DATA PROCESSING METHODS FOR CATALOGUE BUILD-UP AND MAINTENANCE

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ABSTRACT

Human activity in space has caused the growth of a very large population of resident space objects (RSO). More than 19,000 objects are currently catalogued by 18th SPCS (former JSpOC) with sizes starting around 10 centimetres in LEO and around 1 metre in GEO. Most space agencies, and even the private sector, have their own programs to deal with this thread, both from a mitigation point of view and from an operations point of view (e.g., space surveillance and tracking).

One of the key aspects to implement such measures is the availability of a catalogue of RSOs, not only characterising the properties of the objects, but also providing precise ephemerides that allow the prediction of high-risk collision events accurate enough and time in advance. Such a catalogue must be built-up and maintained through the processing of observation data from various types of sensors, including radars and telescopes, both ground-based and space-based, as well as satellite laser ranging stations.

This paper will describe the methods used by GMV focusing on **recent improvements** on correlation algorithms and the resulting **performances** in terms of success rate and false positive detection, as well as in the **orchestration** of all these methods in the overall **data processing scheme** for catalogue build-up and maintenance.

1 INTRODUCTION

Space Surveillance and Tracking (SST) systems are composed of sensors and on-ground processing infrastructure devoted to build-up and maintenance of a catalogue of resident space objects and derive SST products (i.e. high-risk collisions, upcoming re-entries, and fragmentations) based on the orbital information in the catalogue.

The catalogue of resident space objects (RSO) is one of the main outcomes of the SST activities. It is a robust automated database containing information of every detected object. As shown in Figure 1, the catalogue is a key component that allows us to use sensors networks to obtain SST products such as collision, re-entry prediction and fragmentation detection.

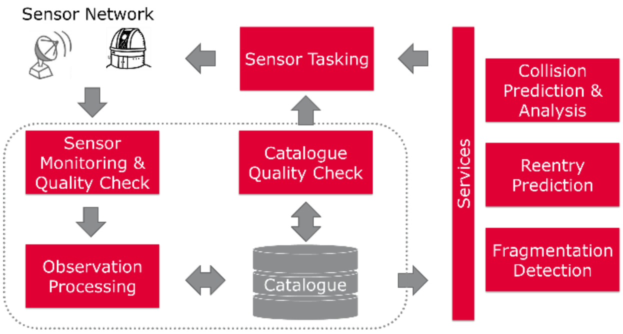

Figure 1. Catalogue role in the SST activities

There are two catalogue related activities:

- **Catalogue build-up:** detection and identification of new objects to include them in the catalogue without any previous information. It depends on the capability to detect new objects from measurements, packed as tracks, provided by a network of sensors.
- **Catalogue maintenance:** update of the orbital information of the objects in the catalogue.

From a global point of view, the data processing scheme entails mainly:

- **Observation correlation:** assigning tracks to the right object. Ideally this is a simple process normally achieved by comparing real measurements with synthetic measurements generated from predicted orbits of the RSOs in the catalogue. However, there are a number of events that may increase the complexity of the process, mainly, new objects, manoeuvres and fragmentations. To achieve this goal, different types of correlation algorithms are normally used: track-to-orbit, track-to-track and orbit-to-orbit.
- **Orbit determination:** estimation of the object's orbits from data generated by the sensors. To do so, the orbital elements are determined from a given set of measurements of the object. Depending on the a-priori knowledge and available measurements, it is common to distinguish between Initial Orbit Determination (IOD) and Orbit Determination (OD) depending on the a-priori knowledge of the orbit.

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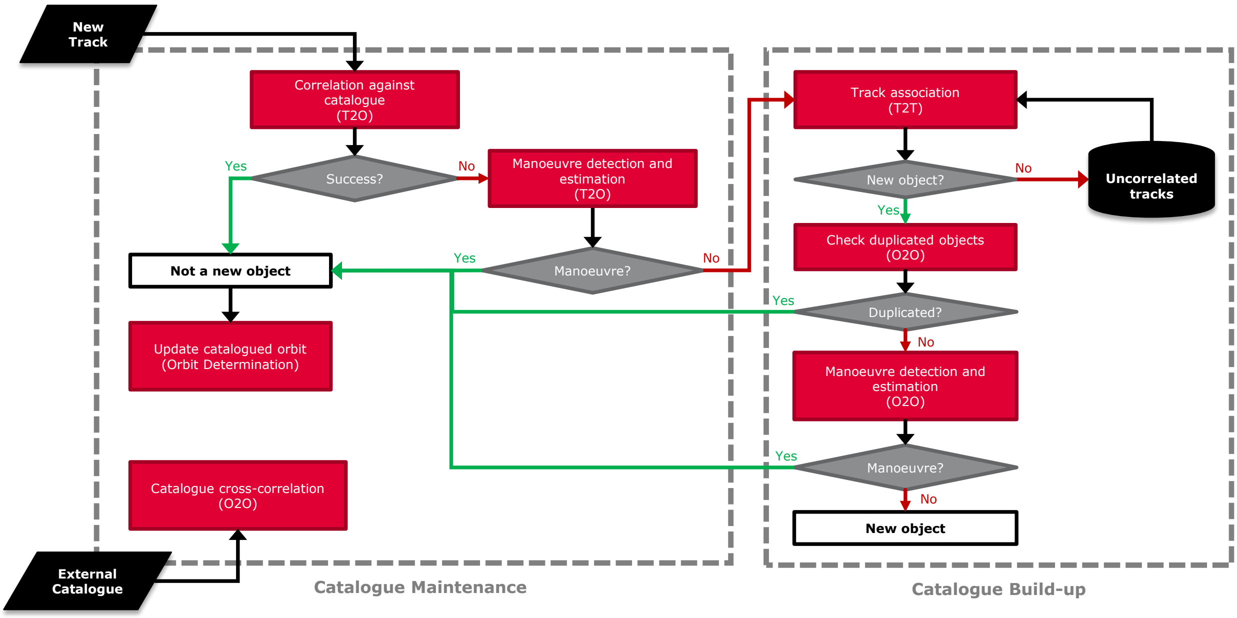

