Debris Measurement Analyzer (DMA): Simulating the Detection of Resident Space Objects using Space-Based Optical Sensors

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ABSTRACT

Debris Measurement Analyzer (DMA) is a simulation environment developed to generate data about in-space surveillance using an optical payload. A novel simulation paradigm is presented which combines physical simulation with statistical data about the resident space object (RSO) environment, resulting in superior accuracy and shorter simulation runtime. DMA implements a finite volume sampling technique that enables the simulation to not only account for the dependence of RSO spatial density on altitude, but also on longitude, latitude, and sensor orientation. The results produced by this tool are aggregated into insights that enable data-driven decision-making whether the detection of RSOs is a primary or secondary mission objective. DMA provides insights about how many RSOs are detected within one orbit, and what size of RSO is visible. It estimates the accuracy of initial orbital determination and finally provides a cost estimate of performing orbit determination using an in-space system. DMA's model-based approach allows mission designers to characterize the in-orbit RSO detection performance throughout the mission development cycle. By implementing simple MATLAB functions DMA's capabilities can be easily extended.

INTRODUCTION

This paper proposes a simulation tool developed to model the number of resident space object (RSO) observations from an in-space optical payload based on factors such as payload orbit, orientation, and intrinsic optical characteristics.

An increasing number of space missions are taking place. Recent missions are impacted by old missions and decommissioned spacecraft in the form of space debris or RSOs. Missions are getting more complex as new systems are designed to achieve compound mission objectives such as refueling, servicing, and in-orbit transport. With the rising utility of the space environment, more accurate surveillance data is required to develop these new missions. Large catalogs are available about the objects currently in space, however, these catalogs become sparse for RSOs with comparatively small diameters. There is a lack of surveillance data available for sub-10 cm diameter RSOs [1]. A promising way to collect this data is in-space optical surveillance systems.

Currently, systems exist that can track RSOs effectively from the ground. Bigger objects such as satellites and asteroids provide a large enough cross-section for ground-based systems to detect. However, there exists additional complexity in tracking small RSOs (<10 cm) from the ground. Two main problems are the large distances involved in measuring from the ground and atmospheric aberration; both cause the signal-to-noise ratio to become too small for high-confidence detection. There are initiatives from space agencies and industry to track small-sized RSOs from space, however, there is a knowledge gap about the potential in-orbit performance of these missions. There is a lack of an accurate estimation of the number of detections an optical mission could yield. This is quite difficult because many of the parameters within such a calculation are coupled together and therefore an analytical solution is very limited. A numerical simulation tool is needed to account for all these challenges. RSOs bigger than 10 cm have a catalog coverage of 95 % meanwhile, for sub 10 cm RSOs this coverage drops to only 6% based on data from [1] and [10]

PRIOR WORK

The field of monitoring RSOs using in-space optical systems is relatively new, current literature focuses on simulating only the detection process [6] [2] [9]. The work done by Clemens [2] creates a numerical simulation that propagates a list of two line elements (TLE) of given RSOs based on the SGP4 algorithm [12]. The simulation workflow then determines the RSOs visible to the observer satellite. The author's approach is adequate to study the detection process itself, however, the critical limitation which prevents the extension of this approach to model the in-orbit performance of optical detection systems lies in scaling. This simulation has been tested with synthetic TLE data, which means that the author generated RSOs based on what observation condition was needed to be achieved by the simulation. In reality, this algorithm is not suited to process an entire catalog of TLE data, such as the space-track catalog [1], as propagating every entry in the catalog is prohibitively expensive. In addition, if such an approach were to be used to try to estimate the number of detections of small-sized RSOs, it would significantly underestimate RSO counts within the sub-10 cm size category as these are under-represented in catalogs containing TLE data [3].

To overcome the problem of simulating vast amounts of RSOs several simulation tools exist that use a statistical representation of the RSO population. There is already a significant effort that has been put forward to quantify the effect of small RSOs on spacecraft missions from major space agencies ESA and NASA with MASTER and ORDEM respectively [4]. A statistical model is generated based on real data about RSOs. The quality of this model is dependent on the input data which is collected from many different systems. These tools are developed to count RSO fluxes through spacecraft, however, their default functions are not fit to produce an estimate of which RSOs can be observed by an optical payload, due to the added complexity of the calculation.

