Object Detection Methods for Optical Survey Measurements

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ABSTRACT

This work presents a novel sequential filtering algorithm able to identify new objects from optical measurement data by associating uncorrelated tracks (UCTs) belonging to the same object. It makes use of both Initial Orbit Determination (IOD) and Orbit Determination (OD) methods to evaluate a figure of merit to help deciding whether certain tracks belong to the same object or not. Instead of using a brute-force approach by evaluating all possible combinations of UCTs, several filters and complexity reduction techniques are used to reduce the computational resources required. Furthermore, the association is performed on the measurements space (track-to-track correlation) rather than in the orbit space (track-to-orbit or orbit-to-orbit correlation).

A generic object detection methodology based on track association is presented, with a special emphasis on the correlation of optical tracks, although it has been already applied to correlation of radar tracks. In the former case, the problem resides in the derivation of enough orbital information from a single track (with less attributables than a radar track) to allow the application of filters and complexity reduction techniques. Hence, optical track association is far more complex and resource-consuming than the radar track association, and thus classical approaches are not enough.

Results have shown that this strategy provides more reliable results than an association made on the orbit space, in terms of both false positives and number of missed objects. A realistic simulated scenario has been set up to evaluate the performance of the correlation procedure under a purely build-up scenario. The performance of the methods is evaluated in terms of clear and well-defined correlation metrics, such as true positives, false positives and false negatives, providing both ratios and absolute values. They prove that the proposed methodology is able to provide excellent results for the track association problem, since most of the objects can be detected while providing a very low number of false detections. This is important during catalog build-up, since the addition of wrong objects is very undesirable. The computational cost of the algorithm allows real-time processing of new tracks thanks to the selective generation and pruning that avoid evaluating all possible combinations of tracks.

1. INTRODUCTION

The number of resident space objects (RSO) is increasing year after year and therefore the sensing capabilities are also growing [1]. Space Surveillance and Tracking (SST) systems are composed by sensors and on-ground processing infrastructure devoted to the generation of a catalog of RSO: a robust automated database that contains information of every detected object. During surveillance, large areas of the sky are scanned to obtain data for both catalog build-up and maintenance activities. The catalog build-up process consists in detecting new objects to include them in the catalog without any previous information, while the maintenance task entails the update of existing objects information. Hence, the catalog build-up depends on the capability to detect new objects from measurements, packed as tracks, provided by a sensor network.

The catalog represents one of the main outcomes of the SST activities and the provision of SST products (e.g. high-risk collisions, upcoming re-entries, fragmentations) is based on the information available on it. Therefore, it is crucial to develop methods that enable the detection of new objects and the orbit estimation with enough accuracy to allow high success rate in the correlation of new tracks (track-to-orbit correlation) to update the already catalogued orbit. One of the most relevant features that make the track association problem so challenging is the coupling between detection and estimation, i.e. to identify a new object it is required to estimate its orbit, while only measurements belonging to the same object should be used in this estimation.

The detection of new objects belongs to the catalog build-up activities and entails track association, since a single track is not enough to reliably estimate the orbit of an object. Some methodologies perform Initial Orbit Determination (IOD) on a single track, i.e. without track association, leading to manual processing and low track usage rates [2]. The track association problem is an NP-hard (Non-deterministic Polynomial-time hard) combinational optimization problem, i.e. the computational cost increases exponentially with the number of objects. Besides, it is an active data fusion area of research with different strategies to tackle the problem. One of the more direct ones is the so-called *association cell* concept, defined by limits on the computed position residuals [3]. It is a track correlation made on the orbit space, and therefore it completely relies on the orbits estimated from the measurements (track-to-orbit or orbit-to-orbit correlation), rather than the measurements themselves. The problem of these strategies is again the reliability of the estimation: more than one track are required to estimate an orbit with enough accuracy to add an object in the catalogue so that it can be used for SST products provision (sensor tasking, collision prediction, reentry analysis, among others).

Apart from an orbit estimation, other approaches try to make use of the uncertainty derived during orbit determination processes [4] by projecting the orbital differences into a frame defined by the covariance of the estimation, i.e. the *Mahalanobis distance* [5]:

$$M = (\mathbf{x}_1 - \mathbf{x}_2)^T (\mathbf{P}_1 + \mathbf{P}_2)^{-1} (\mathbf{x}_1 - \mathbf{x}_2) \tag{1}$$

where $\mathbf{x}_1$ and $\mathbf{x}_2$ are the state vectors estimated from the available observations to be correlated and $\mathbf{P}_1$ and $\mathbf{P}_2$ their associated covariance matrices. This is the correlation figure of merit suggested in recent methodologies [6] and [7]. However, one known flaw of this approach is that it requires the uncertainty to be realistic and well-characterized, which is not an easy task especially when the information available is reduced. Additionally, that formulation tends to favor objects with higher uncertainties in the correlation process. Other strategies include *admissible regions* [8] and even genetic algorithms [9].

The track association problem is sometimes referred to as track correlation. To avoid ambiguities, we prefer the term track association or track-to-track correlation to denote the correlation of tracks against tracks, i.e. catalog build-up. Besides, we leave the term track correlation or track-to-orbit correlation to designate the correlation of tracks against orbits of already cataloged objects, i.e. catalog maintenance .

The proposed track association methodology is performed in the observations space rather than in the orbit space. It consists in a multi-step sequential filter that makes use of IOD and Orbit Determination (OD) methods to evaluate associations of a certain number of tracks. Since there is no previous knowledge on the object orbit to which the measurements correspond, there is a huge number of possible combinations that grows with the number of tracks, n, as n^2. From this point forward, we use the term *step* to denote each of the filters applied to associations of certain number of tracks and *n-stage* to refer to all the steps acting on associations of n-tracks.

Complexity reduction techniques and multiple filtering steps are required because evaluating all possible combinations, i.e. brute-force approach, is not an option. Therefore, simple and fast methods are applied first, leaving the more accurate and computationally expensive methods and dynamical models for the last stages, when most of the false combinations have been filtered out.

2. BACKGROUND

Some of the terms that are used along this paper are now defined for clarification:

- **Measurement**: value assigned to a physical attribute that has been obtained with a certain sensor (e.g., right-ascension, declination, range, azimuth, elevation).