*Figure 2. SST Catalogue Maintainer Software (**catmai**) cataloguing chain*

2 CATALOGUING CHAIN

The cataloguing processing chain is intended to perform the build-up and maintenance of the objects catalogue. The main sources of potential new object detections, in order of decreasing frequency are:

- **Operational satellites manoeuvres:** there are more than 400 operational satellites only in GEO [1], each of which perform orbit correction manoeuvres every week or two weeks
- **Satellites launches:** more than 200 spacecraft are launched per year [2], if considering also small satellites and microsatellites, which are becoming popular during the recent years.
- **Break-up events:** less than 10 break-up events happen per year [3].

Therefore, it is clear that manoeuvre detection is of major interest in terms of catalogue maintenance. Since a manoeuvre results in changes in the satellite orbital elements, a new object would be generated when observing it again after the manoeuvre if no special actions are taken regarding manoeuvre detection and characterization.

The cataloguing sequence proposed here is capable of building-up and maintaining a catalogue of man-made Earth orbiting objects and their orbital information through the processing of measurements from a pre-defined space surveillance network of sensors. Figure 2 shows the main components of its cataloguing chain and the relationships between them. The overall sequence is based on the previous events and differences in frequency of the events. This cataloguing sequence is implemented in GMV's SST catalogue maintainer software (***catmai***).

When a new track arrives to the system, it is first correlated against the existing catalogue objects via **track-to-orbit correlation** (*T2O*). If this first correlation successes, then the new track belongs to an already catalogued object and therefore the corresponding orbit information is updated via orbit determination methods. However, if this first correlation fails then the track may belong to a potential new object, meaning that it may correspond to one of the three sources presented above.

The next step, corresponding to the most frequent source of potential new objects, is **manoeuvre detection and estimation** in the measurements space via track-to-orbit correlation. In the event that a manoeuvre is detected, the track does not belong to a new object and therefore the orbit information is updated as for successfully correlated tracks against the catalogue. If no manoeuvres are detected, then the track is tried to be associated with other uncorrelated tracks (UCTs) to check if they belong to the same new object, via **track-to-track correlation** (*T2T*). Should not the track be associated, it is not discarded but stored for future track-to-track correlation.

In the case of a potential new object detection, i.e. track associated with previous uncorrelated tracks, two additional checks are performed before adding the new object to the catalogue.

- Duplicated object identification, to avoid adding duplicated objects to the catalogue, via **orbit-to-orbit correlation** (*O2O*).
- Manoeuvre detection and estimation on the orbit space, via orbit-to-orbit correlation.
- Fragmentation detection on the orbit space, via orbit-to-orbit correlation.

Apart from the processing of new tracks obtained with the sensor network, external catalogues, such as Space-Track's TLE public catalogue, are used to identify whether objects of the catalogue are present in external catalogues.

3 CORRELATION PROCESSES IN THE CATALOGUING CHAIN

The correlation processes used during the cataloguing chain are presented in this section.

3.1 TRACK-TO-ORBIT CORRELATION

Track-to-orbit correlation consists in the correlation of tracks against the objects in the catalogue. This algorithm is required to update the orbit of already catalogued objects.

The proposed approach relies on the generation of synthetic tracks based on the estimated orbits of the objects, comparison of real vs synthetic tracks and selection of valid correlations.

Unlike other approaches (e.g. [4], [5] and [6]), the correlation is not performed in the orbit domain but in the **measurements domain**. Hence, it is based on the comparison of synthetic measurements against real ones provided by the sensor network. By comparing the real and synthetic tracks it is possible to compute various correlation metrics, and based on different thresholds and weighted correlation quality factors and indexes, it is possible to correlate tracks with a high success rate while minimizing miscorrelation events.

Implemented track-to-orbit correlation is fully performed in the domain of the available measurement types. **Synthetic tracking** is generated for all the sensors in the considered network and all the catalogued objects. Pseudo-measurements are generated from real measurements in order to synchronize the data and then be able to perform a direct match between the set of real measurements and each set of synthetic measurements.