Analytical simulation tools within the literature that rely on statistical RSO population data are limited in scope. A recent work [6] utilized statistical debris data to inform the design process of a constellation gathering space situational awareness (SSA) data. This approach does not offer sufficient flexibility to simulate multiple mission types due to the assumptions made:

1. Fixed satellite orientation: this assumption is only applicable for specifically made constellations for RSO tracking, and fails under the assumption that RSO tracking is a secondary payload on a mission
2. All orbits are perfectly circular: transfers and eccentric orbits are not included in the models
3. RSO 'coverage' model: the approach only provides a 0-1 fraction of what percentage of the RSO population can be observed

The model is not suited for extension to account for the velocities of RSOs or to obtain granular insights about the physical situation during observation [6].

Analytical methods fall short in the area of estimating detection counts for missions where the secondary mission is RSO detection. Current models from literature [6] require the satellites to be primarily configured for RSO detection. This approach, for example, cannot be used to estimate the number of RSO detections in a star-tracker sensor network [5]. Lack of flexibility is the main limitation of analytical methods.

There is a need for simulation tooling capable of verifying the amount of RSOs that can be detected as a secondary capability of optical payloads. For example, a telescope usually tasked to observe a space object can also capture data about RSOs passing through its FOV. This data can be captured and utilized for space traffic management purposes as opposed to being discarded as it does not suit the primary mission objectives [9]. Optical payload missions have many different orbits (inclinations, eccentricities, etc.), hence the simulation tool should be able to account for any mission parameter.

DEBRIS MEASUREMENT ANALYZER (DMA)

The debris measurement analyzer has been developed to address the challenge of estimating the amount of detections that an optical payload platform can obtain in a given period, and mission conditions. Key simulation parameters, the workflow, the statistical approach, and several developed models are discussed in detail in the following sections.

Key Parameters

This section outlines the most important parameters for in-space optical payloads within the application of detecting RSOs. The fundamental operation of an optical system relies on photons hitting the sensor, where the number of these photons is dependent on several parameters which are listed in Table 1.

Table 1: Key Parameters Affecting the Detection of RSOs by Optical Payloads

Parameter	Description
Illumination Geometry	The way in which light is scattered and detected
Phase Angle	The angle between incoming and reflected light of the RSO
Reflectivity	Surface property of the RSO
Exclusion Angles	Effect of direct light from Sun and Earth
Detection Threshold	Maximum visual magnitude for detection
Sensor Optics	Imaging characteristics of the optical payload

Workflow

This section of the paper will provide an overview of the iterative workflow that is performed by DMA to determine whether the detection of an RSO has taken place.

The first step taken by DMA is loading in a debris distribution spectrum. These are files that relate the debris density ($\frac{1}{\text{km}^3}$) and the debris diameter (m) to the altitude above the surface of the earth (km). The source files can be generated via a Debris Analysis tool (such as NASA's Ordem or ESA's Master). In addition, DMA loads in a trajectory file which contains the positions of the satellite and the Sun in the ECI reference frame. Again this file can be generated with any relevant tool (such as STK, GMAT, or a simple propagator). After loading these files, DMA is finished with the initialization of the simulation.

In the next step, DMA begins a finite volume simulation. DMA uses parameters of the view cone of the optical payload (height and field of view angle) to generate a set of points that represent discrete cells of space within the view cone. Next, the workflow calculates the metric of $\frac{\text{km}^3}{\text{point}}$ which will be used to determine the probability of debris existing independently within each discrete cell.

For each of the discrete cells, represented by a set of points at their centers, DMA samples the debris distribution spectrum and obtains a spatial density for that point. DMA then computes the RSO occurrence probability for each point. Next, the workflow utilizes the Monte Carlo method to determine for which of the discrete cells an RSO is generated in the current time step. Should a generation take place, the location of the center point of the discrete cell becomes the position at which the RSO was generated. The altitude of the RSO is used by the workflow to sample the size distribution.

