Optimized Sensor Scheduling & Tasking For Orbital Space Debris Tracking

The Industrial Sciences Group

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Introduction

Currently, around 20,000 orbiting objects (including satellites and space debris elements larger than 10cm) are being tracked by the North American Aerospace Defence Command (NORAD), and this is expected to rise. Finding the most efficient way to monitor and update this extensive catalogue presents a substantial optimisation problem. **In this poster, we present methods and results for a Python-based object-tracking scheduler program developed in collaboration with the Space Environment Research Centre** (Research Program 3). We successfully generate schedules to track 2,000 objects simultaneously within a 24 hour period using optical and laser tracking sensors.

Scheduler Methodology

The implemented scheduler utilises a series of predictions and simulated measurements to determine the optimal sensor-object pairings for each variable "assignment window". For each sensor-'visible object' pair, a reward metric (see Information Gain) is computed, and compiled into a reward dictionary (Figure 2). **An auction algorithm is used to select the sensor-object pairs that maximise the total information gained** [2]. In this case simulated observations are performed, and the remaining objects in the catalogue are propagated forward.

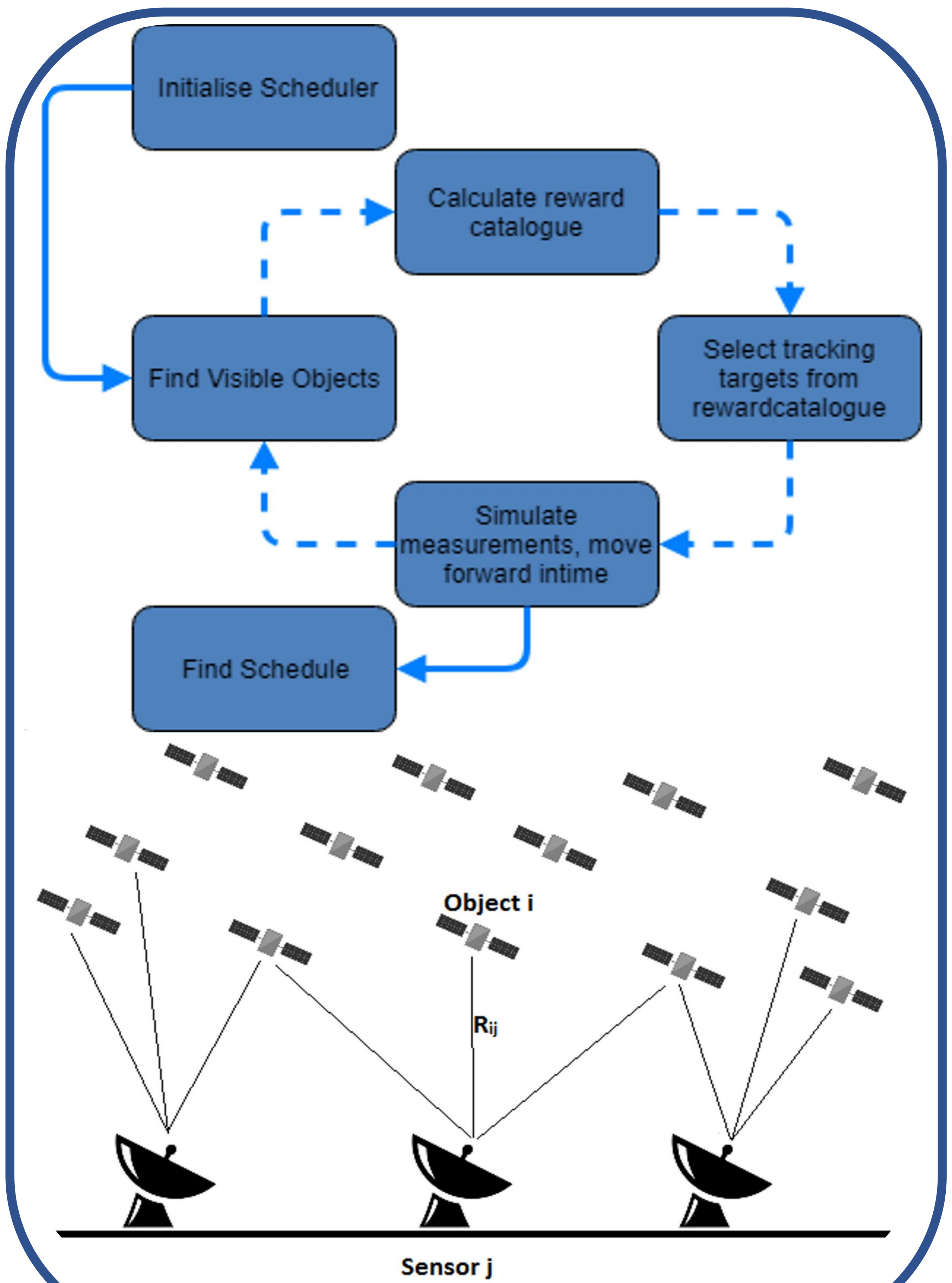


Figure 2. Scheduler – sensor/object selection

Information Gain

Selection of objects-to-track for each sensor is performed based on information gain - **the larger the reduction in uncertainty of object position a measurement would provide, the higher the preference is for that object to be tracked.** We quantify the information gain using the Rényi Entropy [1] or the covariance change (determined using a unscented Kalman filter) of the tracked object (Figure 1).

Covariance

The covariance matrix is an expression for the uncertainty in position and velocity of the tracked object (Figure 3), with the diagonal terms indicating conventional variance, and the off-diagonals representing covariance pairs. Viewing the along-track covariance growth. Figure 1 shows characteristic build-up and collapse as objects are selected to be sensed.