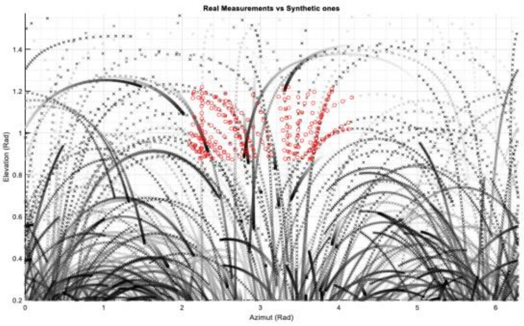

Figure 3. Measurements matching for correlation

Several thresholds, weighted correlation quality factors and indexes have been implemented in order to minimize miscorrelation events. Figure 3 shows an example of synthetic measurements and synchronized real measurements (elevation and azimuth). Red and black circles represent real measurements and synthetic measurements, respectively. This method has been proved to be efficient in terms of computation time and very effective for correlation.

The correlation process is performed in the measurement space rather than in the orbit space and, hence, it is based on the comparison of synthetic measurements against those being processed. This large amount of information is then passed on to the correlator, which performs the following tasks:

- *Synthetic tracking generation*: visibility periods computed considering visibility conditions from the sensor are used to generate synthetic observations for those periods of time with tracking reconstruction algorithms. This step does not need as input the real track from the sensors and can be performed before the arrival of the tracks in order to speed up the overall track-to-orbit correlation process.
- *Pre-filtering:* real and synthetic candidate tracks are compared, based on time overlap considerations and minimum number of contemporary measurements. These complexity reduction techniques are applied so as to avoid evaluating all possible combinations.
- *Synchronization:* real measurements and synthetic tracks are synchronized through fitting (e.g. least squares smoothing) and interpolation of the real track in order to obtain both observations at the same epochs.
- *Residuals computation:* difference between real and synthetic tracks measurements are obtained. This information is required to after compute the correlation figure of merit.
- *Correlation statistics computation:* the correlation metrics are computed for each pair of track association candidates.
- *Selection of best correlations:* the best correlation pairs are selected. Thresholds are considered so as to mitigate the number of false positives.

3.2 TRACK-TO-TRACK CORRELATION

Track-to-track correlation methods are an active area of research. Sometimes, algorithms and strategies proposed are presented as track-to-track correlation, but the correlation is made in the orbit domain instead of in the measurements domain. These algorithms perform initial orbit determination from the tracks and compare them in terms of orbital elements, assuming two tracks are correlated if their estimated orbits lie inside the association cell.

Other approaches rely on the covariance obtained from an OD process [7] thus using figures of merit such as the Mahalanobis distance. Using this figure of merit for correlation allows one to consider not only the differences in the estimated state vector but also the uncertainty of this estimation. This is the main correlation criteria considered in recent methodologies [5], [6] and [8].

Unlike these previous approaches, the figure of merit used in our track-to-track correlator is based on observations residuals data, i.e. the correlation is made in the measurements space rather than in the orbit space. It consist in a multi-step filter that sequentially applies IOD and simple OD methods to all possible combinations of uncorrelated tracks from survey activities. The algorithm generates associations of two, three or even more tracks,as shown in Figure 4.

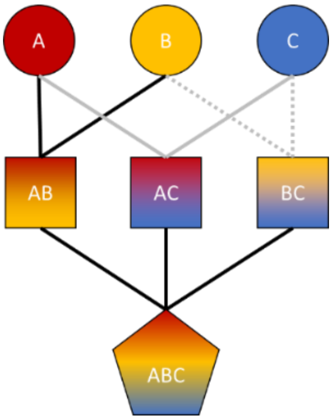

Figure 4: Association tree example of three associations

Given the large number of possible combinations, the process starts by computing correlation metrics that can be computed very fast and allow filtering out the combinations that are invalid with a very high probability. Next steps in the process apply other filters with increasing complexity. Unlike a purely brute-force method, not every possible combination is generated and evaluated, but only those meeting certain criteria related to time separation and orbital elements.

The algorithm is further described in [9].

3.3 ORBIT-TO-ORBIT CORRELATION

Orbit-to-orbit correlation consists in correlating orbits from two catalogues, e.g. it is required to compare objects detected by the sensor network with an external catalogue, such as the TLE catalogue from the 18th SPCS, in order to match objects between them.

For the sake of generality, the two catalogues will be referred to as:

- Catalogue A, containing N_A orbits
- Catalogue B (only if not self-correlation case), containing N_B orbits

It consists in comparing the N_A orbits from Catalogue A with the N_B orbits from a Catalogue B, generating a correlation matrix with dimension (N_A x N_B). Alternatively, this process can be used to perform self-correlation (detection of duplicated objects), generating a (N_A x N_A) symmetrical matrix, as well as for manoeuvre detection.

The algorithm requires performing the following tasks:

- *Clustering:* analyses correlation pairs (pairs of objects, each of which taken from catalogues A and B, or both from A in the self-correlation case).
- *Interpolator:* ensures the state vectors required for the evaluation during the next step are available.
- *Evaluator:* computes the figure of merit for each pair. Each of the feasible pair of orbits, identified during clustering, is analysed and a figure of merit derived from the Root Mean Square (RMS) of the position difference on a relative reference frame.
- *Solver:* once the correlation matrix is fully populated, as shown in Figure 5, it is solved with the Greedy Assignment Method (GAN).