Finally, in the last step, the DMA can identify whether or not the RSO meets the illumination conditions for detection. For this, DMA utilizes a photometric brightness model. This model computes the visual magnitude of the RSO as seen from the optical payload based on the relative positions of the optical payload, the RSO, and the Sun. DMA then accepts RSOs with a visual magnitude lower than the maximum visual magnitude required for detection.

DMA iterates over each point on the trajectory of the observer satellite and produces a record of the number of RSOs that are statistically likely to be detected during the satellite's orbit. The full workflow is visualized in Figure 1

Statistical Approach

The two key advantages of the DMA are the accuracy of the predicted number of RSO detections and the speed of computation. These two advantages stem from this work utilizing a combined statistical-physical environment model. The architecture of the simulation also allows for additional models to be included to tailor the simulation to a specific mission. Pure physical simulations utilize TLEs of real RSO objects to simulate detection events, however, this does not represent the RSO environment adequately as only a limited number of RSOs can be simulated at once due to computing constraints [2]. This paper proposes the use of statistical data about the RSO population combined with a physical model to generate a statistical estimate of how many detections can be made. Instead of utilizing a small set of RSOs defined at the beginning of the simulation, DMA samples a statistical distribution to generate a representative RSO. DMA then utilizes this representative in a physical simulation environment to model the detection event and generate relevant vectors that fully describe each detection. This approach is advantageous as computing resources are not utilized when an RSO is not detected, speeding up simulation.

RSO Environment Model

DMAs approach used to model the RSO environment allows for high-resolution modeling of the spatial density. This paper presents a new paradigm in how to model the RSO environment, mainly the use of local spatial RSO density data. This way data from the catalogs is not modeled directly but rather a statistical distribution is generated via a space debris modeling tool such as ESA's Master or NASA's ORDEM. These distributions are then utilized in a Monte Carlo simulation to define whether an RSO is generated within the field of view of the satellite. An example distribution based on the altitude can be found in Figure 2

