CORRELATION TECHNIQUES TO BUILD-UP AND MAINTAIN SPACE OBJECTS CATALOGUES

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ABSTRACT

To build-up and maintain a resident space objects (RSO) catalogue, in addition to the required sensors (radars, telescopes, SLR stations), it becomes necessary to have the required ground-segment infrastructure able to process efficiently all the data provided, in the form of observation tracks, from those sensors.

Since 2007 GMV has developed and used methods to identify, track and catalogue RSOs. The SST Catalogue Maintainer Software (***catmai***) is GMV's software capable of 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.

catmai is composed of an initial orbit determination tool, an orbit determination module, a track-to-orbit correlator, a track-to-track correlator, an orbit-to-orbit correlator and a catalogue post-processing component for the analysis of the cataloguing performances.

This paper will focus on the **correlation methods** implemented in GMV's cataloguing solution and their performances in terms of success rate and false positive detection for the following processes:

Index Terms**—** space debris, space surveillance and tracking, catalogue build-up, catalogue maintenance, correlation

1. INTRODUCTION

Human activity in the 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 (formerly JFSCC) with sizes starting around 10 centimetres in LEO and around 1 metre in GEO. Space debris has nowadays become a very important threat to space operations as high-risk collisions are predicted daily between operational spacecraft and space debris objects.

Most space agencies have their own programs to deal with this threat, both from a mitigation point of view (IADC guidelines implementation, spacecraft design, active space debris removal), and from an operations point of view (e.g., space surveillance and tracking, collision avoidance). On the other side, the space private sector has been developing and using its own solutions to tackle the problem.

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 and realistic uncertainty characterisation that allow the prediction of high-risk collision events accurate enough and time in advance.

The catalogue is one of the main outputs of the SST activities. It is a robust automated database that contains information of every detected object. There are two catalogue related activities:

- **Catalogue build-up:** detection and identification of new objects to include them into the catalogue without any previous information.
- **Catalogue maintenance:** update the orbital information of the objects in the catalogue.

2. SST CATALOGUE MAINTAINER SOFTWARE

The SST Catalogue Maintainer Software (***catmai***) 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.

catmai is able to manage at all levels of the processing survey and tracking data from the following **types of sensors** both for survey and tracking activities:

- Ground-based monostatic radar
- Ground-based bi-static radar
- Ground-based telescope
- Ground-based SLR sensor
- Space-based telescope

The **measurement types** supported for a ground-based sensor are the following:

- One-way and two-way range
- One-way and two-way range-rate (Doppler)
- Fix angles (right ascension and declination)
- Topocentric angles (azimuth and elevation)

The use of state-of-the-art **measurements reconstruction modelling** and of **accurate corrections** has been ensured by the full reuse of the measurements generation capabilities in previous GMV software solutions. Adequate reconstruction models for the presented types of observations are then defined to optimize the accuracy of the orbital solutions and predictions obtained to support the success of the correlation process. Ground station position and reference system transformations are fully compliant with IERS standards.