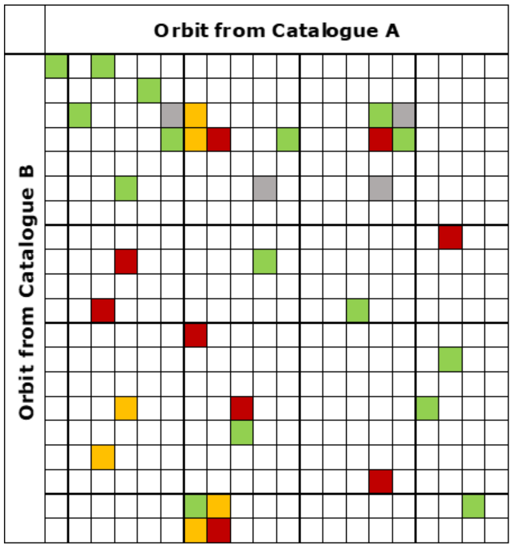

Figure 5: Sample matrix for orbit-to-orbit correlation. Darker squares are the more probable assignment

The correlation information of all objects of both catalogues (correlation matrix) is maintained from one analysis to another in order to solve the complete correlation matrix at each correlation analysis This **history of the correlation** information is saved so that it is used for as much as need ensuring that two objects that used to correlate in the past keep on correlating even if there is a manoeuvre not detected in one of the catalogues. By including the result of previous comparisons, the stability of the correlation is improved and it is easier to correlate the orbit of a manoeuvring object when it has not been considered in one of the two catalogues. As an additional benefit of using the history of the correlation information, the solution of the correlation matrix is stabilised, preventing spurious correlations with different objects.

4 SIMULATED MEASUREMENT GENERATION

The **SST Sensor Data Simulator** (***ssdsim***) is a software application intended to generate SST measurements (in TDM format) obtained by several sensors for objects in a simulated population. The procedure comprises the following steps, depicted in Figure 6:

1. **Retrieval of inputs**: TLE catalogue, MASTER (Meteoroid and Space Debris Terrestrial Environment Reference) or OMM catalogue as input orbital information of the objects populations.
2. **Generation of an object catalogue** with orbital information and physical properties of the specific object. The population can be filtered according to different criteria, such as size, altitude or orbital elements.
3. **Propagation of the orbital information** considering the previously defined physical parameters.
4. **Computation of the object visibilities** per sensor and per object, given the sensor surveying capabilities (type of sensor, field of view, pointing, location, power, accuracy, etc.).
5. **Generation of the sensor measurements** given the object visibilities and several measurement generation parameters (measurement noise, type of measurements of the sensor, etc.).

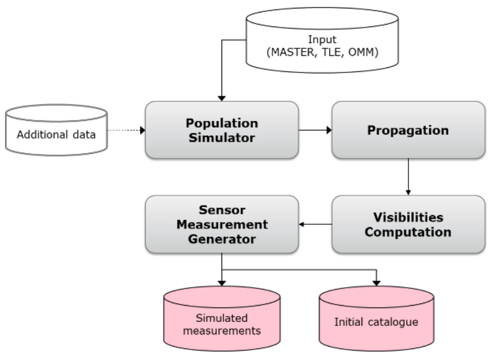

*Figure 6. SST Sensor Data Simulation (**ssdsim**) sequence*

During the first step, the object catalogue is generated and a **preliminary detection condition,** Eq. (1), is evaluated in the case of radars to avoid generating objects that cannot be observed by the sensor network under consideration.

$$\frac{RCS}{r^4} \geq \frac{RCS_{ref}}{{r_{ref}}^4} \propto SNR_{min} \qquad (1)$$

where RCS is the object radar cross section, r is the distance between the object and the sensor and SNR_{min} is the minimum radar Signal to Noise Ratio required for the object detection.

The required parameters that are not available, such as the drag and solar radiation coefficients, are generated using statistical information. The following methods are considered:

- **Uniform distribution** between a minimum and a maximum value set by the user.
- **Statistical theoretical**, based on experimental models, such as the objects size distribution, shown in Figure 7 [10].
- **Statistical realistic**, based on the statistical characteristics of real objects already in a catalogue (e.g. SATCAT).

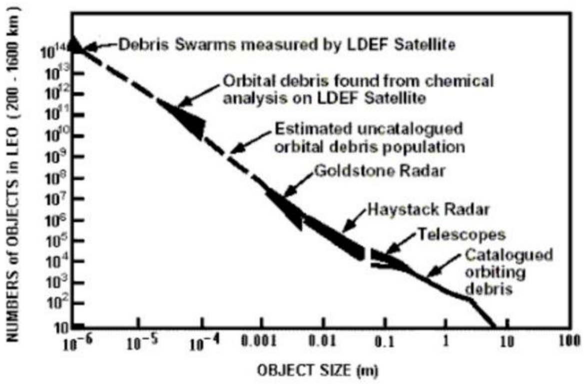

Figure 7. Number of objects greater than a certain diameter threshold (empirical data) [10]

The generation of the objects visibilities is not as simple as the preliminary detection condition. Different algorithms are used to compute the visibilities depending on the sensor (radar stations, optical telescopes and SLR stations), such as the minimum Sun zenith distance for ground-based optical sensors or the minimum spherical angular distance of field-of-view line-of-sight to the sun for space-based telescopes.