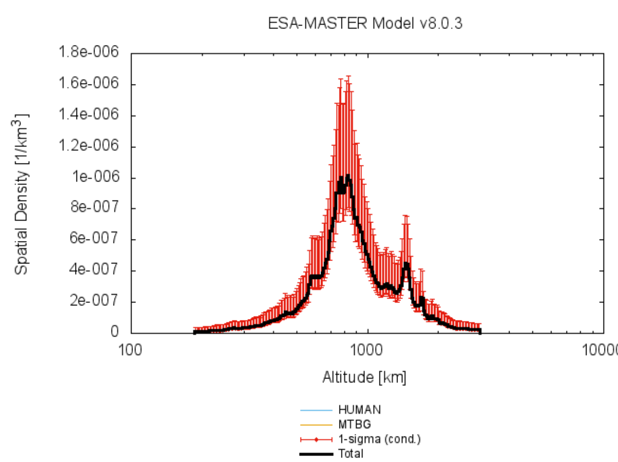

Figure 2: Distribution of Spatial Density as a Function of Altitude

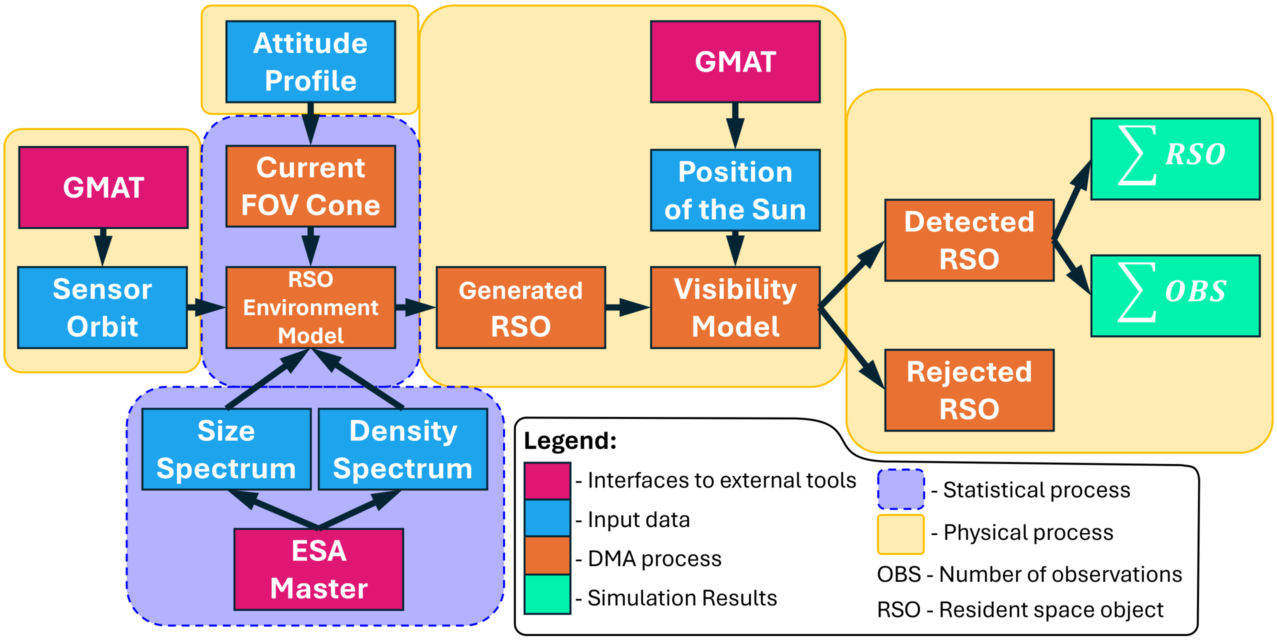

Figure 1: Workflow of the Simulation.

Spatial Density Data

The tool 'Master' utilizes a condensed catalog of TLEs, and given spectra parameters, it generates a spatial distribution for a given volume in space. Given longitude and latitude an appropriate spectrum is selected and with altitude as the independent parameter, the nominal value of spatial density can be determined along with the upper bound and the lower bound, one standard deviation away. DMA generates a skewed distribution to account for the uncertainty. Taking a position of a point in space as an input, this distribution is sampled to obtain a local RSO density with uncertainties included.

Finite Volume Method

The spatial density at a certain point depends on its altitude, longitude, and latitude. Tools similar to DMA in literature use a simplified RSO environment model which is only dependent on altitude [6]. The approach taken by DMA is based on a finite volume method. This allows DMA to account for longitude, latitude, and the orientation of the sensor view-cone in 3D space. This approach is novel as the DMA results contain additional information compared to other approaches. This is further highlighted by the fact that DMA can model orbits with the same altitude but with a range of inclinations which result in varying spatial densities, whereas other simulation tools would produce the same number of generated RSO objects for all inclinations.

Size Spectrum

One of the critical parameters to determine the visual magnitude of an RSO is the diameter. The size of each RSO has to be sampled from a relevant distribution. This distribution is generated by an external tool with an altitude resolution of 2km. DMA takes the altitude of each generated RSO and selects an appropriate size distribution. Finally, this distribution is sampled to determine the size of the RSO.

Photometric Brightness Model

The visual magnitude of the RSO on the optical instrument needs to be calculated to determine whether a detection will occur. This is done via the photometric brightness model, which requires the following vectors to be computed: $\vec{r}_{ES}$ (Earth→Sun), $\vec{r}_{EO}$ (Earth→ Observing Sensor), and $\vec{r}_{ER}$ (Earth→RSO). The model takes these vectors along with the size of the RSO and computes the illumination geometry of the situation as well as accounts for Sun and Earth exclusion angles. To account for the reflectivity of RSO objects DMA utilizes an albedo of 0.175 based on the work of Mulrooney et al [8]. Using this data the photon flux onto the sensor is computed. Furthermore, this calculation outputs a visual magnitude as observed by the sensor. DMA then accepts or rejects the observations based on whether the visual magnitude of the observed RSO is below the visibility threshold of the sensor.

Satellite Dynamics

The volume of observations is strictly dependent on the time step used to perform the simulation, the time step is representative of the integration time of an optical payload. The satellite dynamics model provides the simulation with the observer satellite's trajectory in the ECI frame and accounts for the relative orientation of the sensor within the satellite bus. To reduce computation time, the positions of the satellite and Sun are computed before runtime as they are decoupled from all other aspects of the simulation. The satellite dynamics model parses trajectory files and loads them into the DMA environment. The model can interface with other tools for both the position and the attitude profile. The simulation has support for simulating constellations, which can include multiple sensors per satellite and multiple satellites per time step.

