CREATION OF A SYNTHETIC POPULATION OF SPACE DEBRIS WITH HEURISTIC METHODS

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ABSTRACT

The simulation of a population of space debris matching the real population is a complex task considering the unknown details of the events occurred in space like the number of fragmentations, their nature or their intensity. Moreover, our numerical models are limited by the hypothesis assumed on the source model and by computational means.

We propose to introduce several methods to constrain a population created by space debris models (called reference population) in order to create a new synthetic population which matches better the global statistical characteristics of the reference population. The final purpose is to use in the future large space debris catalog or flux measured as references.

These proposed methods come from the field of microsimulation and the use of algorithms such as the Iterative Proportional Fitting (IPF) or Genetic Algorithm (GA). We give qualitative and quantitative measures of how they reduce the discrepancies between the numerical simulations and the population chosen as reference.

Keywords: space debris; micro-simulation; synthetic population.

1. INTRODUCTION

The space debris models have a great importance to manage the space activities and preserve a safe environment. They allow to evaluate the risk of collision for space missions, and to investigate the consequences for the stability of the space debris population for different scenario. In particular, they allow to evaluate the effectiveness of the mitigation measures and active debris removal measures.

The purpose of the space debris models is to improve our lack of data and the data integration in space debris model. The observations by radar or optical telescopes, or in-situ measurements give us a partial knowledge i.e. only the biggest or brightest objects, or a punctual knowledge, i.e. the flux of space debris during a given period. Then, by modeling the historical sources of space debris we simulate the invisible population but discrepancies exist in reason of the made assumptions. However, the accumulation of observational data can help us to reduce discrepancies when searching conditions to find a way to integrate these data in our models.

We investigate the results coming from methods used in the microsimulation field. First, we start by a description of the GEO region. Second, we describe our space debris model. Third, we propose two methods to improve a population of space debris: the first one with the IPF method, and the second one with a genetic algorithm. Fourth, we finish this paper by a conclusion about the future works.

2. THE SPACE DEBRIS POPULATION IN THE GEO REGION

The geostationary orbit is defined by a semi-major axis equal to 42,164 km, an eccentricity and an inclination equal to zero. The orbital period is equal to the rotation period of the Earth (23h 56min 4s), and thus, a satellite stay fixed in the sky for a ground observer. The specificity of this orbit is important for space applications but the number of slots for satellite is limited. It is capital to preserve this region from the space debris proliferation.

The protected region is defined $\pm$ 200 km around the semi-major axis of the geostationary orbit and for inclination between $\pm$ 15° [2], but unfortunately, several breakups occurred. The first one occurred in 1978 with the Russian satellites Ekran 2. And until now, we count a total of five fragmentations. We summarize the events catalogued in the Table 1. Moreover, a continuous effort is performed since the end of the nineties to improve our knowledge of the GEO space debris population. It was shown the existence of unknown space debris populations [7] and several observational teams hold a catalog of objects more complete than the TLE catalog limited to the biggest and brightest objects. Then, in this work we want to show that it is possible to improve our models using different tools, and at the end, we propose a better integration of the observational data.

Table 1. Confirmed breakup events in the GEO region.

Date	1978/06/25	1992/02/21	2014/06/04	2016/01/16	2016/06/29
Type	Spacecraft	Rocket-body	Rocket-body	Rocket-body	Spacecraft
Name	Ekran 2	Titan Trans. 3C-5	Titan Trans. 3C-17	PROTON-M/BRIZ-M	BEIDOU G2
ID $_{\text{SSN}}$	10365	3432	3692	41122	34779
ID $_{\text{COSPAR}}$	1977-092A	1968-081E	1969-013B	2015-075B	2009-018A
a [m]	42,163.500	41,826.000	42,926.390	40,979.800	42,138.874
e	$1{,}779{\cdot}10^{-4}$	$8{,}488{\cdot}10^{-3}$	$1.291{\cdot}10^{-2}$	$2.868{\cdot}10^{-2}$	$8.934{\cdot}10^{-3}$
i [deg]	0.100	11.900	8.706	0.174	4.716
Ω [deg]	78.390	21.802	313.195	135.143	61.365
ω [deg]	325.277	76.279	91.579	5.856	195.139
M [deg]	78.390	284.560	269.90	221.106	164.399
Mass [kg]	1,750	2,500	2,500	1,220	1,100

3. PRINCIPLES OF A SPACE DEBRIS MODEL

In order to model a space debris population we use a source model and an orbit propagator, and eventually algorithm to handle the collisions. In this paper, we focus on the space debris with a size bigger than 1 cm, which are mainly created by rocket-body or satellite fragmentations. Since the 2000's, the NASA Breakup Model is used by the majority of space debris models [3]. Taking into account the location of the parent body at the moment of the fragmentation, we create a cloud of space debris where each fragment is propagated. We use the numerical propagator named NIMASTEP, developed at the Namur University [1] [5].