This software allows us to generate simulated measurements, such as the two radar scenarios that have been used to study the performance of the correlation algorithms: *RADAR-A* and *RADAR-B*. The orbit spectrum of these scenarios are shown in Figure 16 and Figure 17.

The typical sensor parameters can be configured, such as:

- Maximum pass duration
- Noise sigma of the selected measurements
- Integration time
- Observation spacing
- Measurement correction modelling
- Station positioning modelling

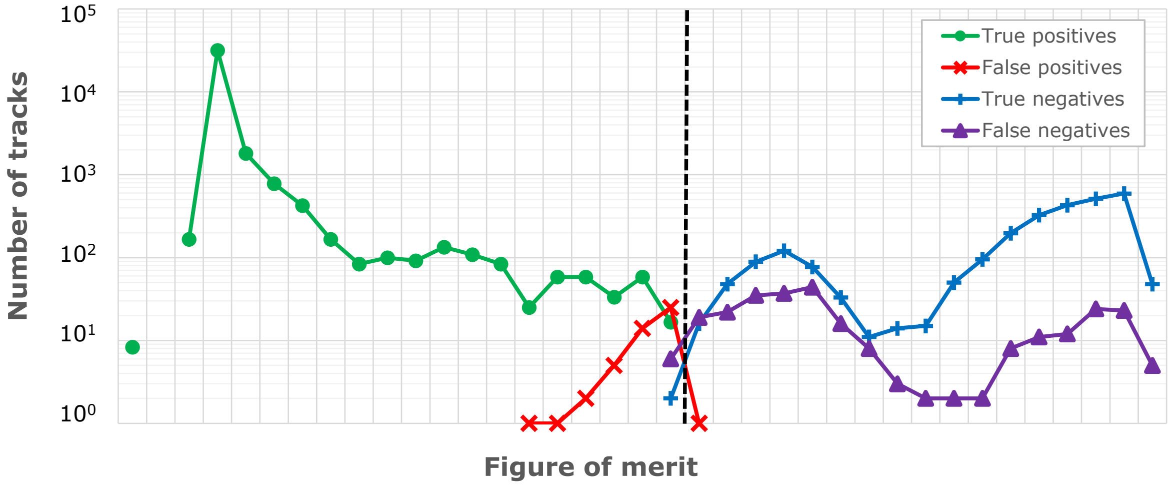

Figure 8. Track-to-orbit standard method figure of merit distribution of the tracks in simulated radar scenario

5 RESULTS

Performance tests with each of the correlation algorithms above have been performed based on both real and simulated data where the correct results are known in order to validate the efficiency of the correlation algorithms.

Performance of correlation algorithms can be evaluated in terms of the following correlation metrics, depicted in Figure 9:

- **True positives:** number of correctly correlated pairs or associations.
- **False positives:** number of wrongly correlated pairs or associations.
- **True negatives:** number of correctly uncorrelated pairs or associations.
- **False negatives:** number of wrongly uncorrelated pairs or associations.
- **Missed:** number of missed pairs or associations.

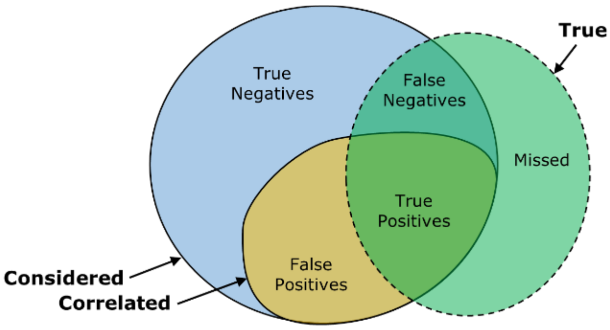

Figure 9. Correlation metrics sketch

5.1 TRACK-TO-ORBIT CORRELATION

This algorithm has been proved to be efficient in terms of computation time and very effective for correlation. One of the main difficulties in the process of correlation is the appearance of false identification (miscorrelation, i.e. track is assigned to the wrong object), as well as actual correlations being missed (false negatives, i.e. track not assigned to an already catalogued object). Its performance has been analysed by using GMV's implementation under a simulated radar scenario, *RADAR-A*. As shown in Figure 8, the considered figure of merit is suitable to distinguish between true positives (green) and false positives (red) by filtering the candidate pairs according to certain threshold, depicted as a black dotted line.

In terms of correlation metrics, these results are summarised in Table 1. Most of the tracks are correctly correlated (99.10%) with less than 0.14% of false positives. Miscorrelations only occur due to values close to the selected correlation figure of merit threshold. Therefore, most could be easily avoided by reducing the threshold value at the expense of a higher percentage of false negatives.

Table 1. Track-to-orbit correlation metrics in simulated radar scenario

Correlation Metrics	RADAR-A
Total tracks	43,337 (100%)
True Positives	42,946 (99.10%)
False Positives	59 (0.14%)
False Negatives	332 (0.77%)

In terms of each measurement component, Figure 10 shows an histogram contribution of each measurement type to the figure of merit for true positive correlations. Straight lines correspond to the initial distribution, at $t = t_0$, while dashed lines represent the final distribution at $t = t_F = t_0 + 2$days. During this time span, catalogued orbits are updated with received tracks and therefore the accuracy of the catalogue is improved. Range and range-rate measurement components behaviour is improved (the peak shifts to lower figure of merit values and the magnitude increases). Angular measurement components figure of merit is mainly driven by sensor noise and therefore there are no major changes on peak magnitude.

