# Sensor Tasking for Catalog Maintenance and Expansion of Geosynchronous Space Objects

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## Introduction

A practical challenge in space situational awareness (SSA) is to jointly allocate sensor resources to optimally update the cataloged targets and search for new targets in the GEO region. Thus, sensor tasking algorithms need to account for several conflicting objectives:

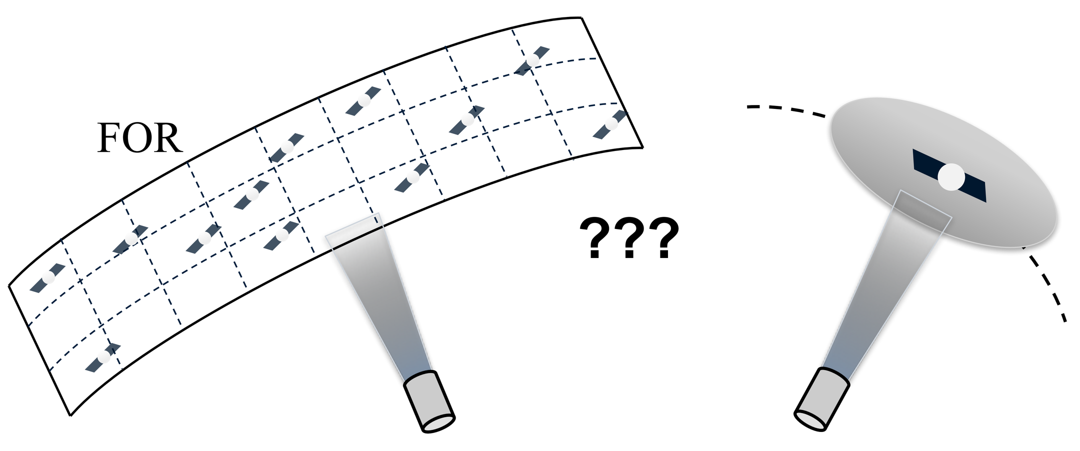


***Figure 1.*** *Management vs Search sensor tasking*

(1) scheduling an optical sensor to refine the orbital state estimation of cataloged targets, (2) optimally searching for more new targets without any prior knowledge, (3) scheduling follow-on tracking to maintain custody of newly discovered targets. This issue has been widely investigated by the SSA community, but it is still considered a challenging task in the practical application. The Bayesian multi-target tracking filtering technique is a potential solution to this issue, which provides an effective solution to maintain custody of multiple existing space objects, and also account for the presence of new targets by using a birth model.

## Methods

- **Framework**

The proposed method is formulated based on utilizing the Labeled Multi-Bernoulli (LMB) filter for object tracking, and a jointly search and management sensor tasking in a Partially Observable Markov Decision Process (POMDP) framework.