The model of fragmentations and the orbit propagator are now integrated in a Python package named CelestialPy, developed at the Namur University and at the IMCCE (Paris Observatory), and handling a databased named ODIN (hosted and maintained by the IMCCE) containing numerous data about the space debris environment as the historical fragmentations, the resident space objects catalogued in the TLE catalog, the launches, the space weather, etc. It allows us to create a space debris model in Python, that can be used as a black box.

Using the data in the Table 1 and our space debris model, we generate clouds of space debris and we propagate each fragment up to the date 2017/10/22. In Figure 1, we compare the result with the TLE data available at that date and we can confirm that the simulated populations have the same mean locations than the clouds seen in the TLE data.

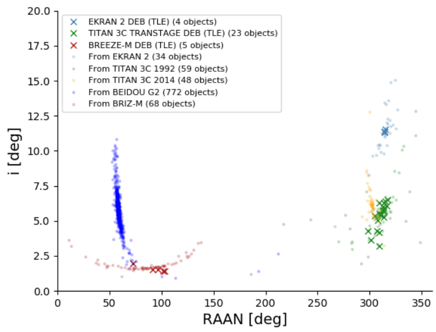

Figure 1. Distribution of the space debris contained in the TLE catalog and objects in our space debris models.

4. MICRO-SIMULATION TECHNIQUES

We introduce two techniques of micro-simulation. The first one is named the Iterative Proportional Fitting (IPF) process, which is used for example to create an initial population, like the population of a country, under statistical constraints. The second one is based on a heuristic algorithm named genetic algorithm, which is used in a large variety of cases.

4.1. Iterative Proportional Fitting

The IPF process is described by [4] and applied on space debris populations by [6]. The purpose is to weight an initial space debris population created with our space debris model, to fit statistical constraints. First, the initial population is discretized, i.e. the parameters of each object (orbital elements and the ratio area-to-mass) take only a range of values. Then, we express our population in a contingency table Π which is a matrix whose the number of dimensions depends on the number of variables considered. The Table 2 gives an example of a two dimensions contingency table where our population depends on the variables a and $\frac{A}{m}$. For example, we can read that 4 fragments have a semi-major axis in the first range of values and a ratio area-to-mass in the second range of values.

The IPF process is an iterative method which will weight the contingency table following different constraints. We estimate the new total number of space debris in the synthetic populations and the new distribution. This data

	a_1	a_2	a_3	
$\frac{A}{M}1$	1	2	1	4
$\frac{A}{M}2$	4	1	1	6
$\frac{A}{M}3$	1	3	3	7
	6	6	5	17

Table 2. Expression of the contingency table restricted with two dimensions.

can come from observations or simulations. Let Π be the contingency table and each cell be denoted by $\Pi_{i,j}$. The marginal controls for the i-th row and j-th column are noted m_i and m_j respectively. The IPF process is an iterative method, which will weight the frequencies to fit the marginal controls one after the other. If we write Π^t the contingency table at the t-iteration, the row-fitting is implemented as,

$$\Pi^t_{i,j} = \Pi^{t-1}_{i,j} \frac{m_i}{\sum_k \Pi^{t-1}_{i,k}} \quad \forall i, j, \tag{1}$$

and the column-fitting is implemented as,

$$\Pi^t_{i,j} = \Pi^{t-1}_{i,j} \frac{m_j}{\sum_k \Pi^{t-1}_{k,j}} \quad \forall i, j. \tag{2}$$

We iterate until we reach a stopping condition. At each iteration we compute the distance between the last and the new contingency table as

$$D(\Pi^t_{i,j}, \Pi^{t-1}_{i,j}) = \sum_{i,j} |\Pi^t_{i,j} - \Pi^{t-1}_{i,j}|, \tag{3}$$

and at the moment we pass a threshold, and the stopping condition is reached.

To illustrate this method, we produce a simulation of a cloud of space debris but we introduce a parameter β in the NASA Breakup Model (NBM) to modify the intensity of the breakup. The increment of velocity computed by the NBM ΔV^{NBM} are modified as $\Delta V^{modif} = \beta \Delta V^{NBM}$. Then, we reproduce a new cloud of space debris which is propagated until the date 2017/10/22 as in Section 3. But we choose $\beta = \frac{1}{10}$ to obtain the cloud less expanded in the plane of $RAAN$ versus the the inclination i. From this second simulation we compute constraints and we apply the IPF method on the first simulation.