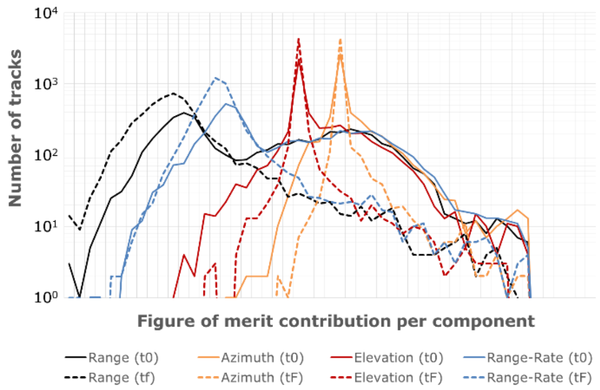

Figure 10. Track-to-orbit standard method figure of merit per component distribution of the tracks in simulated radar scenario

In terms of computational resources, most of the computation time is spend on synthetic tracking generation (even half of the overall time). Figure 11 shows the number of pairs per minute processed during each of the 15-minute step (physical time) of the track-to-orbit analysis. Furthermore, it is relevant to note that each of the steps is processed in less than 15 minutes (less than 5 minutes after step 200 on an Intel(R) Xeon(R) CPU E5-2670 v3 @ 2.30GHz).

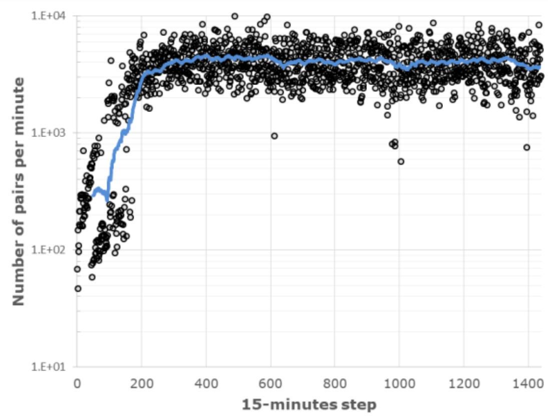

Figure 11. Number of pairs per minute processed by the track-to-orbit algorithm

5.2 TRACK-TO-TRACK CORRELATION

The performance of the track-to-track association algorithm presented above has been analysed in two simulated radar scenarios: *RADAR-A* and *RADAR-B*.

In terms of associations, Figure 12 shows the distribution of the figure of merit of each resulting association in *RADAR-B* scenario as a function of the semi major axis and eccentricity.

In terms of relevant correlation metrics, the results are presented in Table 1, which proves that the algorithm is able to provide excellent results for the track association problem, since most of the objects can be identified while providing a very low number of false detections. This is important during catalogue build-up, since the addition of wrong objects is very undesirable. Missed objects are mainly due to particular observability issues and not very critical since they could be detected in the future, as soon as more tracks of those objects are obtained.

Furthermore, a high rate of track usage is achieved.

Table 2. Track-to-track correlation metrics in simulated radar scenario

Correlation Metrics	**RADAR-A**	**RADAR-B**
Number of objects with enough tracks	3,702	3,953
Track Usage	98.67%	98.10%
True Positive Associations	3,661 (98.89%)	3,891 (98.43%)
False Positive Associations	0 (0.00%)	4 (0.10%)
Missed Objects	41 (1.11%)	62 (1.57%)

These results correspond to one of the most demanding cases, catalogue build-up. In this situation, all tracks are uncorrelated and therefore the algorithm should be able to distinguish between tracks belonging to very similar objects. After this cold start, the algorithm is expected to process only tracks assumed to belong to non-catalogued objects (uncorrelated tracks), thus being the complexity lower due to the lower number of tracks (less similar objects to be miscorrelated).

The association algorithm is able to process the whole *RADAR-A* and *RADAR-B* scenarios in 22 and 17 hours, respectively, by using 6 threads (Intel(R) Xeon(R) CPU E5-2670 v3 @ 2.30GHz). Therefore, it is clear that the algorithm is suitable for real-time processing.