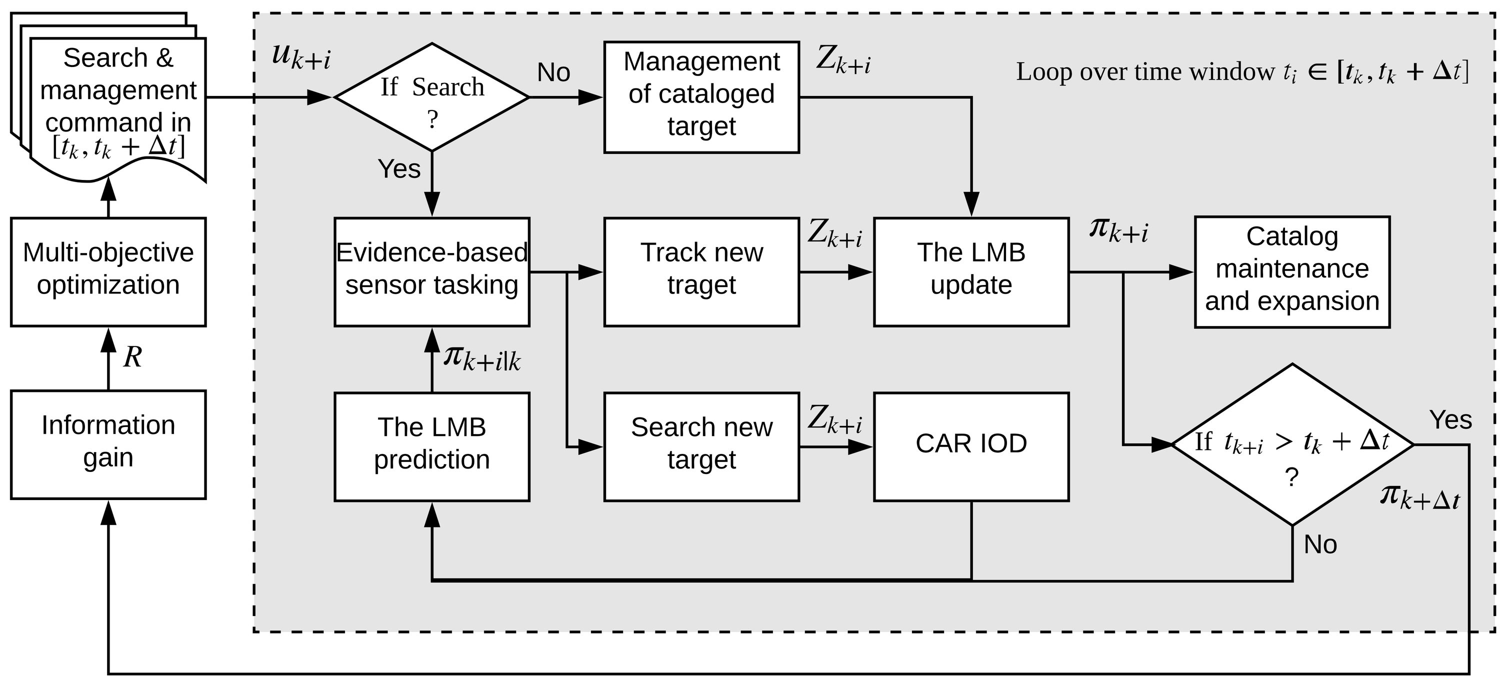


***Figure 2.*** *The flowchart of search & management sensor tasking method*

- **Multi-objective optimization**

The overall objective of the search and management sensor tasking is to allocate sensor resources to maintain custody of cataloged objects and expand the SOC by accommodating more new space objects. Thus, two objectives can be formulated.

**Objective 1 (management):** Refine the orbital state estimation of the cataloged object through continuous tracking. Objective 1 can be converted to maximize the sum of the information content of measurements collected in a given time window.

$$\max F_1(\boldsymbol{u}) = \arg\max_{\boldsymbol{u}} \sum_{i=1}^{t_w} R_i(\boldsymbol{u})$$

The analytical formulation of the Rényi divergence for LMBs is derived by assuming a single Gaussian representation of each target state, which is given by

$$R(u) = -2\log \sum_{L\subseteq\mathbb{L}} (w_0(L))^{\frac{1}{2}}(w_1(L))^{\frac{1}{2}}\left[\left(K_{0,1}^{(\ell)}\right)^{\frac{1}{2}}|8\pi\Sigma_{0,1}^{(\ell)}|^{\frac{1}{4}}\right]^L$$

**Objective 2 (search):** Explore the surveillance space and discover new space objects to increase the accommodation of an SOC. Then, objective 2 is defined as the sum of the time left for search $T_s$ in a given time window.

$$\max F_2(\boldsymbol{u}) = \arg\max_{\boldsymbol{u}} \sum_{i=1}^{t_w} T_s(\boldsymbol{u})$$

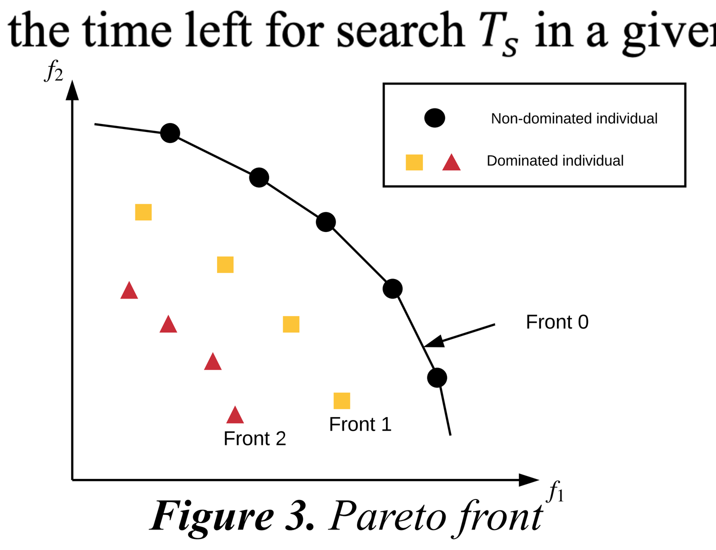


***Figure 3.*** *Pareto front*

The search time is used for grid search and follow-up of new objects. Solving these two objectives can be regarded as a multi-objective optimization (MOO) process, and it can be addressed by the NSGA-II algorithm. NSGA-II iteratively searches for the global Pareto front (Fig. 3) based on non-dominated sort rule and genetic operators, e.g., crossover and mutation.