- **Observation**: set of measurements related to a certain epoch, belonging to a given object and obtained by certain sensor.
- **Track**: set of observations assumed to belong to a common object. In the case of observations from optical sensors is also known as tracklet, but since the proposed methodology is generic and suitable for both radar and optical sensors, we will use the term track for the sake of generalization.
- **Association**: group of tracks under analysis to determine whether they belong to the same object or not. It is our correlation unit.

The main goal of the track association in the object detection problem is to generate true associations, i.e. associations of tracks belonging to a common object, so that one association leads to the addition of a new object in the catalog. Furthermore, as in any correlation procedure, it is important to achieve a low ratio of false associations, i.e. associations of tracks that do not belong to a common object.

In the proposed methodology, each association has one of the following statuses:

- **Not validated (under analysis):** associations whose tracks have not been correlated yet and have not been discarded.
- **Validated:** associations whose tracks have been correlated. A new object will be generated from each validated association.

2.1 Correlation Metrics

To evaluate the performance of the correlation process, we have considered the following metrics:

- **Number of correct associations (*true positives*):** validated associations containing tracks that belong to the same object.
- **Number of incorrect associations (*false positives*):** validated associations containing tracks that do not belong to the same object.
- **Number of correctly not validated associations (*true negatives*):** not validated associations containing tracks that do not belong to the same object. They have been evaluated but not considered as validated.
- **Number of wrongly not validated associations (*false negatives*):** not validated associations containing tracks that belong to the same object. As well as true negatives, they have been evaluated but not considered as validated.
- **Number of missed objects:** those objects that have not been detected. The corresponding associations may have been considered but not validated, or not considered at all.

These correlation metrics can be obtained for the set of tracks and objects, apart from the set of associations. They are depicted in Fig. 1.

2.2 Number of Associated Tracks

A challenging decision in the track association problem is the selection of the minimum number of tracks required to initialize an object from an association. Optical data covering a realistic and wide spectrum of orbit types has been simulated to determine the minimum number of tracks required to perform track association reliably. Fig. 2 shows the figure of merit of each association as a function of the association time span (maximum time difference between associated tracks) for associations of two, three and four tracks. Each point is plotted in green or red color depending on whether it is a true association (associated tracks belong to the same object) or not. The associations have been generated via brute-force, and therefore only tracks within two days have been considered due to the high number of possible track combinations (for this analysis, more than 4.5 million have been considered). However, the complete analysis, presented afterwards, confirms this decision.

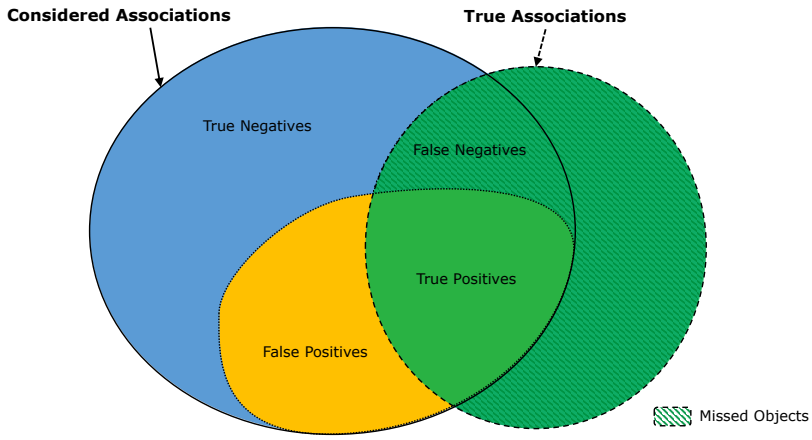

Fig. 1: Sketch of the correlation metrics considered

Two regions arise: the green one, corresponding to true associations, and the red one, corresponding to false associations. It is clear that four associated tracks are enough to isolate true from false associations and thus, obtain two different regions. This conclusion coincides with the requirement from [4] of associating three or four tracks so that a meaningful state can be estimated before adding a new object to the catalog.

In addition to this, Fig. 3 proves the suitability of defining a threshold in our figure of merit to filter false associations. It shows the figure of merit distribution of both true and false associations considering the number of tracks associated during one week. For each number of associated tracks, N, the x-axis value has been linearly scaled with the time span between associated tracks, Δt, as:

$$N - 0.5 + \frac{\Delta t}{1week} \tag{2}$$

Only for associations of four tracks, the regions of true and false associations are clearly separated. For associations of one, two and three tracks the figure of merits are distributed without a clear difference between true and false associations.

2.3 Initial Orbit Determination and 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 structure is not flexible and their use limited. Furthermore, they are suitable for a relatively low number of observations and thus they are usually susceptible to geometrical singularities and measurement errors.

Optical tracks contain only angular measurements, i.e. pairs of right ascension and declination (α and δ, respectively) or line-of-sights ($\mathbf{L}$), depicted in Fig. 4, where $\mathbf{R}$ represents the sensor station position. In contrast to radar tracks (containing range and/or range-rate measurements), a single observation is not enough to obtain a position vector, and classical methods, such as Laplace, Gauss [10] and Gooding [11] methods, require three observations. Although a track may contain more than one observation, it is appropriate to make use of fitting techniques and therefore apply these methods to three fitted tracks well separated tracks.

However, under circular orbit assumption, and fixing the number of revolutions between them, two observations are enough to obtain a circular orbit. Given that most of the objects observable with optical sensors are describing circular orbits, we first apply filters focused low-eccentricity orbits, by processing associations of tracks and leave the remaining tracks for subsequent processing. This allows us to quickly associate nearly-circular objects first with simple methods under circular assumption and then apply more expensive and time consuming double-r iteration methods afterwards for the remaining uncorrelated tracks.