RSO Dynamics

The accuracy of initial orbit determination is directly proportional to the number of observed states of the target object [7]. The number of consecutive observations of the same RSO along with the total number of detected RSOs are key metrics for evaluating the performance of in-space surveillance systems. DMA produces an estimation of this metric based on orbital speeds, the position of the detected RSO within the view cone, and the orbital speed of the observing satellite. The model assumes that all detected RSOs will travel in the shortest path to leave the view cone and that all RSOs move in one plane which is parallel to the base of the view cone. DMA uses the altitude of the detected RSOs to calculate their orbital speed based on the laws of Kepler and then computes the length of the path left for an RSO to leave the view cone. The time after which the RSO will leave the view cone is found, and based on the integration time of the sensor the number of consecutive observations of the RSO is determined.

SIMULATION CAMPAIGN

DMA was tested using 3 scenarios, the results of these simulations were verified with other softwares, and insights from the resulting data were drawn. The paper contains the simulation results for 3 missions: inclined polar orbit at 300 km altitude (IP3), inclined polar orbit at 600 km altitude (IP6), and low altitude equatorial orbit at 300 km altitude (EQ3). These 3 missions will form a spectrum from most to least RSO observations: IP6, IP3, EQ3. The results of these scenarios will demonstrate the ability of DMA to account for the variations in spatial RSO density across different altitudes as well as the impact of different sensor pointing regimes on the number of observations. The pointing regime includes the type of orbit and the vector towards the sun. DMA can simulate any arbitrary attitude profile. For the simulation campaign, the zenith-pointing orientation was selected for all cases to ensure a fair comparison between the different scenarios, and to remove the orientation as a comparison variable. The optical properties for this simulation were defined as that of a small satellite star tracker. The specific orbital parameters for each scenario are listed in Table 2, where: Semi Major Axis (SMA), Eccentricity (ECC), Inclination (INC), Longitude of the ascending node (RAAN), Argument of Periapsis (AOP), and True Anomaly (TA)

Table 2: Simulation Setup

	(IP6)	(IP3)	(EQ3)
Start [UTC]	01 Jan 2024 11:59:28	01 Jan 2024 11:59:28	01 Jan 2024 11:59:28
Duration [sec]	12000	12000	12000
Timestep [ms]	100	100	100
SMA [km]	6971	6671	6671
ECC [-]	0	0	0
INC [deg]	120	120	20
RAAN [deg]	20	20	360
AOP [deg]	0	0	0
TA [deg]	310	310	330

For each orbit type, DMA calculates: the number of RSOs within the field of view, which ones are detected, and the number of consecutive observations per detected RSO. The results of the simulation offer granular insight into each detection event. For each detected RSO the following information is available: Epoch of detection, $\vec{r}_{\text{ES}}$, $\vec{r}_{\text{EO}}$, $\vec{r}_{\text{ER}}$, visual magnitude, and RSO diameter.

The simulation is performed 32 times for each orbit type, resulting in a total simulated orbit time of $3.84 * 10^5$ seconds or about 4.5 days. This was necessary to achieve sufficient confidence in the results due to the use of the Monte Carlo method. The summary statistics of these results can be found in the Table 3.

Table 3: Experiment Results (all 64 orbits)

Scenario	Generated (avg.) [Per Day]	σ	Detected (avg.) [Per Day]	σ
EQ3	1800	23	41	12
IP3	2100	50	100	20
IP6	15400	1002	1200	40

To verify the results of DMA using established simulation tools a special RSO density is calculated based on the generated pieces of RSO and the volume of space imaged. From Table 4 it can be seen that data generated by DMA match with predicted RSO densities from ESA's Master. This demonstrates that DMA's results are representative of the RSO environment. The size-spectrum distribution was verified via the same process.