In Figure 2, we plot the two clouds of space debris produced with our space debris model. The third cloud was produced with the IPF method using the data of the first cloud, and the constrains inferred from the second cloud. The IPF method weight the initial population to obtain a cloud with the statistical characteristic of the used constraints. We plot the linear regression of each cloud to visualize the improvement.

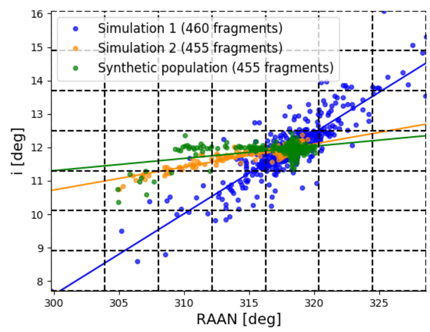

Figure 2. Comparisons between the two simulations created by the space debris model and the synthetic population created with the IPF method.

4.2. Heuristic algorithm

We propose a second way to reach the same purpose. In section 3, we have introduced a space debris model based on an orbit propagator and the NBM. We can consider it as a black box, whose the date and location of the breakups are the inputs and the population of space debris created and propagated until a given date are the outputs. An heuristic algorithm can modify the parameters taken as inputs by our space debris model to find the best population which match the constraints, i.e. the statistical distributions used to create the synthetic population.

Several kinds of heuristic algorithms exist like simulated annealing or genetic algorithm but the second one is more appropriate when the parameters to optimize are numerous and when we do not know even. The genetic algorithm will explore the solution space from a large set of parameters. A selection process inspired by the theory of natural evolution will select in the set of initial populations a part of the best ones, and create sets of parameters by a mechanism of reproduction. At the end, we should converge towards the best solution.

For this work, the parameters used as inputs are: the date, the RAAN, and the inclination. The cost function is computed doing the difference between the distribution $F^{*,i}$ and $F^{*,RAAN}$, of the inclinations and the RAAN respectively. The symbol $*$ means the distribution is related to the population of reference (Ref) or to the space debris model fitted (SDM). Then we write the cost function as:

$$R = \sum_k^N |F_k^{Ref,RAAN} - F_k^{SDM,RAAN}|^2 + \sum_k^N |F_k^{Ref,i} - F_k^{SDM,i}|^2, \tag{4}$$

where N is the number of sampling step of the distribution. In Figure 3, we show the distributions of the inclination and RAAN for the population of reference and

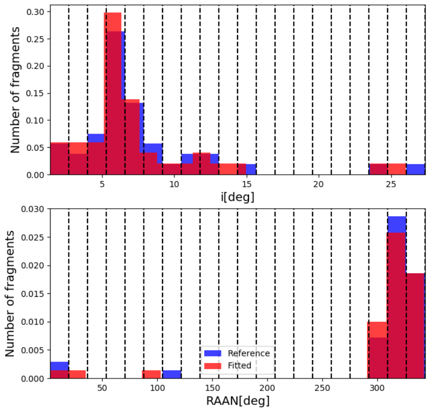

Figure 3. Comparison between the distribution of the inclination and the RAAN for the population of reference and the population fitted by the genetic algorithm.

the distributions for initial and final population fitted by the genetic algorithm. The initial population converge toward the population of reference and the parameters of the space debris models are closes to those of the population of reference as we can see in the Table 3.

Population	Date	i	$RAAN$
Reference	1992/02/21	11.9	21.8
Fitted (initial)	2000/01/01	10	30
Fitted (final)	1991/10/07	10.8	27.4

Table 3. Parameters of space debris model taken as reference and the parameters found by the genetic algorithm.

Unfortunately, during the different runs, we have seen that many different sets of parameters can give us the same result. For this example, the initial location of the breakup is taken close to the location of reference, and we explore a large range of initial date. This is what allows us to converge quickly towards the solution. Moreover, this method has a second disadvantage. The computation is time consuming whereas the IPF method has a very low computation time.

5. CONCLUSION

We investigate different methods to constrain or improve the population produced by a space debris model. The first one come from the microsimulation field and is named Iterative Proportional Fitting (IPF) method. It allows to weight a population with constraints. The second one is a based on heuristic method to fit a space debris model with contraints. The next step will be to complexify the population of space debris studied with several source (differents breakups) and to compare the efficiency of the algorithms introduced.

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