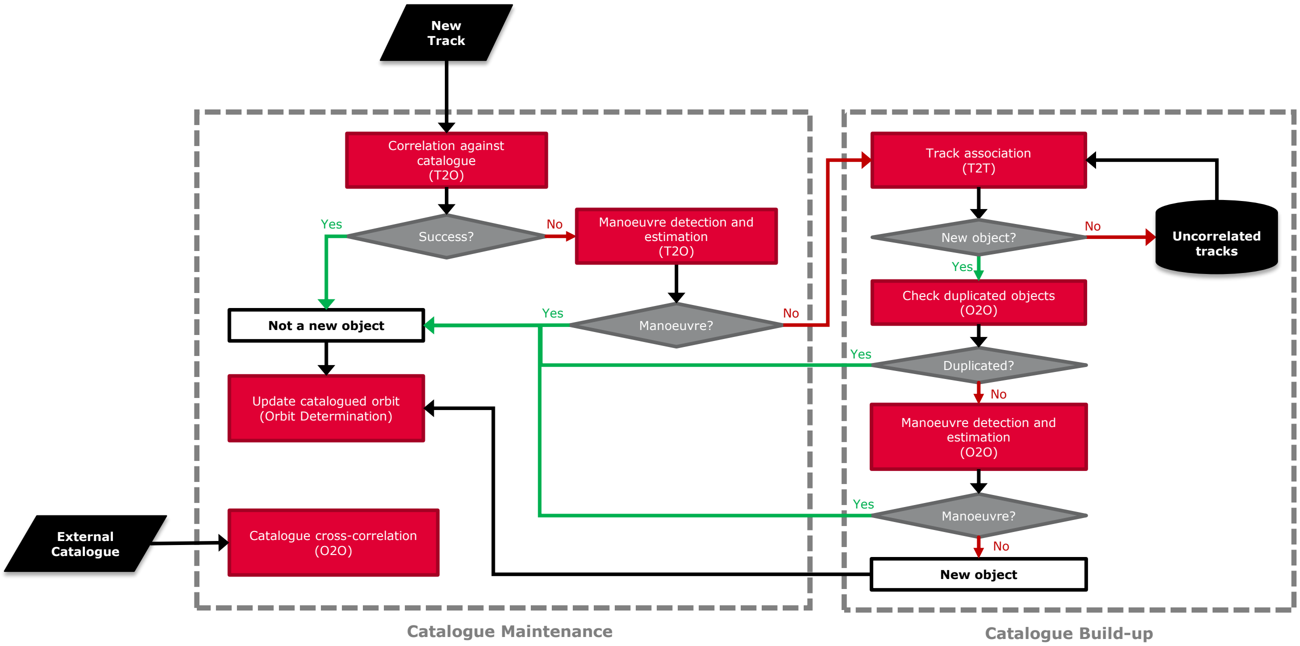

Figure 1: Cataloguing chain

catmai implements a **fully automated process manager**. The process manager is in charge of running the sequence of sub-processes for the build-up and maintenance of the catalogue. This manager accesses the data in the catalogue in order to collect it as input for the processing of a function in the system or to update it as a result of that processing.

The main information stored in the **catalogue** is the **orbit and covariance information** for the catalogued objects. In addition, other information such as the historical information necessary for running the sequential orbit determination process (in case of revisit), the history of the measurement passes processed and the history of the correlation processes performed (including results of the correlation process and computed quality factors) is also maintained.

The **cataloguing chain** is described next. It is essentially the same regardless of the sensor network, although some steps of the chain may change slightly depending on the sensor architecture. This processing chain consists on the execution of several sequences of components of ***catmai***.

3. 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 objects 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.

Figure 1 shows the main components of the cataloguing chain and the relationships between them. The overall sequence is based on the previous events and differences in frequency of the events.

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 success, 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 to check if they belong to the same 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 catalogue.

4. ALGORITHMS

The algorithms used during the cataloguing chain are presented in this section. A high-level description of initial orbit determination and orbit determination algorithms is provided in first place. Then, more information is given to correlation algorithms, as these are the focus of the current analysis.

4.1. Initial Orbit Determination

Initial Orbit Determination (IOD) algorithms allow to obtain the first estimation of the orbits from very few observations and with no a-priori information. A set of initial orbit determination methods are available for different number and type of measurements.

4.2. Orbit Determination

IOD methods are limited in the sense that they require a certain number of observations with a fixed number and type of measurements (e.g.: right ascension, declination and range at each observation epoch) and provide certain orbit data (e.g.: state vector at the first observation epoch). Their architecture is not flexible and thus, their use limited. Furthermore, they are suitable for a relatively low number of observations and thus they are vulnerable to geometry singularities and measurement errors.

Orbit Determination (OD) algorithms allow to improve IOD solutions by considering larger sets of data and taking into account related statistics, as well as additional information, if available.

There are two families of estimation methods:

- *Batch or Least-Squares estimator*: improves an IOD solution by processing all available measurements. All measurements are simultaneously processed and the solution is obtained after an iterative method over the whole dataset is performed.
- *Sequential estimator*: instead of processing all available measurements at a certain time, it processes only one and improves the previous solution. The advantage of this estimator is that it is not required to re-process all the measurements when new measurements are available. That is why it is suitable for on-board real-time applications. **Square Root Information Filter (SRIF)** is used for updating the orbit information of already catalogued objects when a new track is correlated against them.

Both methods are available for use in ***catmai***, and have different features with respect to computational speed, robustness, etc.

4.3. 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 2 represents the module dataflow diagram.