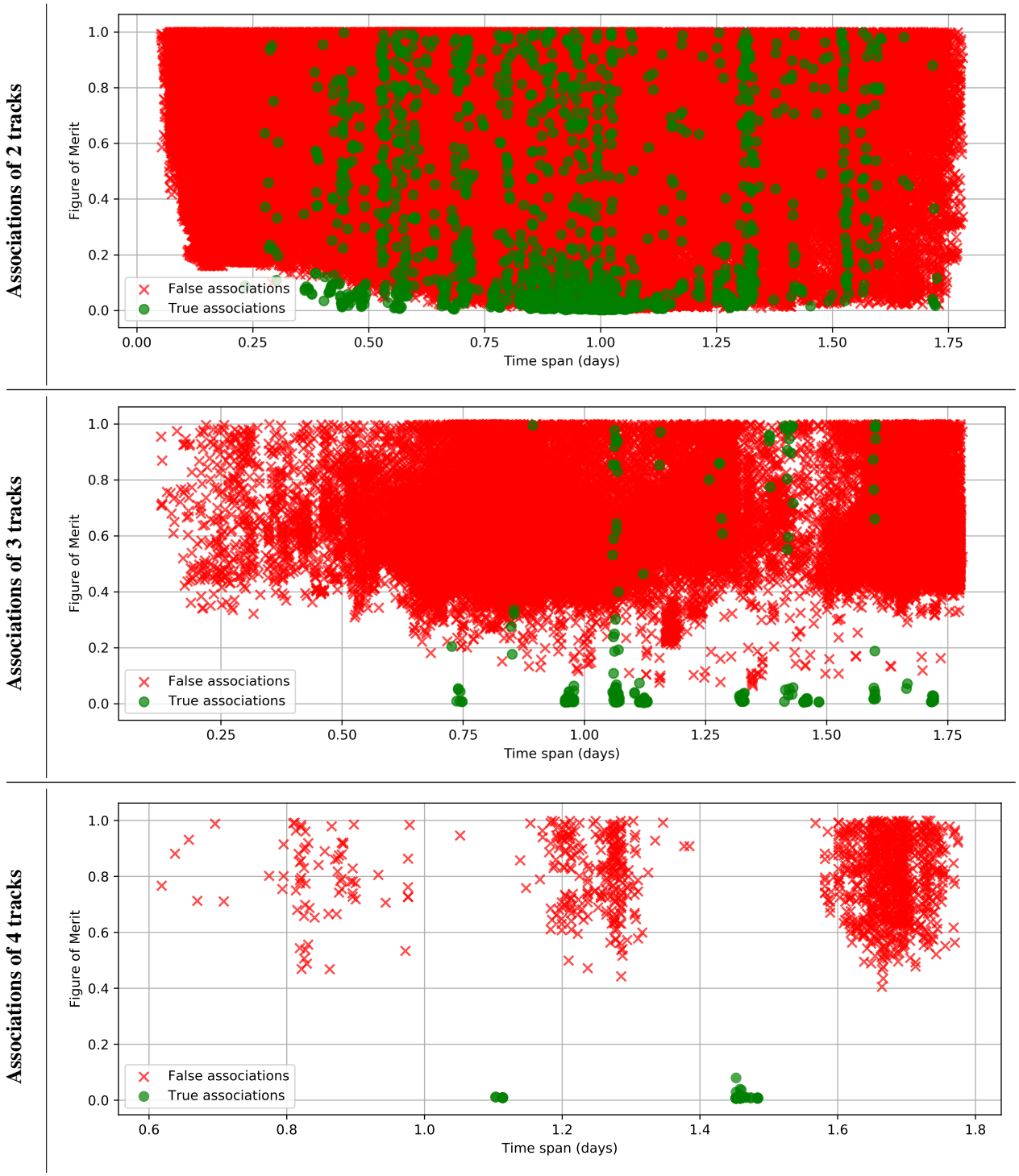

Fig. 2: Distribution of the figure of merit for true associations (green) and false associations (red) for different number of associated tracks in a simulated brute-force association scenario

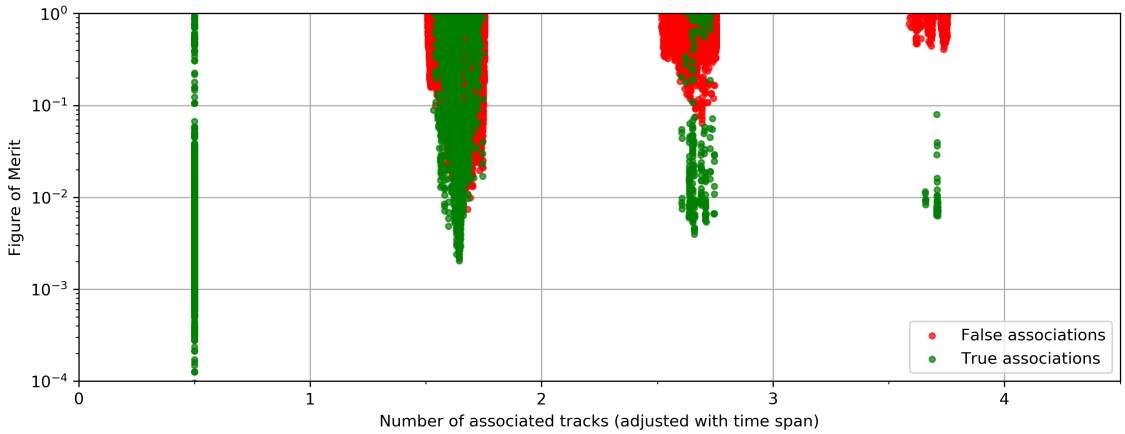

Fig. 3: Distribution of the figure of merit for true associations (green) and false associations (red) for different number of associated tracks in a simulated brute-force association scenario

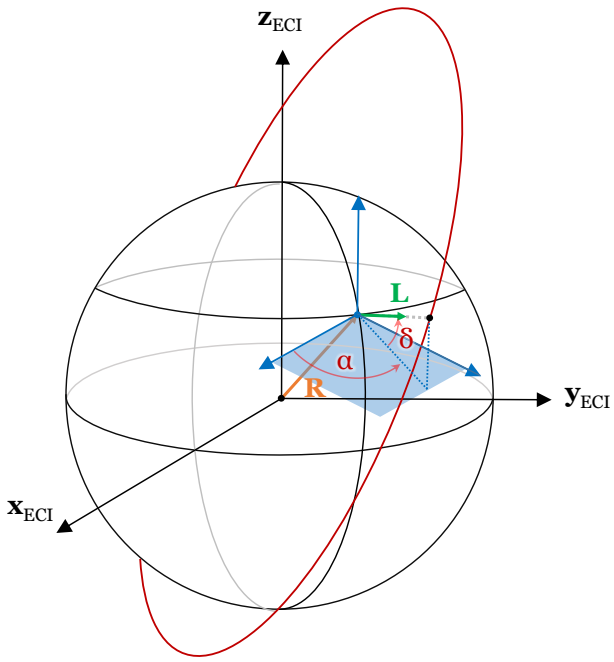

Fig. 4: Observation geometry for optical measurements

3. ASSOCIATION METHODOLOGY

The proposed track association methodology generates associations of two, three or even more tracks, by sequentially applying the different association steps, depicted in Fig. 5 and presented in this section.