Table 4: Experiment Verification Results

Sample Size (number of orbits n=64)	Calculated Spatial debris Density [1/km3]	ESA Master nominal $\sigma(-)$	ESA Master nominal	ESA Master nominal $\sigma(+)$
EQ3	1800	800	1200	2000
IP3	2100	800	1200	2000
IP6	15400	12000	14000	17000

Figure 3 demonstrates an example simulation result for each scenario. It can be seen that for all scenarios DMA results show detections near the target orbits.

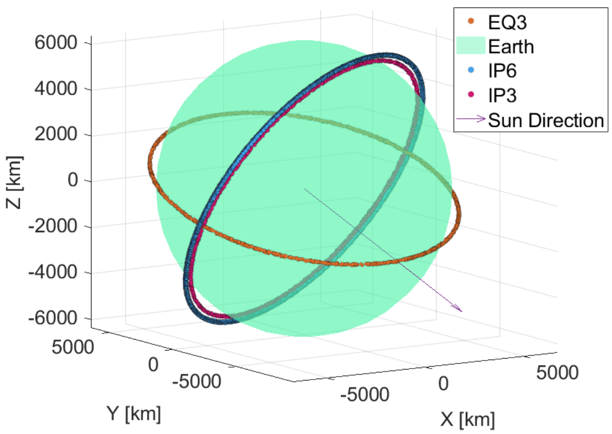

Figure 3: Detected RSOs Along the Orbit.

The approach taken by DMA is sufficiently robust to account for complex visibility conditions in any arbitrary orbit. The observation data from all 64 simulated orbits for scenario EQ3 are aggregated according to the true anomaly of the satellite at which the observation took place, these results are found in Figure 4. In this figure there are two regions where no detections take place, the larger region is related to the sun exclusion angle, and the smaller region is related to the fact the sensor cannot detect RSOs within the Earth's shadow.

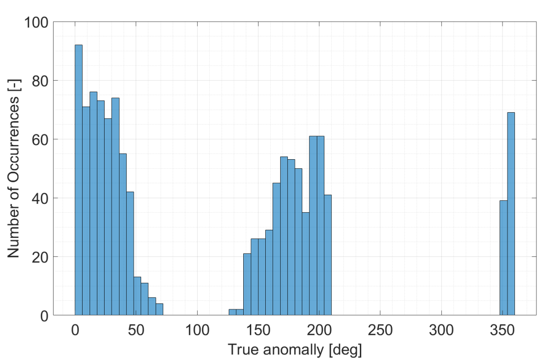

Figure 4: Detected RSO Count as a Function of True Anomaly.

Furthermore, DMA results provide insights into the most common conditions under which RSO detection occurs. Figure 5 plots the phase angle between incoming light onto the RSO and reflected light towards the sensor, the plotted data is for scenario IP6. From the figure it can be seen that in this type of orbit there is a large spread of the phase angles.

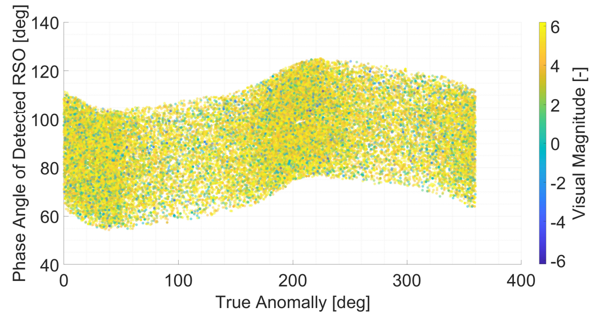

Figure 5: Phase Angle as a Function of True Anomaly (Scenario: IP6)

Contrary to Figure 5 in Figure 6 the spread between phase angles is much tighter, and a sharp pattern is visible. DMA provides data about RSO detection with context as all necessary vectors for most types of analysis are computed, this capability allows for DMA results to be post-processed to uncover deeper insights.