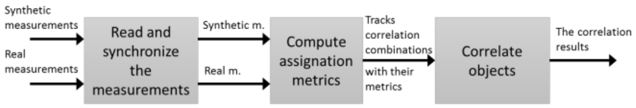

Figure 2: Track correlator module dataflow diagram.

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). Blue squares represent real measurements, purple circles synthetic measurements and red squares real measurements that have been correlated with synthetic ones. This method 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. tracklet is assigned to the wrong object), as well as actual correlations being missed (wrong uncorrelated tracklets, i.e. tracklet not assigned to an already catalogued object).

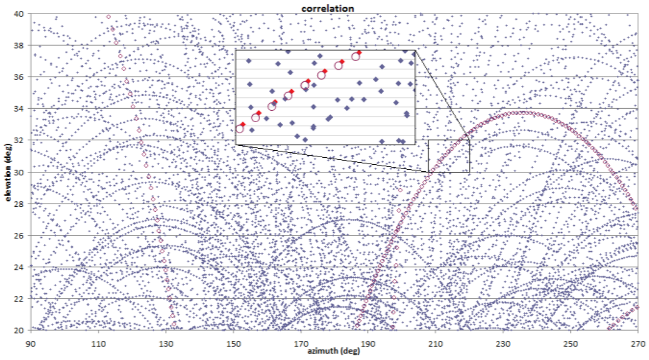

Figure 3: Measurements matching for correlation

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:

1. *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.
2. *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.
3. *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.
4. *Residuals Computation:* difference between real and synthetic tracks measurements are obtained. This information is required to after compute the correlation figure of merit.
5. *Correlation Statistics Computation:* the correlation metrics are computed for each pair of track association candidates.
6. *Selection of Best Correlations:* the best correlation pairs are selected. Thresholds are considered so as to mitigate the number of false positives.

4.4. Track-to-Track Correlation

The main concept behind the track-to-track association method is 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.

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 more filters with increasing complexity.

The algorithm is further presented in [7].

4.5. 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:

1. *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).
2. *Interpolator:* ensures the state vectors required for the evaluation during the next step are available.
3. *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.
4. *Solver:* once the correlation matrix is fully populated, as shown in Figure 4, it is solved with the Greedy Assignment Method (GAN)

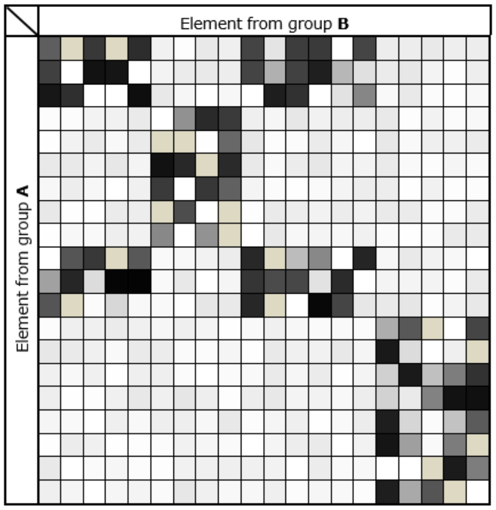

Figure 4: Sample matrix for orbit-to-orbit correlation. Darker squares are the more probable assignment

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 keep on correlating even if there is a manoeuvre not detected in one of the orbits. 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.

4.6. Manoeuvre Detection and Estimation

Manoeuvre detection can be understood as a correlation problem between two objects.

Performing this correlation in the measurement domain, as done in proposed track-to-track algorithm, is too ambitious considering current technology level [8]. This topic is still on a very preliminary research level.

In recent years, the interest in the automatic detection of manoeuvres has increased due to the growth in the size of the catalogues of objects in orbit to maintain. The approaches to the problem can be categorized in two broad categories:

- Use of historical data to establish the possible correlation
- Use of stochastic filters

Regarding the former, several works in the recent years are devoted to exploring and analysing the possibility of using historical data to associate new observations of an object with the catalogue entry after a manoeuvre [9]. Criticisms to this approach lay in the fact that the use of historical data is based on the repetitiveness of the manoeuvres [10], which is not always guaranteed. New estimators have been recently developed to specifically tackle the problem of the manoeuvre detection. Among them, it is worth citing the Optimal Control-Based Estimator, to detect and reconstruct manoeuvres with no a priori information [11]. This work is based on the definition of a control distance metric to address the feasibility of an alleged manoeuvre [12]. The metric is the necessary control effort and is used similarly to the Mahalanobis distance [13].

