

SPACE NAVIGATOR: A TOOL FOR THE OPTIMIZATION OF COLLISION AVOIDANCE MANEUVERS

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The number of space objects will grow several times in a few years due to the planned launches of constellations of thousands of microsatellites. It leads to a significant increase in the threat of satellite collisions. Spacecraft must undertake collision avoidance maneuvers to mitigate the risk. According to publicly available information, conjunction events are now manually handled by operators on the Earth. The manual maneuver planning requires qualified personnel and will be impractical for constellations of thousands of satellites. In this paper we propose a new modular autonomous collision avoidance system called "Space Navigator". It is based on a novel maneuver optimization approach that combines domain knowledge with Reinforcement Learning methods.

INTRODUCTION

It is estimated that there are about 22,000 pieces of debris, measuring at least 10 cm in diameter, and over 600,000 pieces larger than 1 cm.¹ All of them travel fast enough to damage a spacecraft. Currently, there are about 1,800 operational satellites orbiting the Earth.[¶] With such number of objects, satellite collision avoidance maneuvers (CAM) are necessary, for example, Landsat 7 executed 4 maneuvers in 2017.^{||} At the same time the amount of working satellites is increasing. For example, SpaceX is planning to launch 4,425 units by 2024.²

The other thing to consider is that if two large items collide in space, the result is a huge number of new dangerous objects.³ Only Iridium-Cosmos collision in 2009 produced almost 1,850 pieces of debris larger than 10 cm and thousands more smaller pieces.⁴

According to publicly available information, conjunction events are now manually handled by operators on the Earth.⁵ The manual decision-making process requires qualified personnel and will be impractical for constellations of thousands of satellites. Therefore, there is a need to develop an automated collision avoidance system. ESA has recently launched a tender for such a system.^{††}

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[¶]http://m.esa.int/Our_Activities/Operations/Space_Debris/Space_debris_by_the_numbers

^{||}<https://satellitesafety.gsfc.nasa.gov/maneuvers.html>

^{††}<https://artes.esa.int/funding/autonomous-collision-avoidance-system-ngso-artes-3a093>

Designing an automated collision avoidance system is a challenging task. The optimal maneuver must balance multiple factors such as collision probability, propellant consumption, mission objective, and radio visibility zones. In the face of the increasing number of space objects, it might be necessary to take account several debris pieces when planning maneuvers.^{6,7}

There are several systems for CAM calculation such as CORAM (Reference 8) and OCCAM (Reference 9).

CORAM is employed in Collision Avoidance service by ESA's Space Debris Office and provides an operator with comprehensive information about conjunctions, maneuvers, and trajectories. This system provides the capacity to cope with Multi-Encounter and Multi-Maneuver cases. CORAM allows to define a flexible optimization function, taking into account the collision probability, maneuver size, and miss distance.

OCCAM is a software tool for fast CAM computation based on analytical formulation of the collision problem.¹⁰ This system is able to cope with conjunction with just one dangerous space object. OCCAM supports only three optimization goals: conditional optimization of fuel consumption, collision probability minimization, and miss distance maximization. Among the advantages, there is computation speed and a variety of methods of collision probability estimation. The demo version of OCCAM is freely available online.*

In this paper, we propose a new system, "Space Navigator" (SpaceNav), based on a novel maneuver optimization algorithm that combines domain knowledge with Reinforcement Learning (RL) methods. We also describe the SpaceNav architecture and system features. One of the key features of SpaceNav is modularity which allows the system to be used by different satellite operators with different propagators, methods of collision probability estimation, and optimization requirements. Furthermore, SpaceNav can be configured to cope with various tasks such as Multi-Encounter, Multi-Maneuver, and Maneuvering in a Cluster.

SpaceNav is a result of joint efforts of the Roscosmos Corporate Academy and the Laboratory of Methods for Big Data Analysis at the NRU Higher School of Economics. Virtual Reality interface is a contribution of Phygitalism.

This paper is organized as follows. First, we briefly introduce the concept of Reinforcement Learning. Next, we present the SpaceNav architecture and discuss its capabilities. Then we turn to the maneuver optimization algorithms and introduce a novel application of a well-established Reinforcement Learning algorithm for the purpose. Finally, we discuss the experimental sample of dangerous situations and show the optimization algorithms performance.