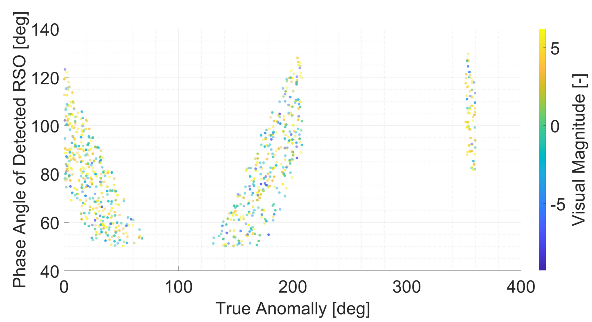

Figure 6: Phase Angle as a Function of True Anomaly (Scenario: EQ3)

Figure 7 plots the visual magnitude and size of detected RSOs against the distance from the sensor at which they were detected using the data for the IP6 scenario where all 64 orbits were used. Figure 7 demonstrates the distribution of detected RSOs within the view cone of the observing sensor and their size. DMA simulation results offer insight into the relationship between the smallest size of RSO detected as a function of the distance away from the satellite.

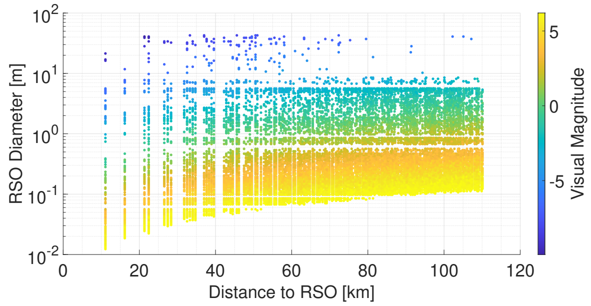

Figure 7: RSO Diameter and Visual Magnitude as a Function of Distance Away from the Sensor .

DMA simulation results are aggregated to estimate the accuracy of orbit determination for each size of RSO. Figure 8 presents the number of observations per detected RSO vs the size of the RSO. DMA data enables the estimation of the average amount of observations for each RSO size category based on data scenarios IP3.

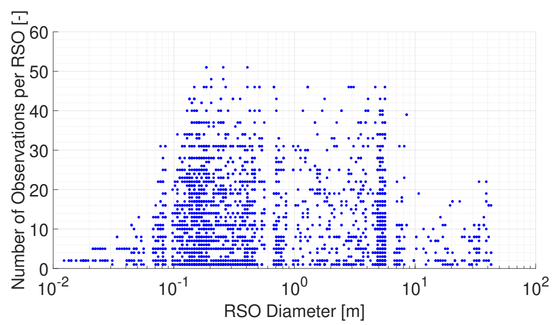

Figure 8: Graph of Visual Magnitude as a Function of Distance Away from the Sensor.

Additionally, based on the amount of observations DMA can estimate the operational costs of down-linking the data necessary to perform initial orbit determination. DMA assumes that all observations of the RSO are cached on the platform so they may be transmitted together. All assumptions for this cost estimate are listed in Table 5

Table 5: Data Cost Estimation

Data per observation		
Variable	Type	Bits
time	Float	32
x-pos	Float	32
y-pos	Float	32
attitude q	4 x Float	128
Data per a series of observations		
state	6 x Double	384
Data cost		
Total Mission cost	5,000,000	USD
Data Downlinked	20	$\frac{Mb}{day}$
Mission Life	3	years
Cost per Kb	0.22	$\frac{USD}{Kb}$

Due to the differences in detection ranges the number of observations varies with size, therefore DMA computes the cost for the following RSO size categories: 1-5cm, 5-10cm, 10-30cm, 30cm-6m, and 6m+. These estimates based on simulation data for all scenarios are available in Table 6.

Table 6: Cost Analysis for Object Size Categories

Size Range [cm]	Average Cost [USD]	Number of Obser-vations [-]	σ
$x \leq 5$	\$0.28	4	3.19
$5 < x \leq 10$	\$0.47	8	7.21
$10 < x \leq 30$	\$0.72	13	11.71
$30 < x \leq 600$	\$0.67	12	11.41
$x < 600$	\$0.52	9	8.57

Advancements in communication technology are set to increase the link budgets of future missions [11]. As the volume of data down-linked from orbit is set to increase in the coming years, the overall cost of detecting an RSO using a space-borne platform will become very competitive with ground-based systems [5].

FUTURE WORK

The knowledge gap that DMA is designed to fill is the lack of simulations for optical RSO detections based on real RSO data. Improvements in the simulation relate mostly to generating data for specific missions and applications involving optical in-orbit RSO detection. DMA is created with an open architecture which allows for modules to be connected as functions within the MATLAB environment. This allows for easy integration with a suite of existing tools used in the industry and allows it to be improved to enable new capabilities.