It is important to note that estimating low-thrust manoeuvres is far from the current state of the art, not only from the operational point of view, but also considering ongoing research activities [8].

Two possible strategies are proposed which can be applied in a cascade as they are related to different stages of the processing:

- **Track-to-orbit** correlation using a “manoeuvre” transition matrix on the candidates.
- **Orbit-to-orbit** correlation using the new created objects against the candidates.

As a clarification, the estimated manoeuvres do not necessarily represent the actual manoeuvres of the objects, as they are considered impulsive and multiple solutions can be found, but with the available observation information, this solution allows to link correctly the received tracks and to obtain a **continuous** solution on the orbit.

5. RESULTS

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:

- **Number of correctly correlated pairs or associations (*true positives*):** those correlated pairs or associations containing orbits that belong to the same object (e.g. the two orbits correspond to the same NORAD ID or two or more tracks belonging to the same object).
- **Number of wrongly correlated pairs or associations (*false positives*):** those correlated pairs or associations containing orbits or tracks that do not belong to the same object.
- **Number of correctly uncorrelated pairs or associations (*true negatives*):** those uncorrelated pairs or associations containing orbits or tracks that do not belong to the same object. They have been evaluated but not considered as correlated.
- **Number of wrongly uncorrelated pairs or associations (*false negatives*)**: those uncorrelated pairs/associations containing orbits or tracks that belong to the same object. As well as true negatives, they have been evaluated but not considered as correlated.
- **Number of missed pairs or associations**: those that have not been considered but belong to the same object. They have not been evaluated nor generated and sometimes it is more representative to consider them as false negatives.

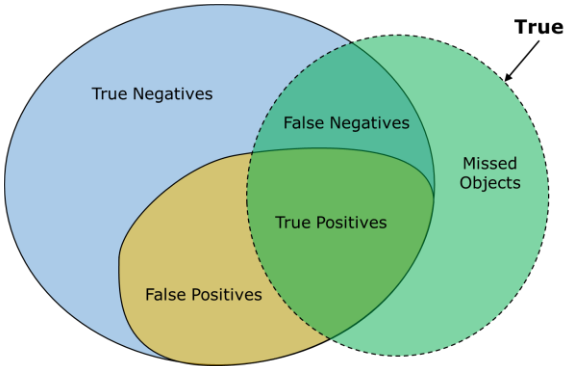

Figure 5: Sketch of correlation metrics

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* (see Annex A: *RADAR-A* Scenario). As shown in Figure 6, 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.

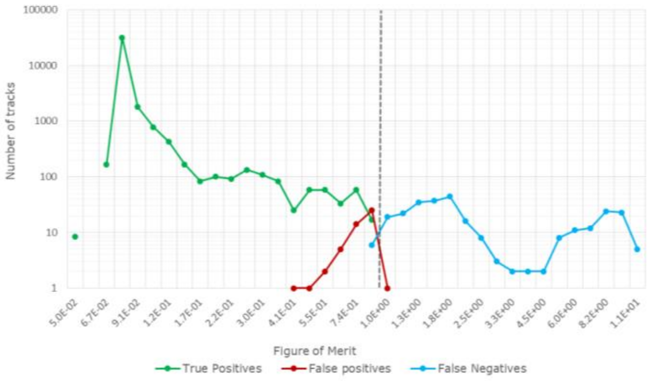

Figure 6: Track-to-orbit standard method figure of merit distribution of the tracks in simulated radar scenario

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 computation resources, most of the computation time is spend on synthetic tracking generation (even half of the overall time). Figure 7 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).

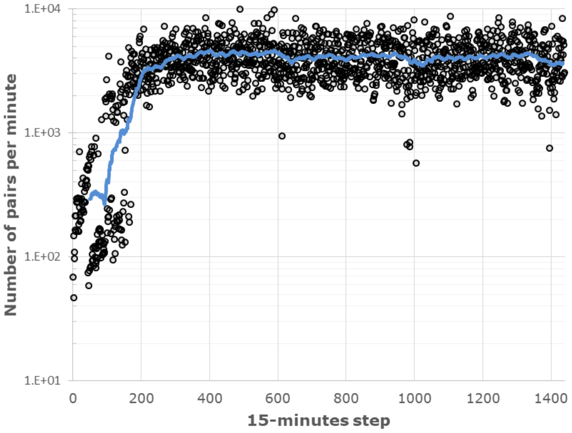

Figure 7: Number of pairs per minute processed by the track-to-orbit algorithm

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* (see Annex A: RADAR-A Scenario and Annex B: RADAR-B Scenario).