REINFORCEMENT LEARNING

Reinforcement Learning (RL) is a field of Machine Learning. The key idea of RL is to develop Agent which provides optimal Actions for some State of some Environment so as to maximize a numerical Reward signal.¹¹ This approach has already been applied to the spacecraft maneuvering task.^{12,13}

The simplified training process of Agent is presented in Figure 1. State of Environment represents the current information about objects position, velocities, and any additional parameters. State get to the input of Agent which provides Actions. After that, Environment implements the Actions and

*<http://sdg.aero.upm.es/index.php/online-apps/occam-lite>

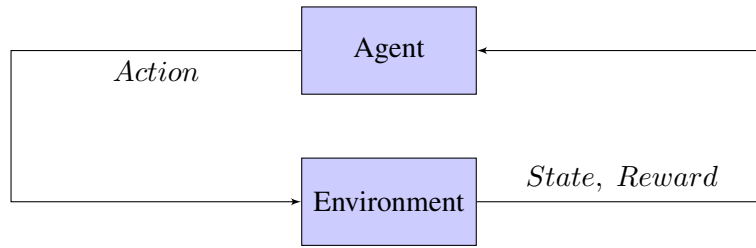


Figure 1. The Reinforcement Learning scheme

State is changed to another State. Also, Environment returns an assessment (Reward) of Action, new State, or whole session. Reward helps to improve the Agent.

Such a principle of training has benefits.¹¹ Reinforcement Learning, being a numeric method, does not require the Environment to be simple enough to allow for an explicit mathematical solution for the problem of finding the best action. In contrast with numerical optimization methods, RL allows building an operator that explicitly maps State into the optimal Action (usually a neural network), without requiring the reward function to be differentiable.

SPACE NAVIGATOR

About

Operator decisions depend on a variety of mission-specific concerns. The state-of-the-art systems mentioned in the introduction are designed to provide the operator with full information about the conjunction event and possible avoidance maneuvers as input for decision-making. In contrast, Space Navigator is built from the ground up as an automated modular system, which is loaded by a set of evaluations important to a particular case. The optimization objective function can be arbitrarily defined. This allows taking into account not only collision probability and fuel consumption, but also other complicated optimization requirements, for example, allowed orbit deviation. SpaceNav allows simultaneously considering many space objects (up to 10 in experiments).

Architecture

The SpaceNav pipeline is presented in Figure 2. Inputs for SpaceNav are:

- Space objects coordinates, velocities, their uncertainties, and epoch;
- Optimization requirements such as a threshold of collision probability or miss distance, thresholds of orbital elements deviation, maneuver restrictions, maximum fuel consumption, fuel level and so on.

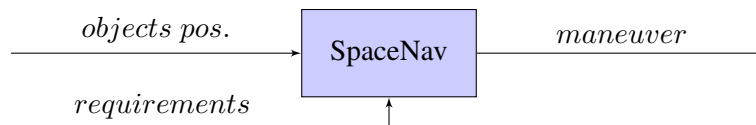


Figure 2. SpaceNav pipeline

SpaceNav returns one or several maneuvers according to the maximum value of an optimized objective function. Having a convenient API, SpaceNav allows easily utilizing different propagators, optimization strategies, and collision probability computation approaches. The simplified architecture of SpaceNav is shown in Figure 3.