DMA can be combined with a photon flux model to generate synthetic in-orbit images, given that DMA provides a fully physical simulation environment, this combination of ground truth data and synthetic images empowers the creation of machine-learning image processing techniques for RSO detection. Additionally, the simulation can be extended via an RSO velocity simulation to model the streak seen in long-exposure images of space objects.

Furthermore, DMA can be extended to include orbit propagation for detected RSOs. This would enable DMA to generate data to test sensor fusion libraries for satellites observing the same RSO. This application would benefit from DMA's ability to generate paired results: observation and ground truth. The advantage of this type of approach as compared to using real data is that the source of errors in orbit determination can easily be traced through the workflow by comparing results with the ground truth.

CONCLUSION

This paper demonstrates the utility of DMA as a simulation tool in the field of optical RSO detection. Results from DMA simulations act as enablers to develop and verify key technologies required for in-space surveillance using small satellite optical payloads, such as star trackers and dedicated satellites for RSO monitoring. Before any RSO can be detected there needs to be a strong baseline that ensures that technologies developed will work once in space, DMA fulfills this role with combined statistical and physical simulations that provide all data needed to fully describe each RSO detection.

BIBLIOGRAPHY

1. Saic Admin@space-track. org. *Space-Track.org*. [Online; accessed 8. May 2024]. May 2024. URL: https://www.space-track.org.
2. Samuel David Clemens. *On-Orbit Resident Space Object (RSO) Detection Using Commercial Grade Star Trackers*. [Online; accessed 8. May 2024]. May 2019. URL: https://yorkspace.library.yorku.ca/items/07ccf3a9-4f28-40c7-b201-1255689ea8e9.
3. *Frequently asked questions – EU SST*. [Online; accessed 9. May 2024]. May 2024. URL: https://www.eusst.eu/about-us/faq.
4. Andre Horstmann et al. *Flux comparison of MASTER-8 and ORDEM 3.1 modelled space debris population*. [Online; accessed 8. May 2024]. 2021. URL: https://conference.sdo.esoc.esa.int/proceedings/sdc8/paper/11.
5. Bartlomiej Koszek. "OPTICAL SPACE DEBRIS SENSOR NETWORK WHITEPAPER". In: *ResearchGate* (Mar. 2024). URL: https://www.researchgate.net/publication/380427177_OPTICAL_SPACE_DEBRIS_SENSOR_NETWORK_WHITEPAPER.
6. Gongqiang Li et al. "Research on the Efficient Space Debris Observation Method Based on Optical Satellite Constellations". In: *Appl. Sci.* 13.7 (Mar. 2023), p. 4127. ISSN: 2076-3417. DOI: 10.3390/app13074127.
7. Lin Liu. "Formulation and Calculation of Initial Orbit Determination". In: *Algorithms for Satellite Orbital Dynamics*. Singapore: Springer Nature Singapore, 2023, pp. 473–497. ISBN: 978-981-19-4839-8. DOI: 10.1007/978-981-19-4839-8_9. URL: https://doi.org/10.1007/978-981-19-4839-8_9.

8. M. Mulrooney et al. "An Investigation of Global Albedo Values". In: (Jan. 2008). DOI: https://www.researchgate.net/publication/241291746_An_Investigation_of_Global_Albedo_Values.
9. *On-orbit recognition of resident space objects by using star trackers*. [Online; accessed 8. May 2024]. Dec. 2020. DOI: 10.1016/j.actaastro.2020.08.009.
10. *Space Environment Statistics · Space Debris User Portal*. [Online; accessed 8. May 2024]. May 2024. URL: https://sdup.esoc.esa.int/discosweb/statistics.
11. Ariana Tantillo. "Communications System Achieves Fastest Laser Link from Space Yet". In: *MIT LL website* (Aug. 2022). URL: https://ntrs.nasa.gov/citations/20220012887.
12. David Vallado and Paul Crawford. "SGP4 orbit determination". In: *AIAA/AAS Astrodynamics Specialist Conference and Exhibit*. 2008, p. 6770.