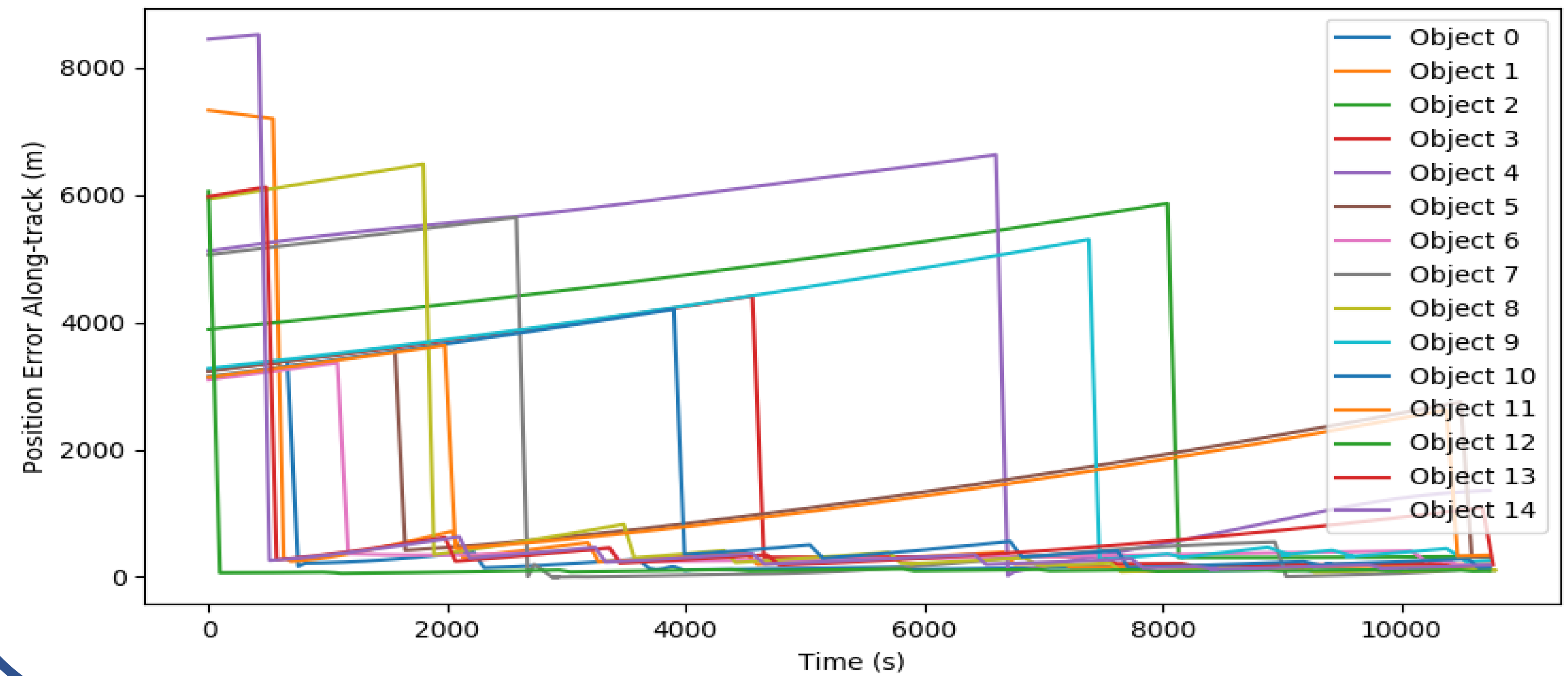


Figure 1. Object covariances over time

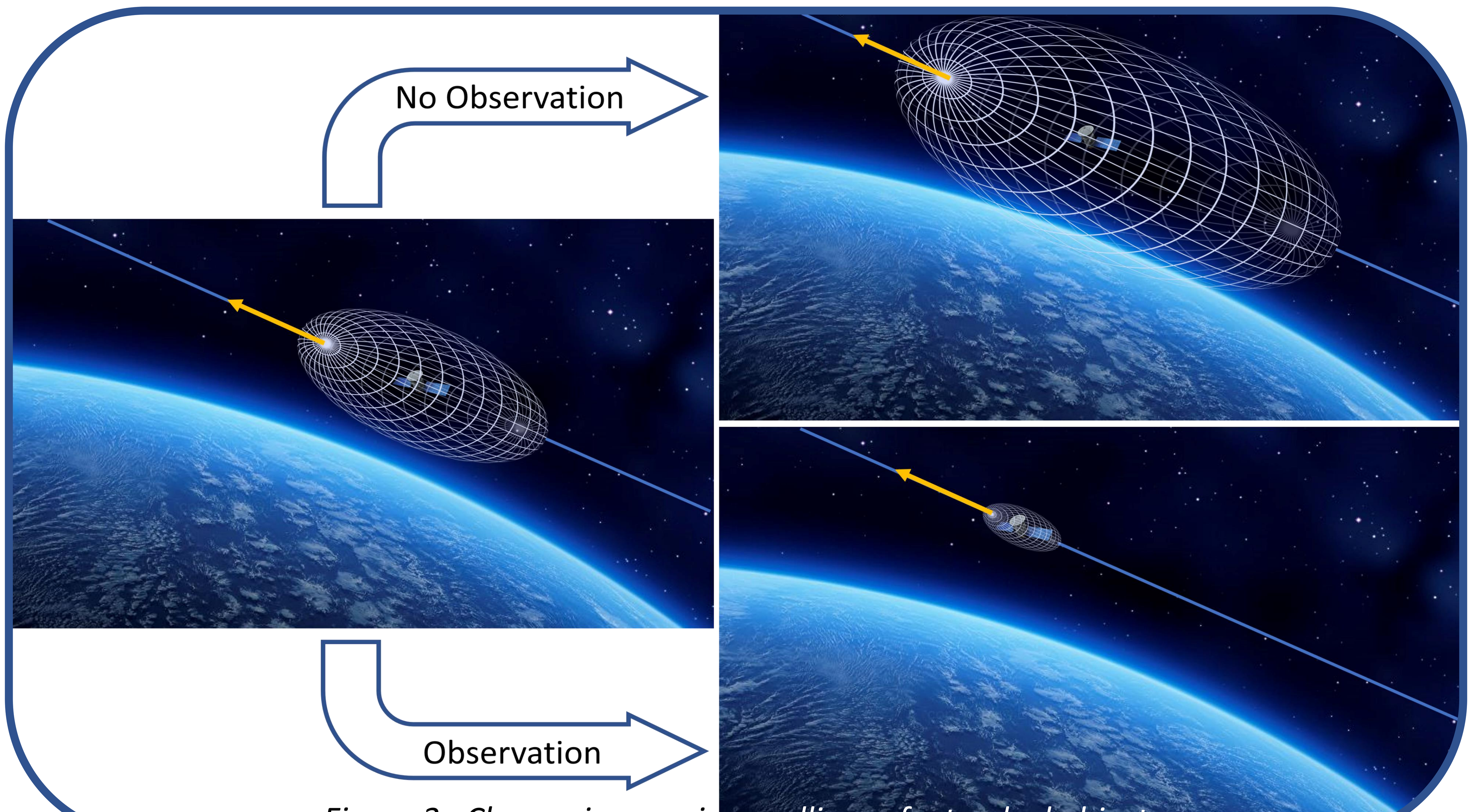
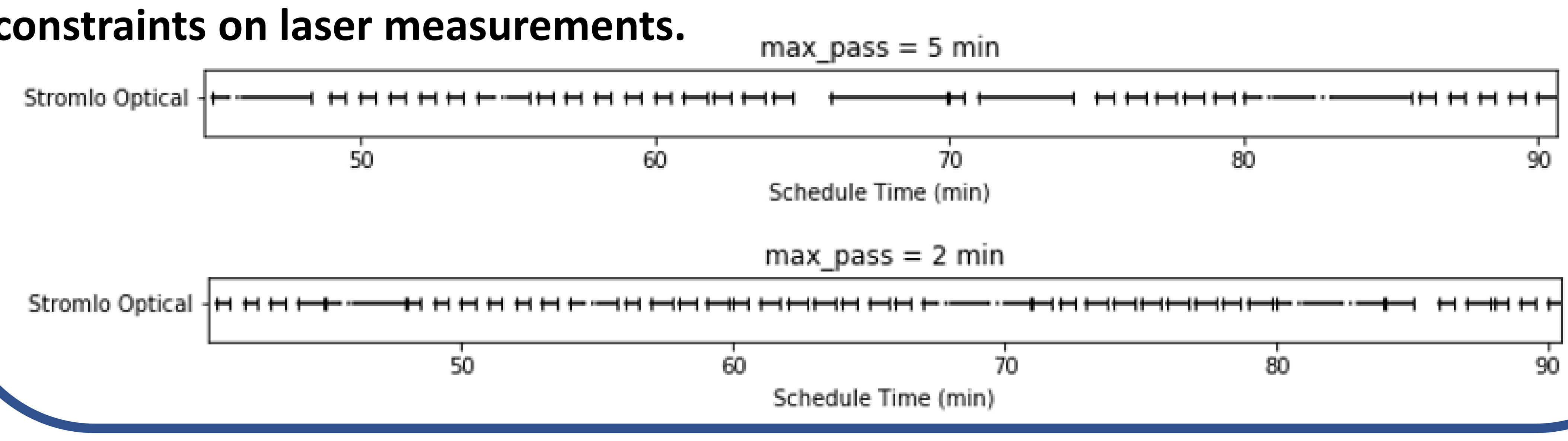


Figure 3. Change in covariance ellipse of a tracked object

Reduced Idle time

The scheduler was successfully run on lists of 200 and 2000 objects to benchmark the performance. All sensors are now continuously engaged throughout the observation period, mitigating idle time. **The program now accounts for asynchronous assignment windows, computing the cumulative information gain from multiple observations, scaling the information gain for high priority targets, and adding constraints on laser measurements.**



[1] S. Gehly and J. Bennett, "Incorporating Target Priorities in the Sensor Tasking Reward Function," in Advanced Maui Optical and Space Surveillance Technologies Conference, Sept. 2016, p. 34.
[2] D. P. Bertsekas, "Auction algorithms for network flow problems: A tutorial introduction, "Computational optimization and applications, vol. 1,no. 1, pp. 7–66, 1992.