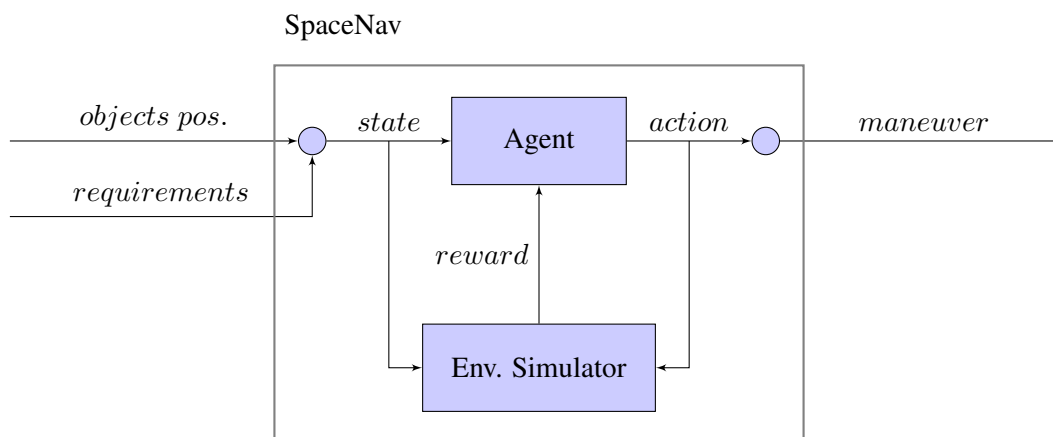


Figure 3. The simplified architecture of SpaceNav

The Agent module gets optimization requirements and a description of a dangerous situation, which is a situation with critical conjunctions with one or more objects. Such an input represents State. After calculation, Agent provides a maneuver, i. e. Action, for the input State.

The Agent module could represent an optimization instrument, such as Grid Search or Stochastic Optimization model. Such a model solves the optimization problem for each collision situation without using any previous experience. Therefore, it could be a general-purpose module which require a lot of sessions. On the other hand, Agent could represent some trained specialized model, such as Neural Network. Such a model could rapidly provide CAM, but it would not necessary be a global optimum. Eventually, Agent could represent several models at once.

According to the selected model, the Agent is trained. For training, it is necessary to gain some response from the Environment and somehow evaluate the obtained Actions (maneuvers) with Reward. In our case, Environment represents a simulator with propagator of orbital movement. Simulator returns the values of the optimized parameters at the end of the propagation session. The goal is to choose the best maneuver according to the maximum value of Reward. Depending on the model, the training process could be carried out for a specific set of input parameters or in advance.

The next question is how to evaluate Agent Actions. SpaceNav provides flexible and easy-to-tune Total Reward function for different purposes. For example, a user could set critical values of collision probability, fuel consumption, and semi-major axis deviation as thresholds. This approach will help to obtain optimal maneuvers also considering maintenance of semi-major axis. Users can also adjust the Total Reward function for their own purpose or replace it with a custom one.

In this paper, we provide the function of Total Reward which is a sum of several reward components, such as a penalty for the collision probability, fuel consumption, and trajectory deviation (Equation (1)). Each reward component is a piecewise linear function of the component value and threshold. This function consists of two linear areas. The first one, with a low slope, is for component values which are lower than the threshold and the second one, with a high slope, is for

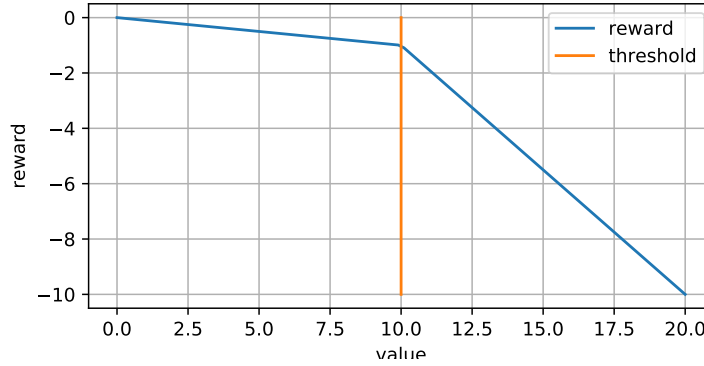


Figure 4. The reward component function, threshold = 10

component values which exceed the threshold (Figure 4). The Total Reward function is designed with the purpose of dramatically increasing the penalty if the values are above the threshold.

$$R_{total} = R_p(P_{collision}) + R_{dV}(dV_{maneuver}) + \dots = \sum_i R_i(component_i) \quad (1)$$

Visualization

We also developed an experimental Virtual Reality (VR) frontend to aid with outreach activities. The VR system includes:

- a hologram of the Earth and space objects with orbital tracks;
- a 2-D interface with a scaled visualization of the maneuvering process;
- an ability to interactively select the evasion trajectory;
- a collision alert signal;
- a collision animation.