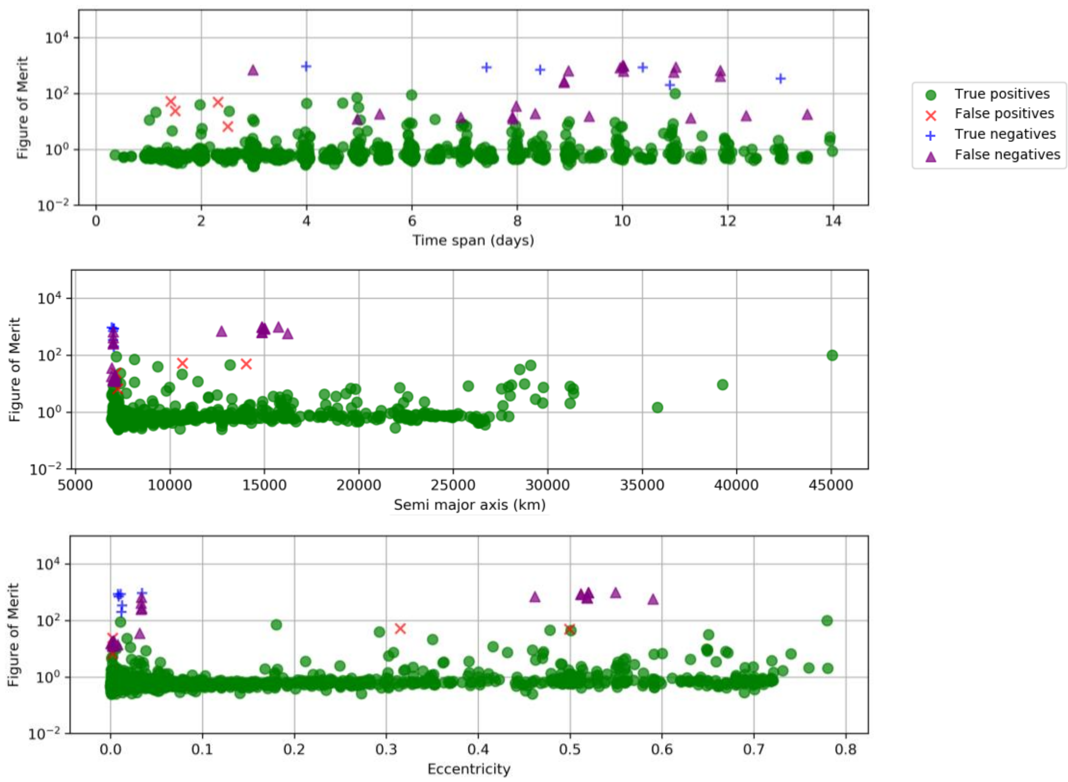

Figure 12. Distribution of the figure of merit of each track-to-track association in RADAR-B scenario as a function of the time span between tracks, semi major axis and eccentricity

5.3 ORBIT-TO-ORBIT CORRELATION

The performance of the orbit-to-orbit correlation algorithm presented above has been analysed with a software application implemented by GMV in a scenario of two independent catalogues: a low accuracy one, and a high accuracy one.

Historic data has been considered during May 2018 (i.e. 31 analyses have been performed).

In terms of relevant correlation metrics, the results are presented in Table 3, which proves that the algorithm is able to provide excellent results for the orbit correlation problem, since most of the orbits can be correctly correlated while providing a very low number of false positives. Regarding the false negatives, they have been grouped into:

- **Young:** not enough history data to ensure correlation. Could be correlated in the future when confident enough orbit pairs are available
- **Missed:** correlation not evaluated. Most of them related to TLE catalogue accuracy limitations
- **Effective:** enough history data but was not correlated. Most of them are operational satellites with high manoeuvring frequencies not properly captured by the TLE catalogue

Table 3. Correlation metrics at the end of the analysis

Correlation Metrics	Number	Relative Number
True Positives	16,013	99.91%
False Positives	1	0.01%
True Negatives	13,476	84.08%
False Negatives	709	4.42%
False Negatives: Young	696	4.34%
False Negatives: Missed	1	0.01%
False Negatives: Effective	12	0.07%
Reference	16,027	100.00%

The reference value used to obtain the relative results is the number of true positives, false positives and false negatives (missed and effective).

It is worth mentioning that the only false positive remaining at the end of the analysis corresponds to *ISS (ZARYA) (NORAD ID: 25544)* with *SOYUZ MS-08 (NORAD ID: 43238).*

As shown in Figure 13, the correlation process converges along the analyses and the consideration of the history allows to detect outliers.

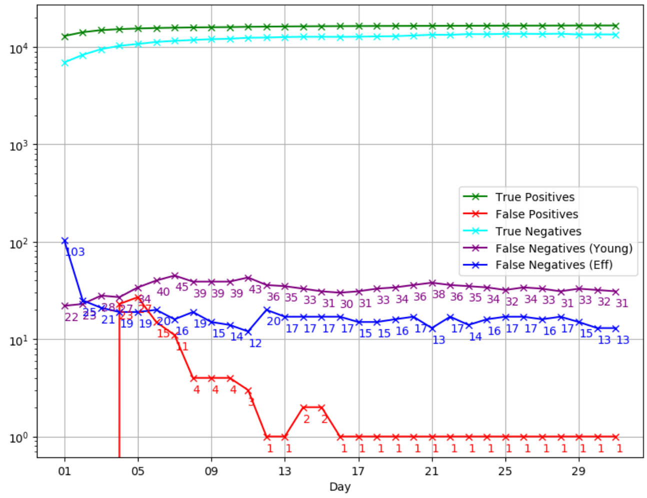

Figure 13. Evolution of the correlation metrics trough day analyses

One of the main outliers' source is a manoeuvre that is detected at a different epoch on each catalogue. They can be detected via statistical methods since the RMS history is available. Figure 14 shows the evolution of figure of merit of a GEO satellite, *BRAZILSAT B3 (NORAD ID: 25152)*, whose figure of merit evolution exhibits two clear outliers on day 8 and 24. Despite of the manoeuvres, the orbits are correlated during the whole analysis thanks to correlation history. If it had not been considered, then these orbits would have been left uncorrelated or even worse, they would have been wrongly correlated.