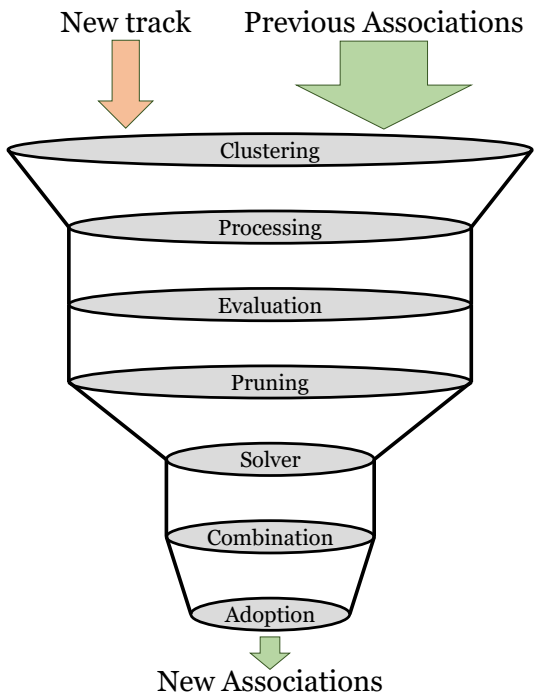

Fig. 5: Proposed association steps methodology

These association steps are applied sequentially for each new track and at each association stage. For instance, starting when the first track arrives, an association (of a single track) is generated, processed, and evaluated. Nothing else can be done with a single track, so the next track is considered. The first association stage of this second track is analogous to that of the first one and then, during the second stage, an association of two tracks is generated (if below described criteria are met), processed and evaluated.

Furthermore, the remaining uncorrelated tracks and associations can be considered in subsequent analyses, since past uncorrelated tracks may be associated with future tracks. In this way, we also consider previous associations that may lead to the generation of new associations with subsequent tracks. Because of this fact, and in order to avoid considering a too wide separation between tracks, a **time window** is defined, thus taking into account only tracks whose epoch lies inside it.

This methodology can be applied to catalog build-up processes of **multi sensor networks** of both radars and optical sensors and the approach is capable of real-time track processing. The different association steps are now introduced.

3.1 Association Clustering

The clustering step is in charge of generating new associations by combining two associations from previous association stages. Therefore, associations of n tracks are generated from associations of $n-1$ tracks, e.g. associations of two tracks are generated by combining two associations of one track (i.e. by combining two tracks), while associations of three tracks are generated from associations of two tracks.

Not every possible combination is generated, but only those combinations of two associations meeting the following criteria:

- **Time span criterion:** the time span between the associated tracks of the two associations must be higher than certain fraction of the average orbital period. The rationale behind this criterion is avoiding associating tracks

that are not very timely spaced, since this is a non-desirable situation in terms of orbit observability. This criterion becomes less relevant as more tracks are associated.

- **Angular rates difference criterion:** since we are interested in nearly circular objects first, the angles rates can be used to avoid generating associations whose angles rates differences excess certain threshold. The expression of the line-of-sight rate is:

$$\dot{\mathbf{L}} = \frac{1}{\rho}\left(\mathbf{v} - \dot{\mathbf{R}} - \dot{\rho}\mathbf{L}\right) \tag{3}$$

where $\mathbf{v}$ is the orbital velocity, $\mathbf{R}$ the sensor station position, ρ the range and dot denotes derivative with respect to time. By assuming typical values for a geosynchronous orbit, it can be easily found that the maximum angular rate in the topocentric frame for a circular geosynchronous orbit is of the order of 10^{-5} rad/s. This is the threshold we have considered and, it allows us to filter out many false associations. In fact, this is a conservative threshold, that filters only true association with eccentricity above 0.1, as Fig. 6 suggests. Both figures have been obtained with a brute-force analysis of a realistic scenario of objects.

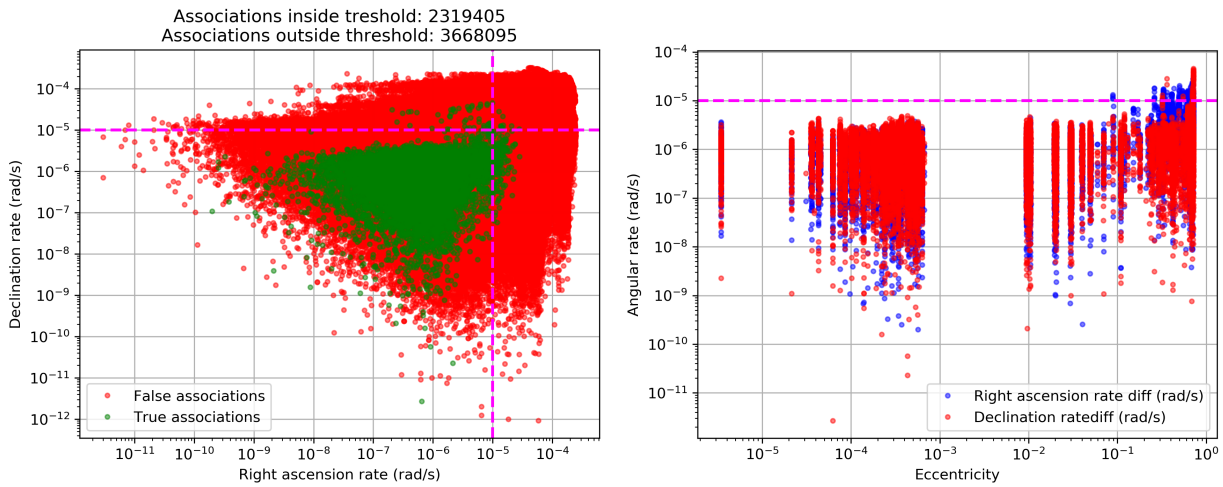

Fig. 6: Distribution of the angles rates differences of true associations (green) and false asociations (red) of two tracks (left). Distribution of the angles rates differences of true associations of two tracks as a function of the object eccentricity (right)

- **Estimated orbit difference criterion:** the difference between the most representative orbital elements, such as semi-major axis, eccentricity and orbital plane, is evaluated to avoid combining two associations that clearly belong to two very different orbits. Since the estimation of the orbit may not be accurate enough, particularly from associations two tracks, this criterion is not applied to associations of less than two tracks, and high enough threshold values are considered for associations of more tracks.