- **CAR birth model**

Modeling new target birth is equivalent to a process of initial orbit determination (IOD). The constrained admissible region (CAR) is used for IOD using optical measurements from a single observational arc, i.e., tracklet. The CAR is approximated by a Gaussian mixture model. The CAR birth model generally results in a large initial uncertainty. Thus, it is essential to schedule prompt follow-on observations to avoid losing custody of the object after orbit propagation over long time intervals.

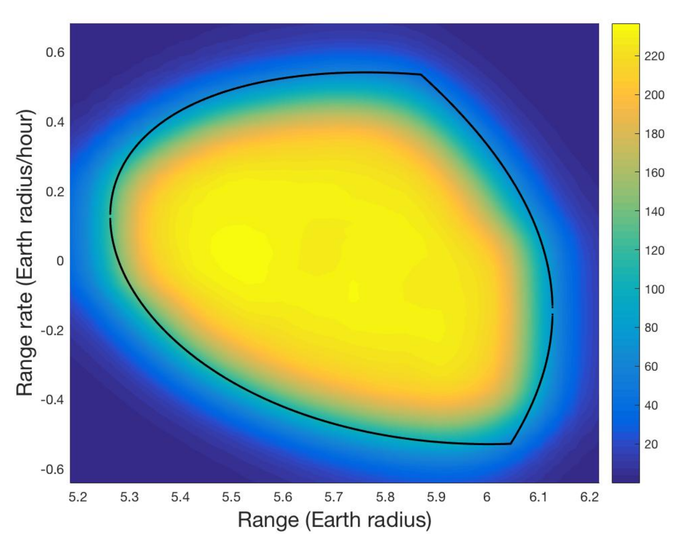


***Figure 4.*** *The GMM PDF of CAR*

- **Evidence-based Search vs Track Sensor Tasking**

Another challenging task in joint search and track sensor management is to appropriately switch between the search and follow-on tracking to avoid losing custody of the newly discovered object. The Dempster-Shafer theory (DST) or evidence theory is utilized as the decision-making strategy to determine the switch point between search and follow-on tracking. The DST-based sensor tasking scheme applies binary hypotheses to the search and follow-on tacking modes, and the hypotheses are confirmed or rejected by evaluating all available evidence. Minimizing the weighted ignorance of all hypotheses provides the best sensor control command between search and track at a specific epoch.

**Hypothesis of search:** a sensor tasking command results in successful detection of new space objects. The ignorance of search is

$$ig(\Theta_s) = 1 - P_{search}$$

**Hypothesis of track:** a sensor tasking command results in successful detection of tracked objects. The ignorance of track is

$$ig(\Theta^{(\ell)}) = 1 - P_v^{(\ell)} P_D^{(\ell)} r^{(\ell)}$$

**Objective function:** The weighted sum of total ignorance of all hypotheses

$$\min_{\boldsymbol{u}} \; ig(H) = \sum_{i}^{|\boldsymbol{X}|+1} w_i ig(H_i)$$

A greedy optimization strategy is used in this study. Minimizing the objective function at every epoch yields best sensor control command for search and track sensor tasking.