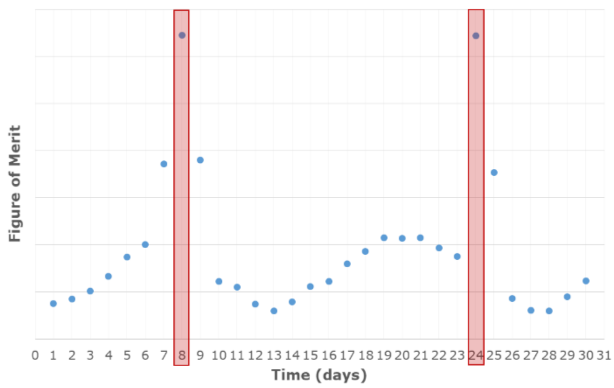

Figure 14. Evolution of the correlation metrics trough day analyses

The runtime performance of the algorithm has been evaluated in terms of the CPU time usage. Results are presented in (Intel(R) Xeon(R) CPU E5-2670 v3 @ 2.30GHz). Each analysis takes less than 40 minutes and should have been performed on its corresponding day.

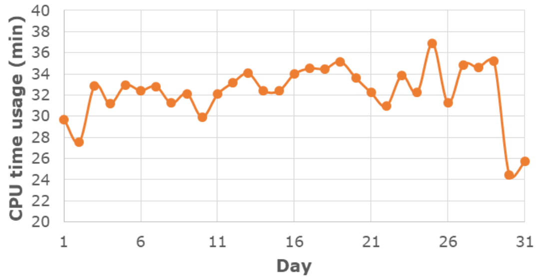

Figure 15: Orbit-to-orbit CPU time usage for each analysis

6 CONCLUSIONS

This paper has presented novel correlation techniques as part of the cataloguing sequence to build-up and maintain an objects catalogue as implemented in the SST Catalogue Maintainer Software (***catmai***). The different components of the cataloguing chain have been discussed, focusing on the correlation algorithms used for them. Furthermore, the SST Sensor Data Simulator (***ssdsim***) has been introduced as a software to generate simulated measurements for testing purposes.

Finally, results for each of the three correlation processes on representative and operational-like scenarios have been discussed. The success rates obtained allow us to study the performance of the isolated components of the cataloguing chain.

We are currently working on simulations of the whole cataloguing process with which evaluate the performance of the complete process: from the reception of the tracks to the build-up and maintenance of the catalogue.

7 ACKNOWLDEGMENTS

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ANNEX: ORBIT SPECTRUMS OF SIMULATED RADAR SCENARIOS

RADAR-A scenario

Figure 16 shows the orbit spectrum of *RADAR-A* simulated scenario.

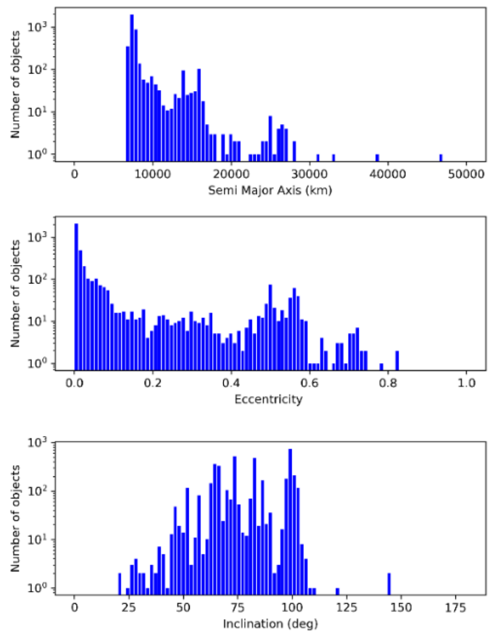

Figure 16. Orbit spectrum of RADAR-A objects

RADAR-B scenario

Figure 17 shows the orbit spectrum of RADAR-B simulated scenario.

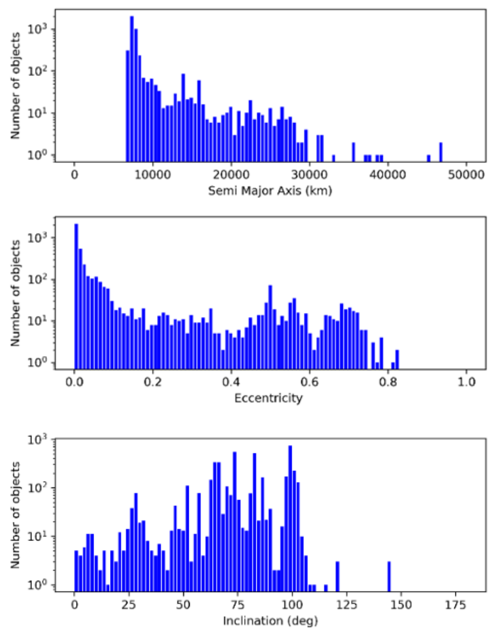

Figure 17. Orbit spectrum of RADAR-B objects