Simulation tuning

SpaceNav relies on simulation of space objects motion. To be precise, the simulation must take into account the variability of atmospheric, solar, and geomagnetic conditions. Moreover, their influence depends on the properties of a space object, that may not be known for debris objects.¹⁴ However, since those parameters influence the object motion, it might be possible to recover them by observing the object motion.

The problem can be formulated as follows: given the history of a space object motion and a simulator state, find the simulator parameters that would provide the best match between the simulated and real space object motion. We think that Reinforcement Learning can be applicable here as well. We did a pilot study on simulator tuning which produced the promising result.¹⁵ As an ad-hock

feasibility test of this approach for space motion simulation, we used the open source poliastro simulator which supports modelling of atmospheric drag.¹⁶ Using the Cross Entropy method we were able to tune the simulator to find the unknown space object cross-sectional area.

ALGORITHMS

For the sake of brevity, we use the following notations to indicate the direction of maneuver:

- in-track maneuver – a maneuver collinear to the satellite’s velocity vector;
- in-plane maneuver – a maneuver in the satellite’s orbital plane;
- out-of-plane maneuver – a maneuver in any direction.

In this paper we describe Cross Entropy (CE) and In-track Grid Search (GS) methods.

The GS method provides in-track maneuver before $n + 0.5$ orbital periods of a dangerous conjunction. This model iterates over the grid of in-track maneuvers in the range from $-dV_{max}$ to dV_{max} , where dV_{max} is the maximum allowed fuel consumption. We developed two modifications of GS:

- Baseline mode: takes into account only closest dangerous object. After each maneuver, the algorithm is restarted and offers new maneuvers if necessary.
- General mode: takes into account all input objects at once and provide only one maneuver.

CE is a method based on the Stochastic Optimization approach.¹⁷ This method is able to offer maneuvers in different directions and find the optimal maneuver epoch. The first step is to choose an initial maneuver and an appropriate random distribution. The expected value E of the distribution is equal to initial maneuver parameters. The distribution will be used for generating new maneuvers based on the initial one. Next, the algorithm repeats following iterations:

1. generate a random sample of maneuvers from the distribution;
2. evaluate each maneuver by a reward;
3. select some maneuvers with the best reward;
4. shift E in the direction of the selected maneuvers;
5. additional modifications, such as a dispersion decay.

Iterations are repeated until the stopping criterion, such as a limit on the number of iterations, is satisfied. CE is a well-known method and there are many ways to improve the algorithm, for example, by an introduction of a learning rate and a dynamic decay of the standard deviation of the maneuver parameters during sampling.¹⁸

Stochastic Optimization approach is explored in the literature on maneuvers optimization.⁶ However, we have not seen the use of CE in this field. In addition to the immediate maneuvers optimization, the CE method can be effectively used for tuning maneuvers obtained by other models or theoretically.

We compare the following algorithms (designation of the algorithm is mentioned in the brackets):

- In-track Grid Search:
 - Baseline mode (baseline);
 - General mode (GS);
 - General mode with CE in-plane tuning (GS + CE).
- Cross-Entropy method:
 - in-track, maneuver half an orbital period before the conjunction (CE in-track half);
 - in-plane, maneuver half an orbital period before the conjunction (CE in-plane half);
 - out-of-plane, maneuver half an orbital period before the conjunction (CE out-of-plane half);
 - in-track, automatic maneuver timing (CE in-track auto);
 - in-plane, automatic maneuver timing (CE in-plane auto);
 - out-of-plane, automatic maneuver timing (CE out-of-plane auto).

RESULTS

Experiment description

For the experiment, we assumed the worst-case scenario. According to the assumption, a collision warning is one orbital period before a dangerous conjunction. After the first encounter, there are nine other dangerous objects, whose trajectories almost intersect the trajectory of the protected object. Such additional objects represent obstacles for maneuvers because taking into account only one object will lead to a potential collision with another object. The duration of each simulation is twenty-four hours plus one orbital period of the protected object. The time before the dangerous conjunction with the first object is one orbital period. The epochs of the other dangerous conjunctions are randomly located on the simulated time interval. We used the collision probability computation method proposed in (Reference¹⁹) and a Keplerian propagator (Reference²⁰). To improve the stochastic optimization results, CE-based algorithms are run two times for each situation and the best result is recorded.