During the generation of new associations, it is important to retain traceability of the *parent associations*, those of $n-1$ tracks considered for the generation of the one of n tracks, in order to be able to reconstruct the **association tree**. Only by making use of this association tree it is possible to identify and discard false hypotheses in future association steps and stages.

The association clustering only generates new associations, it does not perform any further operation. Besides, it can be easily parallelized: each potential association can be independently considered and generated if the criteria are met.

3.2 Association Processing

The processing step performs first IOD with selected observations and secondly OD considering all the associated tracks. IOD algorithm makes use of the circular hypothesis and can be replaced by the solution of parent associations when the number of associated tracks is high enough, while OD algorithm consists in a **batch least-squares estimator**

that uses all available measurements to refine the initial solution. All measurements are simultaneously processed and the solution is obtained once an iterative method is performed over the associated tracks.

Although this step is the most demanding in terms of computational cost, it can be parallelized as each association can be independently processed.

3.3 Association Evaluation

The evaluation step assigns each association a figure of merit value that is used in posterior steps to determine whether the associated tracks correspond to the same object or not. This step uses data provided by the association processing step and it is also parallelizable.

3.4 Association Pruning

The pruning step removes associations not expected to belong to the same object, according to a figure of merit threshold value. The rationale behind this process is to discard those associations that are clearly false in order to avoid considering them later on in subsequent analyses. Otherwise, more false associations would be generated, leading to an increase of the overall computational cost.

3.5 Association Solver

The solver step is in charge of identifying those associations expected to belong to the same object, according to a user-defined limit in the figure of merit. It is based on the simple but efficient *Greedy Assignment Method (GAN)*.

First, candidate associations are selected and sorted according to their figure of merit. Second, the best association, in terms of figure of merit, is tagged as correlated. Those associations with at least one track in common with the correlated association (*incompatible associations*) are invalidated, since each track cannot belong to two different objects. This is a simple but robust approach to *Multiple Hypothesis Tracking (MHT)*, consisting in evaluating all possible combinations of assignments and following the tracks until they prove to be false hypotheses [12]. This procedure continues until all the candidates have been correlated or invalidated.

3.6 Association Combination

The combination step merges already correlated associations to avoid duplicated objects, i.e. two different correlated associations corresponding to the same object. The procedure consists in combining two already correlated associations into a new association that contains all the tracks from the involved associations. This association is re-processed and re-evaluated. If correlated, the two associations are replaced by the new combined association.

Since combination comprises pruning and evaluation, it can be parallelized as the corresponding association steps. This association step is not mandatory but optional, since the usual situation is that tracks are processed sequentially and given the high success rate of the method, objects are detected much before new tracks are processed.

3.7 Association Adoption

The adoption step adds tracks that could not been correlated to already correlated associations, when possible. A new association, containing the tracks of the already correlated association and the track to be adopted, is processed and evaluated. If the new association figure of merit is lower than the correlation threshold, the adoption is assumed successful, i.e. this association replaces the previous one and incompatible associations are identified and removed, as in the solver step. Otherwise, this new association is discarded.

This association step is not mandatory but optional, since the usual situation is that these remaining tracks are associated in the future when more tracks from the corresponding object are received.

3.8 Association Verification

This last association step processes correlated associations to confirm or discard already correlated associations. The purpose of this step is to detect any remaining false positive association that may have not be filtered out in the previous steps. The estimated orbit and covariance are then ready to be added to the catalogue. This final step is also demanding from the computational cost point of view but can be easily parallelized, since each association is completely independent from the others.

4. RESULTS

The track association methodology presented above has been analyzed in a simulated scenario of an optical survey sensor network. The location of the four optical sensors of the survey network is depicted in Fig. 7 and the measurements have been simulated assuming Gaussian noise of 1 arcsec sigma error. This sensor network is able to observe 806 objects, whose orbit spectrum is shown in in Fig. 8.