## Results

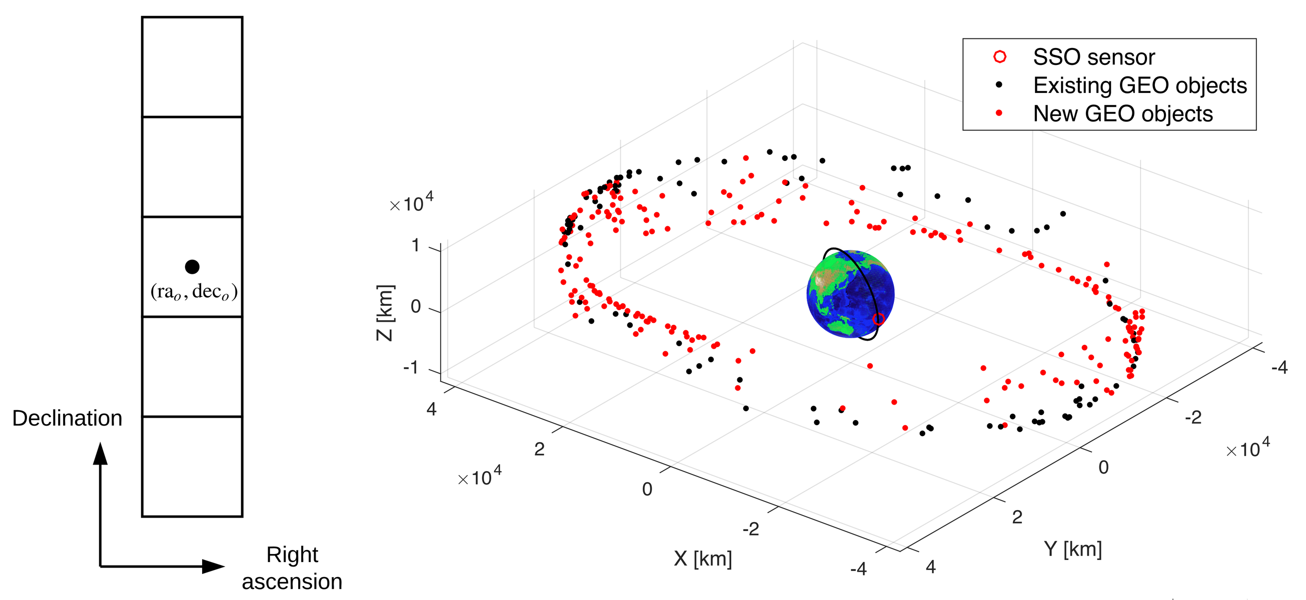


***Figure 5.*** *(left) The reduced FOR of the SSO sensor defined in the geocentric coordinates; (right) The trajectory of the SSO sensor and tested GEO objects*

A catalog contains 100 GEO objects is established and maintained using an SSO sensor, and 200 new GEO objects need to be discovered. Three time windows, i.e., 8 hours, 16 hours and 24 hours, are used for the multi-objective optimization of joint search and tracking sensor management. Among all individuals in the Pareto front, the one whose time for search most closes to 50% of the total time window is selected.