To evaluate and train the Agent models, we have developed a dangerous situations generator. The sizes of space objects, angles of intersection of orbits, and other parameters are randomly generated from distributions described in Appendix A. Using the generator we have obtained a sample of 100 random situations. An example of a generated situation could be seen in Appendix B.

Table 1. Thresholds

parameter	threshold
collision probability	1e-4
a - semi-major axis deviation (meters)	200
e - eccentricity deviation	0.01
i - inclination deviation (rad)	0.01
Ω - longitude of the ascending node (rad)	0.01
ω - argument of periapsis (rad)	0.01
fuel (m^2/s)	1.0

Table 1 shows the threshold values used for the experiment. The algorithms were required not only to mitigate the collisions risk but also to remain within the specified limits of the trajectory deviation.

Evaluation Results

Table 2 shows the results of evaluation of the performance of the algorithms on the 100 randomly generated dangerous situations. Also in the appendices we provide detailed results for one of the generated dangerous situations. The situation description is in Appendix B, the obtained maneuvers and result values are in Appendix C, and conjunctions tables are in Appendix D.

Table 2. Results (%), where: top 10% – model reward differs from the best model by no more than 10 percent, \leq thr – all values are below the thresholds, o/c baseline – model overcomes baseline in terms of reward, o/c GS – model overcomes GS in terms of reward, P_c – total collision probability.

	top 10%	\leq thr	o/c baseline	o/c GS	$P_c \leq 1e-4$	$P_c \leq 2e-4$	$P_c \leq 1e-3$
baseline	0	20	-	31	70	89	97
GS	3	23	83	-	68	84	97
GS+CE	53	66	100	100	99	100	100
CE in-track half	3	18	57	20	66	90	93
CE in-plane half	47	46	91	88	96	100	100
CE out-plane half	48	54	86	80	99	99	100
CE in-track auto	64	55	94	96	91	98	100
CE in-plane auto	66	57	95	92	94	98	100
CE out-plane auto	72	68	97	96	96	99	100

The results show that in the majority (68%) of cases SpaceNav is able to find maneuvers for these worst case scenario satisfying all the complex constraints. In almost every case (99%) it reduces the total collision probability to the level of $2 \cdot 10^{-4}$.

The reward function in this example has been configured to aggressively save fuel and maintain orbit deviation small. By configuring the reward function it is possible to achieve any desired level of collision risk.

The results provide useful insight into the behaviour of the optimization algorithms. CE with automatic maneuver timing outperforms CE with fixed timing – in the case of multiple conjunctions optimal maneuver time is not half an orbital period before the first conjunction, and CE seems to find it. Performance of CE with zero initialization (CE in-plane half) and CE initialized with the Grid Search are close with GS+CE slightly better. CE is a stochastic algorithm, so a good initial approximation allows it make better use of the limited number of iterations.

ROADMAP

A prototype of the SpaceNav project is completed. Further roadmap includes the following items:

1. add fast initial maneuver approximation using Neural Networks;
2. develop GUI for SpaceNav;
3. add optimization of sequence of maneuvers;
4. integration with data sources, such as DISCOS;

5. elaboration of integration into systems of the ground control complex of space objects.

We also experiment with various other models such as Neural Networks,²¹ Evolution Strategies,²¹ and Monte Carlo Tree Search,²² the results of which are not provided in this paper.

CONCLUSION

In this paper, we present an autonomous modular collision avoidance system called SpaceNav. This system is based on the Reinforcement Learning approach to for maneuver optimization. Furthermore, we provide a description of the new maneuver optimization algorithm and the objective function (reward function). Also, we show the results of experimental evaluation of SpaceNav on a sample of 100 randomly generated dangerous situations, as well as full information of one particular situation.