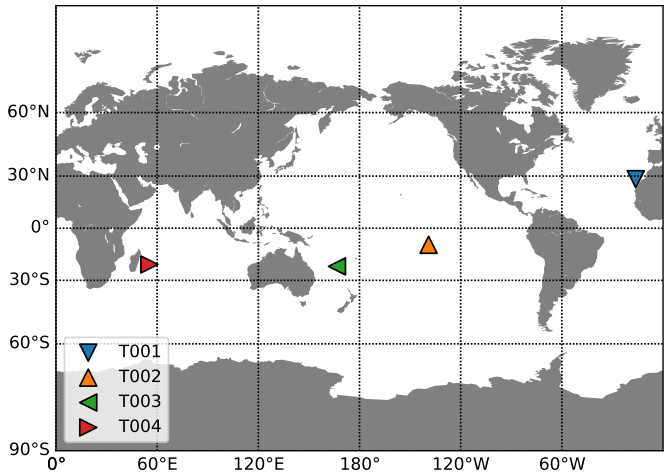

Fig. 7: Location of the optical sensor stations

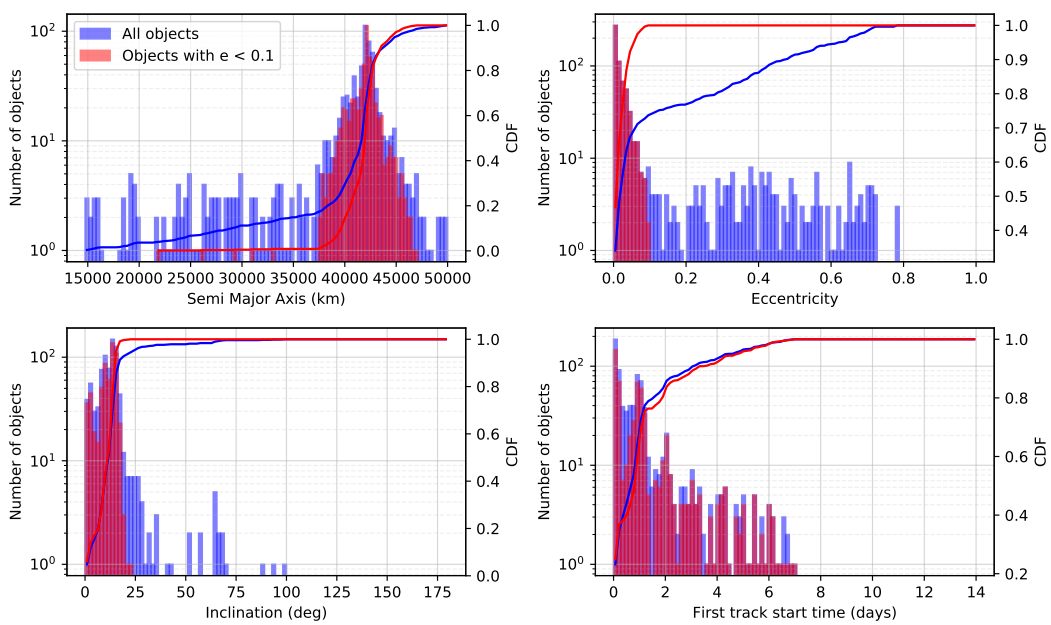

Fig. 8: Orbit spectrum of all simulated objects (blue) and those with eccentricity lower than 0.1 (red)

Furthermore, a very simple preliminary track-to-orbit simulator has been added to avoid processing more tracks from an object that has been already detected and cataloged. This allows us emulating a typical cataloguing process with a track-to-orbit correlation method.

The number of objects and tracks is presented in Table 1. From all the objects, we are interested in detecting those

with eccentricity lower than 0.1, i.e. 588 objects, and since we require at least 4 tracks to initialize an object in the catalogue, then the number of a-priori detectable objects is of 381.

	All objects		Objects with ecc <0.1	
Number of tracks	5549	*100%*	3556	*100%*
...from objects with at least 2 tracks	5489	*98.92%*	3506	*98.59%*
...from objects with at least 3 tracks	5263	*94.85%*	3302	*92.86%*
...from objects with at least 4 tracks	4938	*88.99%*	3019	*84.90%*
Number of objects	806	*100%*	588	*100%*
...with at least 2 tracks	752	*93.30%*	544	*92.52%*
...with at least 3 tracks	658	*81.64%*	461	*78.40%*
...with at least 4 tracks	565	*70.10%*	381	*64.80%*

Table 1: Number of tracks and objects in the simulated scenario

4.1 Correlation Performance

In terms of relevant correlation metrics, the results are presented in Table 2, which proves that the algorithm is able to provide excellent results for the circular objects detection problem, since most of the circular objects (98.95%) 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.

Correlation Metric	All objects		Objects with ecc <0.1	
Number of objects with enough tracks	565	*100.00%*	381	*100.00%*
True Positive Associations	428	*75.75%*	377	*98.95%*
False Positive Associations	2	*0.35%*	2	*0.52%*
Missed Objects	137	*24.25%*	4	*1.05%*

Table 2: Resulting correlation metrics. Relative values with respect to number of objects with enough tracks

From the point of view of the associations, Fig. 9 shows the distribution of the figure of merit from associations of four tracks along the semi-major axis, eccentricity and time span between associated tracks. Regarding the time span, Fig. 9 (top), the typical value is around three days. In principle, this is not due to any limitation of the figure of merit when evaluated for greater time spans but a mere consequence of the efficiency of the correlation process itself. Tracks are associated as they are available through time and therefore, less object detections are pending as time increases. In terms of both dependency with semi major axis and eccentricity, presented in Fig. 9 (middle) and Fig. 9 (bottom), the association density corresponds to the one of the population.

As previously stated during a preliminary brute-force simulation, less than four tracks are not enough to validate an association hypothesis. This can be notice in Fig. 10 (top) and Fig. 10 (bottom), where the true negative and false negative associations are not clearly isolated if associating two or three tracks.

In terms of objects, the distribution of the detected (i.e. true positive associations) and undetected (missed objects) is shown in Fig. 11 (left), with respect of semi-major axis, and Fig. 11 (right), with respect to eccentricity. Moreover, Fig. 12 shows the semi-major axis and eccentricity of the detected and undetected objects. Although the association processing step is focused on circular orbits, thanks to the capability of the OD method to solve the least-squares problem even when the initial solution, provided by the IOD methods, is far from the true solution, some objects with eccentricity greater than 0.1 can be detected. However, as stated before, our current target are nearly-circular objects.

The details of the false positives associations are presented in Table 3, where the estimated semi-major axis and eccentricity is shown, as well as the object identifier to which each associated track belongs. In both false positives, only one of the four tracks do not belong to the same object as the rest of associated tracks. The three objects involved in these false negative are describing similar orbits and their orbit observability is reduced.

