018-5-27 0:00:00. Each scenario is evaluated in these 5 schedule horizons.

As depicted in Table 2, the proposed genetic algorithm improves the performance of the image acquisition to a large degree compared with the greedy search which is commonly used in practical circumstances. In order to reveal the improvement for the scenarios precisely, three histograms are applied as illustrated in Figure 7. For each instance, the total profit (i.e. coverage rate) is presented on y-axis and the schedule horizon is presented on x-axis. Surprisingly, the increment of the performance does not cost considerable computational time. The maximal computational second reached to 223.2, which is quite within the scope of our acceptance. Meanwhile, as illustrated in Figure 8, the multi-objective genetic algorithm presents better performance in reducing the overlaps and improving utilization efficiency.

Note that the rewards obtained by the 14 involved satellites for Scenario China have an obvious advantage over the rewards of other two scenarios under the condition that all the scenarios are scheduled in a same given time horizon. This may be because 14 involved satellites come from Chinas satellite platform and are designed to observe the whole land of China and its surroundings. On the other hand, this indicates that the observation performance by multiple satellites still needs to be improved, possibly by means of coordination and cooperation of satellites from satellite platforms in other countries.

**Figure 7.** The performance increment of multi-objective genetic algorithm versus greedy-based heuristic algorithm in the aspect of coverage.

**Figure 8.** The decrement of multi-objective genetic algorithm versus greedy-based heuristic algorithm in the aspect of observation overlaps.
Remarkably, the computational time consumed by our algorithm is never larger than 5 min for the tested scenarios, which reveals the outstanding performance in terms of speed and reliability in practice. This allows useful information and images acquired by ground scheduling personnel in order to support large area supervision such as worldwide forests.

6. Conclusions
The main contributions of our research are summarized as follows: (1) The multi-satellite scheduling problem for large area observation is introduced for the first time and a multi-objective mathematical model is established. (2) A new three-phase solving framework is proposed. In the discretizing phase, an area discretization method is adopted. In the target decomposing phase, area target is decomposed into strips and corresponding visible time windows are calculated. In the scheduling phase, a multi-objective genetic algorithm is introduced to generate an optimal observation schedule. (3) Extensive computational experiments have been conducted on realistically generated problem instances to evaluate the performance the proposed multi-objective genetic algorithm compared with greedy-based heuristic algorithm. The results indicate the superiority of the proposed algorithm in terms of reliability and speed over the other algorithm.

Acknowledgments
This work was supported by the National Natural Science Foundation of China (Nos. 61473301, 71501180).

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