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In terms of associations, Figure 8 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.

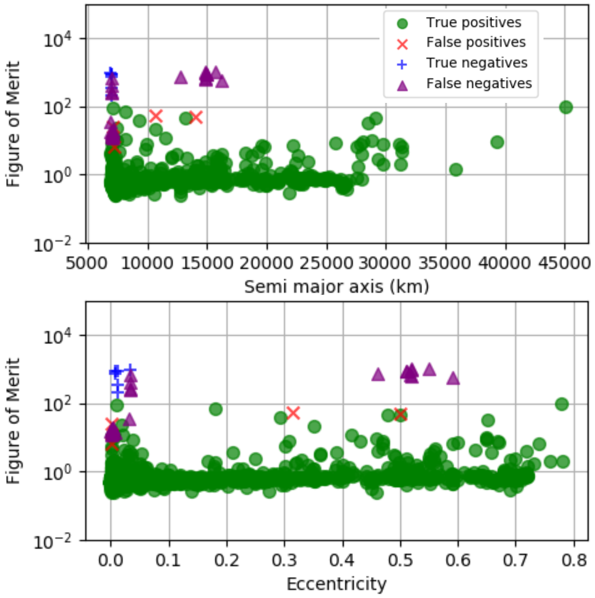

Figure 8: Distribution of the track-to-track figure of merit of each association in *RADAR-B*

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.

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:

- 18th SPCS low accuracy catalogue [14]
- 18th SPCS high accuracy catalogue [14]

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 9, the correlation process converges along the analyses and the consideration of the history allows to detect outliers.

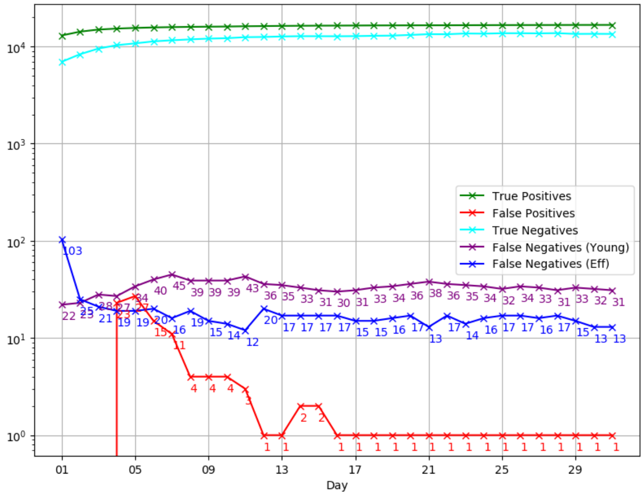

Figure 9: Evolution of the correlation metrics trough day analyses

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 10 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 correlated or even worse, they would have been wrongly correlated.

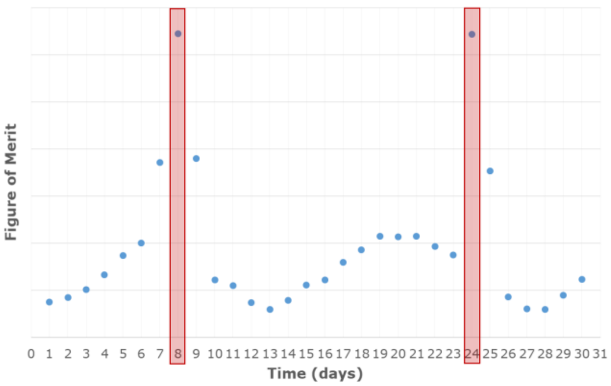

Figure 10: Evolution of the correlation metrics trough day analyses

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.