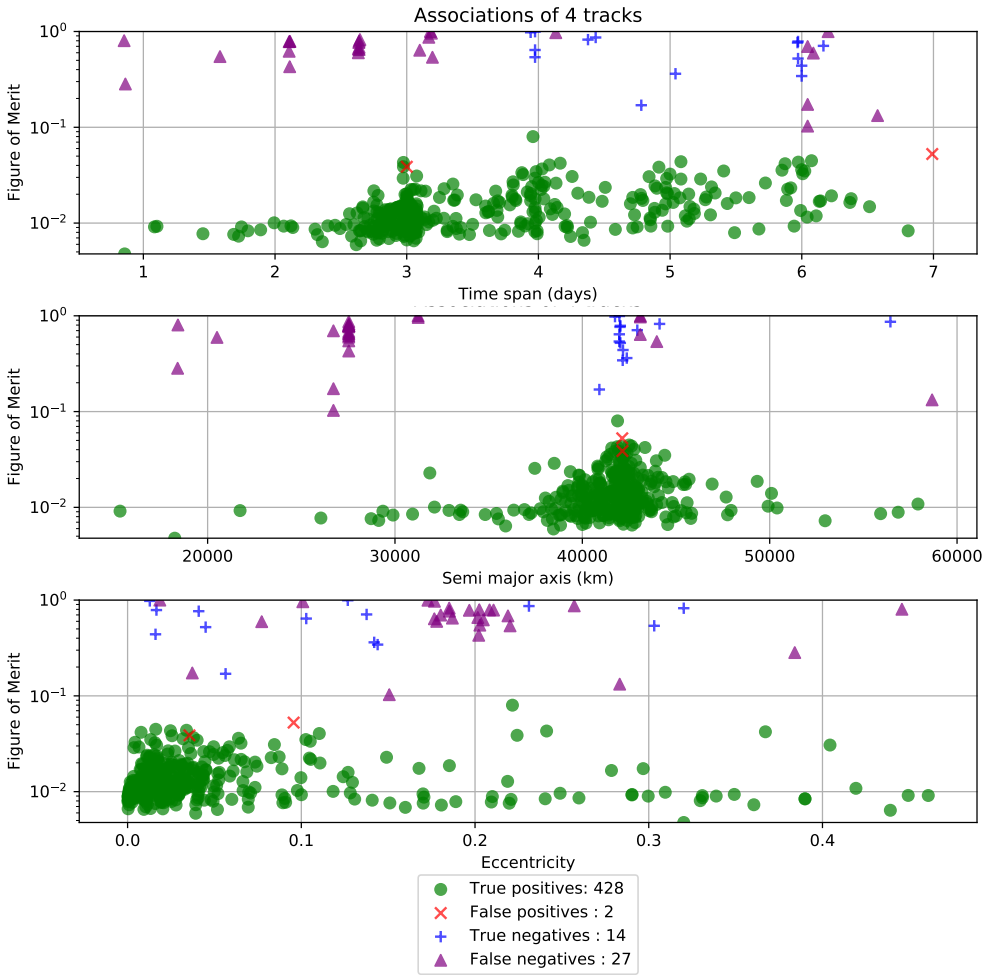

Fig. 9: Distribution of the figure of merit of associations of four tracks along the time span between tracks (top), semi-major axis (middle) and eccentricity (bottom)

Association ID	Semi-major axis (km)	Eccentricity	Object ID from associated tracks			
			Track #1	Track #2	Track #3	Track #4
40	42139.82698	0.035607	45287	45287	45287	24521
428	42131.06376	0.095575	45287	45287	45287	34174

Table 3: Details of the false positive associations

Missed objects, i.e. undetected, are mainly due to a combination of particular observability issues and low number of available tracks. The details of the 4 missed objects with eccentricity lower than 0.1 are presented in Table 4, where maximum observability refers to the maximum difference between the true anomaly of the object at the epoch of the different available observations.

4.2 Number of Associations

The evolution of the number of both uncorrelated and correlated associations along the track processing is shown in Fig. 13, where the number of tracks squared, n^2, is presented for reference. The number of uncorrelated associations grows with a slower rate than n^2, which would correspond to a brute-force approach. This growth rate decreases as more associations are generated thanks to the removal of incompatible associations.

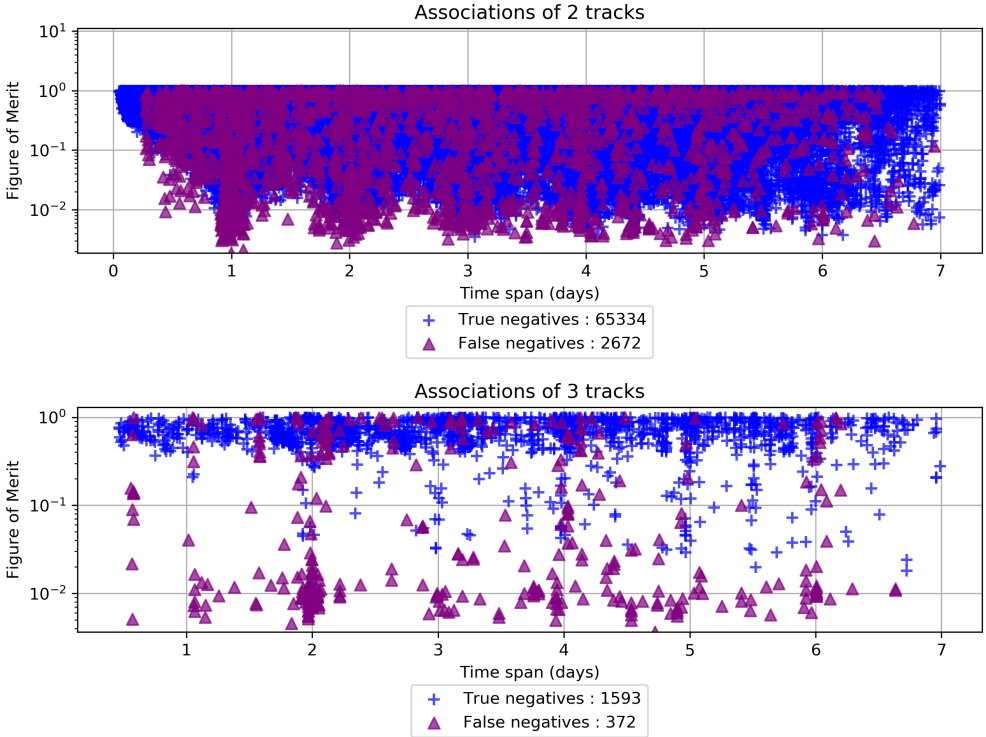

Fig. 10: Distribution of the figure of merit along the time span between tracks for associations of two tracks (top) and three tracks (bottom)