ACKNOWLEDGMENT

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APPENDIX A: GENERATOR DISTRIBUTIONS

Distribution of protected object parameters:

- semi-major axis (m): $a \sim \mathcal{U}(7 \cdot 10^6, 8 \cdot 10^6)$;^{*}
- eccentricity: $e \sim \mathcal{U}(0, 0.003)$;
- inclination (rad): $i \sim \mathcal{U}(0, 2\pi)$;
- longitude of the ascending node (rad): $\Omega \sim \mathcal{U}(0, 2\pi)$;
- argument of periapsis (rad): $\omega \sim \mathcal{U}(0, 2\pi)$;
- mean anomaly (rad): $v \sim \mathcal{U}(0, 2\pi)$;
- radius (m): $r \sim \mathcal{U}(0.3, 55)$.[†]

Distribution of debris object parameters:

- angle between protected and debris orbital planes (rad): $\alpha \sim \mathcal{U}(0.5, 2.64)$;
- position at the conjunction moment:
 - first conjunction: $x_{debris} \sim \mathcal{N}(x_{protected}, 50)$, same for y and z (m);
 - other conjunctions: $x_{debris} \sim \mathcal{N}(x_{protected}, 500)$, same for y and z (m).
- velocity vector magnitude (lies on a debris object plane and is tangent to the Earth): $v_{debris} \sim \pm \mathcal{N}(v_{protected}, 0.05)$ (m/s);
- radius (m) $r \sim \mathcal{U}(0.05, 1)$.[‡]

^{*}https://upload.wikimedia.org/wikipedia/commons/b/b4/Comparison_satellite_navigation_orbits.svg

[†]<http://www.businessinsider.com/size-of-most-famous-satellites-2015-10>

[‡]https://m.esa.int/Our_Activities/Operations/Space_Debris/Space_debris_by_the_numbers

APPENDIX B: AN EXAMPLE GENERATED DANGEROUS SITUATION

Tables 3 and 4 present one danger situation from the generated sample. Simulation interval - from 6599.921 to 6601.0 (mjd2000).

Table 3. Dangerous situation - part 1

	PROTECTED	DEBRIS0	DEBRIS1	DEBRIS2	DEBRIS3	DEBRIS4
<i>a</i>	7530537.215	7360115.107	8033345.687	7682829.226	6203113.774	7679322.768
<i>e</i>	0.003	0.025	0.060	0.022	0.212	0.017
<i>i</i>	0.562	1.555	0.896	1.146	2.103	0.591
Ω	2.551	1.809	5.957	2.022	3.738	0.852
ω	0.153	5.915	6.143	5.930	3.677	5.567
<i>v</i>	2.153	3.103	-0.000	-0.076	-3.139	-0.068
epoch	6600.000	6600.000	6600.389	6600.791	6600.887	6600.923
<i>r</i>	20.686	0.738	0.367	0.562	0.564	0.276

Table 4. Dangerous situation - part 2

	DEBRIS5	DEBRIS6	DEBRIS7	DEBRIS8	DEBRIS9
<i>a</i>	8738088.965	8101742.447	7084346.824	7150262.637	7468758.271
<i>e</i>	0.140	0.072	0.063	0.056	0.006
<i>i</i>	0.376	1.856	2.168	2.882	2.484
Ω	0.657	3.769	4.917	3.179	2.870
ω	2.312	0.527	3.765	0.461	3.314
<i>v</i>	0.005	-0.002	-3.105	3.140	-3.134
epoch	6600.581	6600.061	6600.597	6600.238	6600.652
<i>r</i>	0.107	0.053	0.320	0.674	0.895

- *a* - semi-major axis (m);
- *e* - eccentricity;
- *i* - inclination (rad);
- Ω - longitude of the ascending node (rad);
- ω - argument of periapsis (rad);
- *v* - mean anomaly (rad);
- epoch - reference epoch (mjd2000);
- *r* - radius (m).

APPENDIX C: AN EXAMPLE OF MANEUVERS AND RESULT VALUES

Table 5 and Table 6 show maneuvers and Environment values obtained by different agent models for the dangerous situation described in Appendix B.