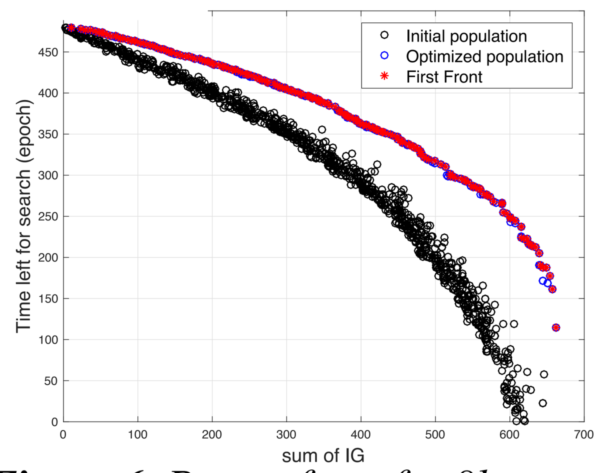


***Figure 6.*** *Pareto front for 8h case*

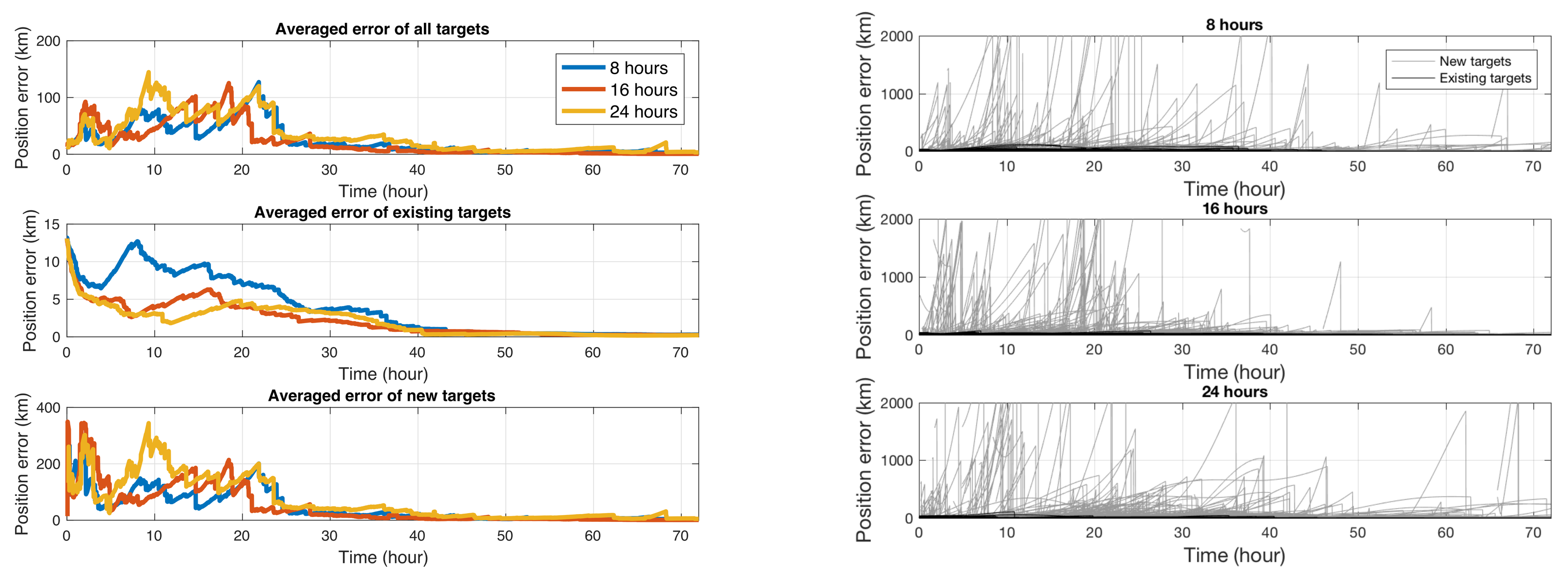


***Figure 7.*** *(left) Averaged position errors; (right) Position errors of all targets*

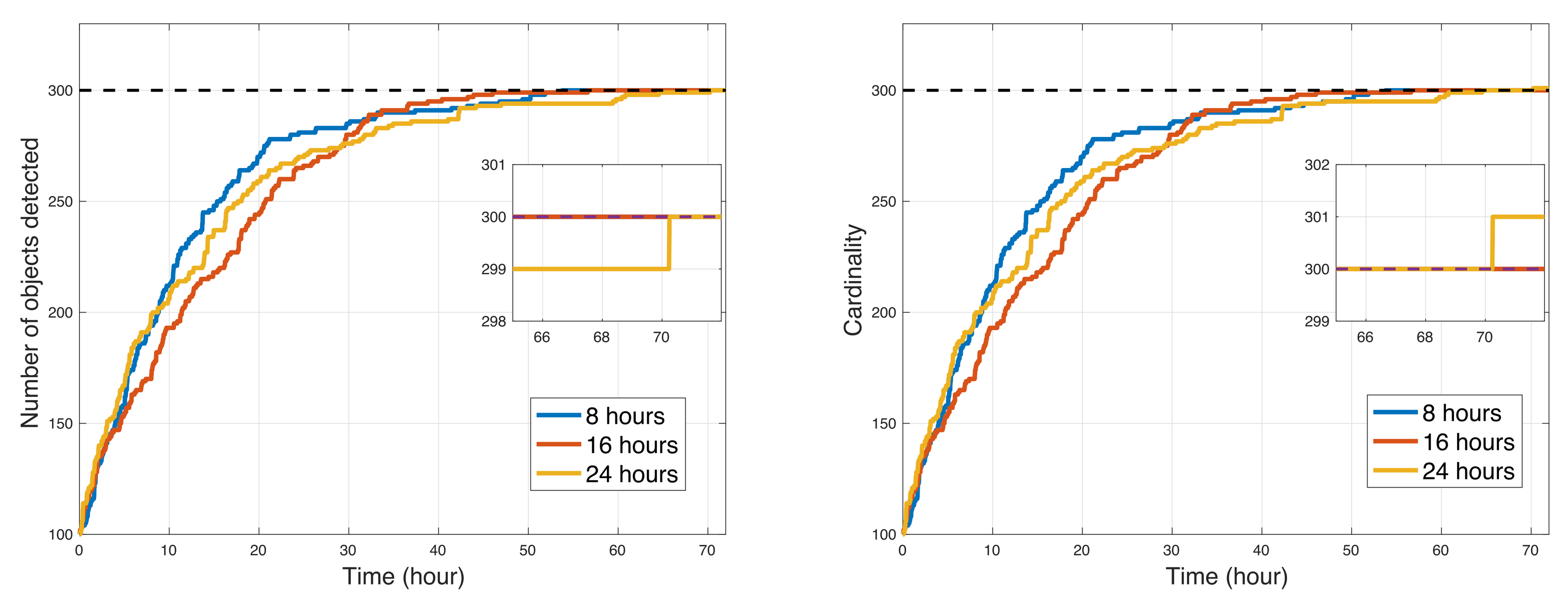


***Figure 8.*** *(left) Number of targets; (right) Cardinality estimation*

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