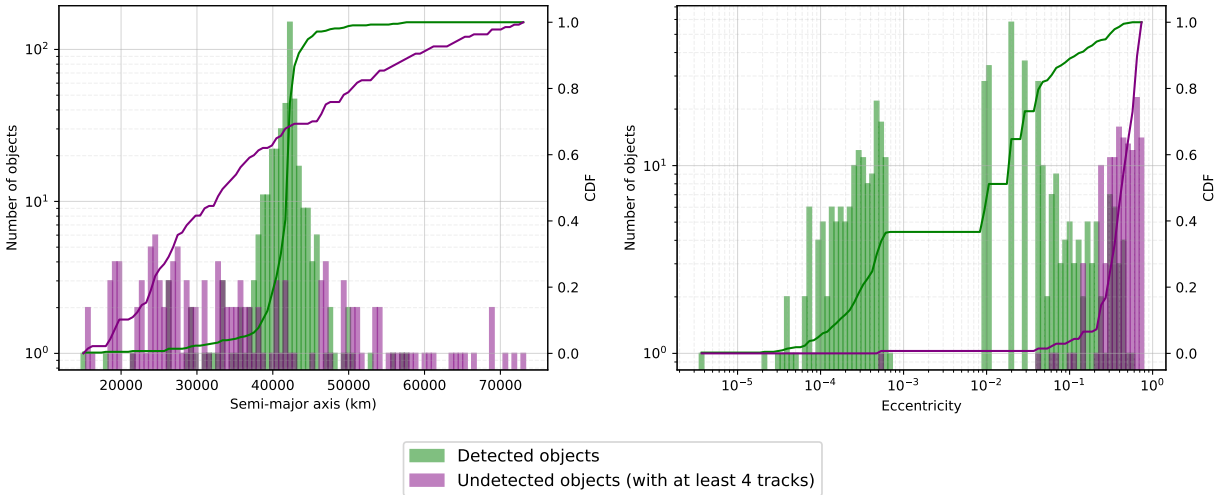

Fig. 11: Histogram of the detected (green) and undetected objects with at least 4 tracks (purple) with respect to the semi-major axis (left) and eccentricity (right)

4.3 Computation Time

The association algorithm is able to process the whole scenario in 2.5 hours by using 30 threads (Intel(R) Xeon(R) Gold 6142 CPU @ 2.60GHz). It is important to remark that these analyses correspond to a completely cold start from measurement data for an optical sensor network during one week. Therefore, it is clear that the algorithm is suitable for real-time processing.

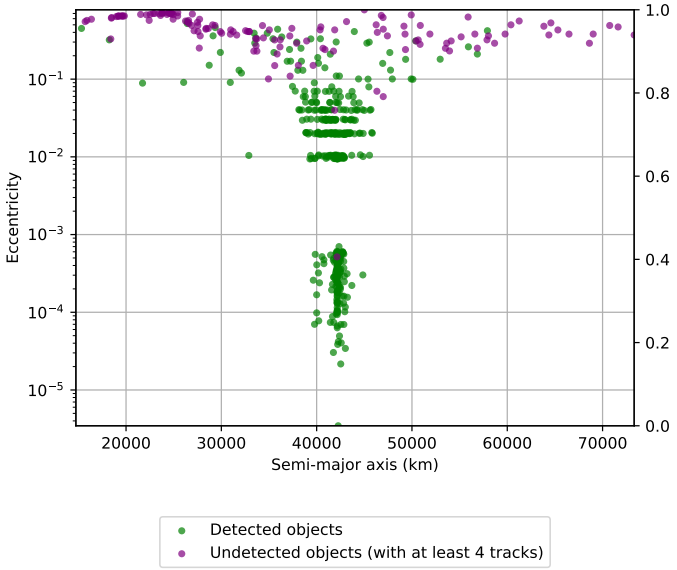

Fig. 12: Distribution of the detected (green) and undetected objects with at least 4 tracks (purple) along the semi-major axis and eccentricity

Object ID	Semi-major axis (km)	Eccentricity	Number of tracks	Maximum observability (deg)
45287	42136	0.00052	4	22.15
33556	46323	0.06982	4	6.62
40186	46986	0.05959	4	3.74
26232	41891	0.03975	4	4.1

Table 4: Details of the undetected objects. Semi-major axis and eccentricity correspond to average values

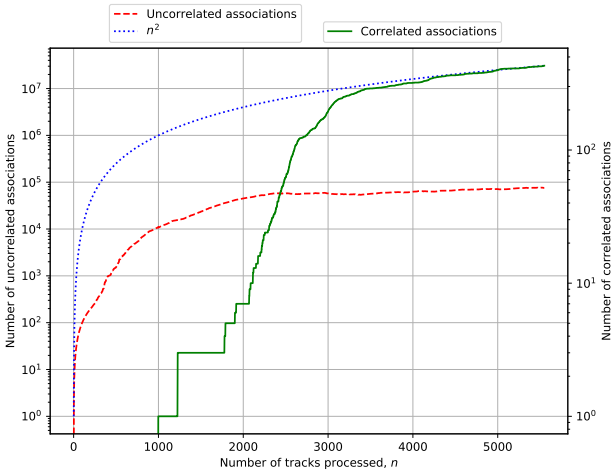

Fig. 13: Evolution of the number of uncorrelated associations (red, dashed), correlated associations (green) and number of tracks squared (blue, dotted)

5. CONCLUSIONS

This paper has presented the main features of a track association algorithm, able to detect new objects by ingesting optical measurements from a sensor network. The need of track association for the detection of new objects has been justified, and the importance of the number of associated tracks assessed. The methodology has been also successfully applied to radar survey measurements[13].

It has been shown how our methodology is applicable to detect almost all the objects describing nearly-circular orbits by associating tracks. The chosen figure of merit and complexity reduction techniques allow detecting most of the objects, corresponding the remaining ones to either very particular cases or objects with eccentricity higher than 0.1. The success rate is almost 99% and the false positive rate lower than 0.52%, while keeping the number of undetected objects low at the same time. This means that the proposed methodology is able to use efficiently most of the available information provided by the optical sensor network to build-up a catalogue of RSOs. Moreover, the orbit resulting from the association of the tracks is accurate enough for initializing an orbit in the catalogue and ensure correlation of future tracks to the new object through standard track-to-orbit methods.

This work is still under research and the paper focused on objects describing nearly-circular orbits. We are currently working on the extension of the methodology, able to detect also eccentric objects by following an analogous strategy. Once processed those tracks belonging to nearly-circular objects, the remaining tracks are processed with an alternative IOD method that does use the circular assumption. This method is a modified double-r iteration, more expensive than the previous one, reason why it should be only applied to a subset of tracks to avoid worsening the overall computation performance.

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