Table 5. Maneuvers

	dV_x	dV_y	dV_z	epoch (mjd2000)
baseline	0.077	0.005	-0.03	6599.962
GS	0.089	0.005	-0.034	6599.962
GS+CE	-0.072	0.235	-0.098	6599.962
CE in-track half	-0.088	-0.005	0.033	6599.962
CE in-plane half	0.078	-0.187	0.07	6599.962
CE out-of-plane half	0.091	0.343	0.469	6599.962
CE in-track auto	-0.106	-0.15	0.116	6599.950
CE in-plane auto	-0.058	-0.113	0.079	6599.951
CE out-of-plane auto	-0.191	-0.219	0.022	6599.951

Table 6. Result values

	$P_{collision}$	Fuel	Dev. a	Dev. e	Dev. i	Dev. Ω	Dev. ω	Dev. v	Reward
threshold	0.0001	1.0	200.0	0.01	0.01	0.01	0.01	-	-7.0
without maneuvers	8.54e-03	0.0	-0.0	0.0	0.0	0.0	-0.0	0.0	-761.0
baseline	9.98e-05	0.083	-172.241	-1e-05	0.0	0.0	0.00696	-0.00706	-2.639
GS	3.68e-05	0.095	-197.142	-1e-05	0.0	0.0	0.00797	-0.00809	-2.247
GS+CE	1.17e-05	0.265	44.135	-3e-05	0.0	0.0	-0.00898	0.00894	-1.503
CE in-track half	4.87e-05	0.094	194.788	1e-05	0.0	0.0	-0.00779	0.00791	-2.335
CE in-plane half	3.68e-05	0.215	-81.006	2e-05	0.0	0.0	0.0089	-0.00889	-1.88
CE out-of-plane half	4.52e-05	0.589	132.594	-0.0	5e-05	-1e-4	-0.00801	0.00816	-2.521
CE in-track auto	2e-07	0.217	-127.87	3e-05	0.0	0.0	0.00092	-0.00091	-0.954
CE in-plane auto	1.7e-06	0.15	-122.371	2e-05	0.0	-0.0	0.00222	-0.00224	-1.004
CE out-of-plane auto	2.3e-06	0.291	-88.725	4e-05	1e-05	3e-05	-0.00178	0.00178	-0.943

- Rows:
 - threshold – defined threshold requirements;
 - without maneuvers – results of simulation without maneuvers.
- Columns:
 - Coll. Prob. – total collision probability;
 - Fuel – fuel consumption (m^2/s);
 - Dev. a – semi-major axis deviation (m);
 - Dev. e – eccentricity deviation;
 - Dev. i – inclination deviation (rad);
 - Dev. Ω - longitude of the ascending node deviation (rad);
 - Dev. ω – argument of periapsis deviation (rad);
 - Dev. v – mean anomaly deviation (rad).

APPENDIX D: AN EXAMPLE OF CONJUNCTION

For the example of the dangerous situation described in Appendix B, Table 7 and Table 8 show information about conjunctions (miss distance < 2000 m) without maneuvers and Conjunctions with maneuvers obtained with the "CE out-of-plane auto" algorithm respectively.

Table 7. Conjunctions without maneuvers

	debris name	miss distance (m)	epoch (mjd2000)	collision probability	collision danger
1	DEBRIS0	307.033	6600.0	0.0024134	True
2	DEBRIS6	226.991	6600.061	0.0019874	True
3	DEBRIS8	1544.347	6600.238	0.0	False
4	DEBRIS1	750.614	6600.389	0.0001279	True
5	DEBRIS5	367.326	6600.581	0.00133	True
6	DEBRIS7	440.747	6600.597	0.0008903	True
7	DEBRIS9	617.282	6600.652	0.0005554	True
8	DEBRIS2	983.557	6600.791	1.32e-05	False
9	DEBRIS3	477.438	6600.887	0.0009085	True
10	DEBRIS4	617.896	6600.923	0.0003476	True

Table 8. Conjunctions with maneuvers obtained with the "CE out-of-plane auto" algorithm

	debris name	miss distance (m)	epoch (mjd2000)	collision probability	collision danger
1	DEBRIS0	1254.839	6600.0	7e-07	False
2	DEBRIS6	1456.678	6600.061	0.0	False
3	DEBRIS8	1295.103	6600.238	1.6e-06	False
4	DEBRIS5	1493.772	6600.957	0.0	False

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