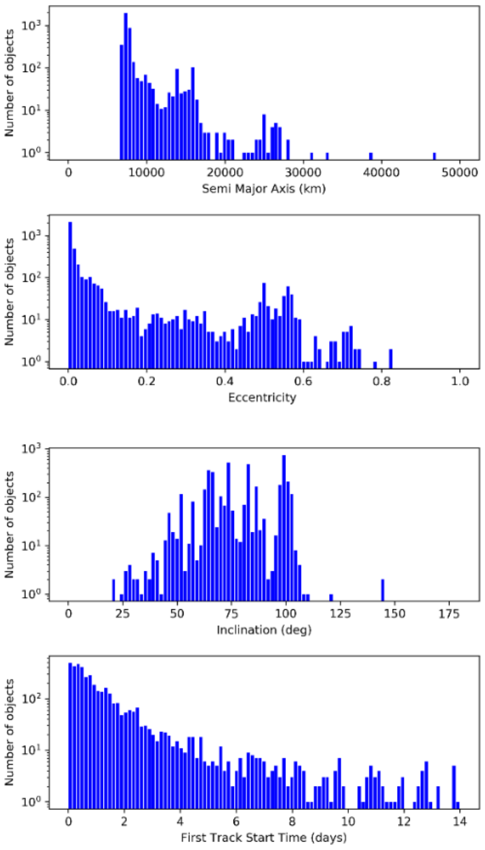

Figure 11: Orbit spectrum of RADAR-A objects

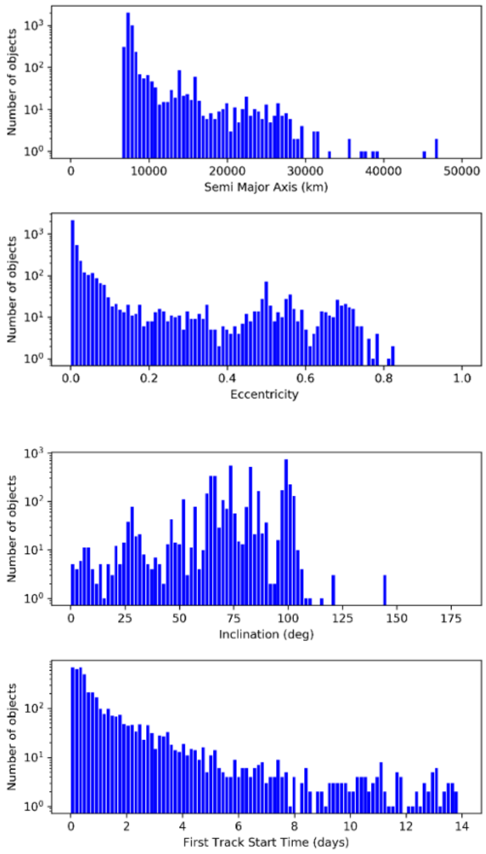

Figure 12: Orbit spectrum of RADAR-B objects

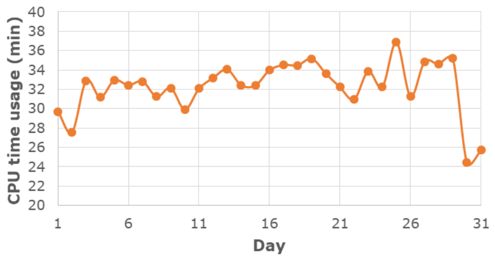

Figure 13: Orbit-to-orbit CPU time usage for each analysis

6. CONCLUSIONS

This paper has presented the SST Catalogue Maintainer Software (***catmai***), as well as its main correlation techniques and algorithms.

The different components of the cataloguing chain have been presented, focusing on the correlation techniques present on them.

Finally, results for each of the three correlation problems 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. ACKNOWLEDGEMENTS

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ANNEX A: *RADAR-A* SCENARIO

The orbit spectrum of *RADAR-A* scenario is shown in Figure 11.

The scenario contains one radar sensor and the measurements have been generated by considering Gaussian noise with state of the art noise figures:

- 1-Sigma error in range: 3 m
- 1-Sigma error in azimuth and elevation: 64.5 mdeg

The field of view of the radar is so that average revisit time is of 60 seconds.

ANNEX B: RADAR-B SCENARIO

The orbit spectrum of *RADAR-B* scenario is shown in Figure 12.

The scenario contains one radar sensor and the measurements have also been generated by considering the same noise model and parameters as *RADAR-A* scenario.

The field of view of the radar is so that average revisit time is of 30 seconds, i.e. lower than the one for *RADAR-A*.

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