A Review of Data Correlation Methods for Space Surveillance

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Abstract

There are many algorithms that can be used for correlating observations to established orbits and to identify new space objects. A perfect assignment algorithm does not exist and a 100% perfect assignment is impossible. That leaves us with the task of choosing an algorithm that is "best" by one of several measures. Some of the basic correlation methods are reviewed here, with some discussion of advantages and disadvantages for each method. However, no recommendation can be made at this time for handling 100,000 object catalogs. We do recommend a way to choose the "best" algorithm using elements of the assignment process. Specifically the correlation processes of gating, miss-distance metrics, and Assignment Matrices are common to all algorithms and can be used together with simulations to characterize the assignment problem for 100,000 objects.

The Space Surveillance Assignment Problem

The backbone of space surveillance is the Space Catalog. The algorithms that are used to assign observations to orbits date to the late 1960's and early 1970's, when the catalog was sparse. A few changes have been made over the years (e.g. SGP4 replaced SGP), but the process is basically a single-assignment Greedy Method (which is defined below). There are several indications that the current assignment algorithm has difficulties with complex tracking scenarios, and as a result the catalog is not as robust as we would like. The assignment algorithm is known to cross-tag closely spaced objects, such as multiple payloads, the rocket body, and debris or shrouds, all from a single new launch. Further evidence is the many months it has taken to catalog the debris from the recent Chinese ASAT test, and failure to catalog a recent high eccentricity breakup.

Given plans to use more sensitive instruments to track and catalog 100,000-150,000 objects, there is a need to improve the assignment algorithms. Fear of the complexity of the problem has driven many to assume that new science is required and that only the most complex algorithms will solve the problem. However, no-one has really examined the problem from first principles to characterize the true complexity of the problem and thus derive the algorithmic requirements. It is not yet clear whether single hypothesis assignment is sufficient, or if multiple hypothesis approaches are necessary for catalog maintenance. It is certainly not clear that new science is required.

Terminology

A short review of terminology may be necessary, as the literature uses several terms interchangeably, which can be confusing. For example, the "correlation" process that results in the "assignment" of observations to an orbit is also called an "association process" or an "assignment process" and the software implementation is sometimes called a “tracker”. In the general literature the “observations” are assigned to a “track”; which is the ephemeris of the object. Sometimes a “track” is simply a short arc fit to a sequence of observations collected by one sensor and sometimes a “track” refers to the longer historical ephemeris. A “track state” is the instantaneous array of estimated position and velocity (or an equivalent set of 6 orbit parameters) plus ballistic coefficient, solar pressure coefficient, observation biases, mean radar cross section, mean visual magnitude and any other solve-for parameters that are used to solve the assignment problem. An “observation” is any set of “measurements” collected at a common epoch from one sensor to one target. For example, if measurements are range, azimuth, elevation, and range rate, then the corresponding “observation” is the set of the four measurements reported simultaneously. If a sequence of measurements is used to produce a short arc position and velocity “track”, then the track can be treated as a six-dimensional observation; it is advisable to also compute a covariance for a short arc track treated as a measurement. A “target” is any space-borne object observed by a sensor, not the target of a weapon system. A “sensor” is any measuring device, such as a single-spectrum or multiple-spectra telescope, radar, ladar, etc. A “frame” is the collection of all observations made within the sensor’s field of view or field of regard, such that they constitute a set of distinct objects, due to being seen separately and simultaneously[1]. Finally, if observations are assigned to a track and if the orbit determination algorithm uses the observations to update the track state, then we say the track is “extended”.

The Uncorrelated Track (UCT) Problem

The Uncorrelated Track (UCT) problem is defined as a collection of single-sensor tracks of unknown objects that do not correlate to any known object, nor correlate to any other uncorrelated track. UCTs are collected and maintained in a file for a long time, hoping for a later match to unravel the mystery. Of course other measurements, for known objects, may also end up in the UCT file, if they are not recognized by the real-time correlation algorithms. This is particularly true after a large maneuver or even a very large solar flare. So the UCT Problem involves a persistent UCT population which makes assignment more difficult, because the persistent UCTs mask the good observations that can be correlated.

The Marginally Detectable Target Problem

The Space Catalog is defined by the tracking data provided by a diverse collection of radar and optical sensors on a diverse set of targets and defined by a collection of orbit elements or state vectors on various targets. Very few of these sensors have the same capability; some can detect targets that others can not detect. This includes targets that have significant optical signature, but very low radar cross section, and it includes small targets that are detectable to some radars, but not to others. It also includes a difficult set of targets that present variable cross sections such as small tumbling fragments, such that the targets can be tracked only when the aspect angle is favorable.

We’ll refer to these difficult targets as Marginally Detectable Targets (MDTs). MDTs are tracked less often than larger targets due to cross-section issues, so the correlation process must contend with larger gaps in the data and orbit determination must work

[1] Simultaneity is not strictly required, for example all targets found in one 360° sweep of a scanning radar could constitute a “frame”, if no target is fast enough to be in two parts of a scan.

across longer fit intervals. The key to maintaining orbits for the MDTs may not be the correlation algorithm, but in the orbit prediction algorithm, allowing better prediction accuracy across long data gaps.

It is reasonable to assume that a majority of the UCTs are also MDTs. It is also reasonable to conclude that MDTs will always be a source of UCTs, regardless of the sensor or the assignment algorithm used.

Sensor Tasking Complexities

The way that space surveillance sensors are used complicates the assignment process and handling of MDTs. In many surveillance systems all detected targets are reported to the correlation algorithms, and if a target is not detected, then the correlator can use that fact to make decisions about the target's detectability or the track's reliability. In space surveillance for 100,000 objects, however, it may not be practical to report all detections; the sheer volume of data would require a very large computer farm. This leads to a "track-but-do-not-report" strategy, where the reporting rate is set by policy, and the policy is set without regard to the real-time accuracy or reliability of the target orbit. In this case the sensor will only report on certain overflight opportunities, and simply confirm, but not report, the detected target for any other opportunities.

Observation Tagging Issues

Observation assignment methods often rely on the sensors to tag distinct detections with distinct IDs. This aids in counting the number of targets in a frame and in setting up the data indices for more complicated correlation methods. Unfortunately radar and optical sites do not always tag distinct observations with distinct tracking IDs. These problems can arise because of policy and operator procedures and observations on multiple targets can be assigned the same tracking ID by the site operator or software.

This problem generates a requirement for the centralized correlation algorithm to detect distinct targets without relying on the site-assigned target IDs, which complicates the assignment problem unnecessarily.

One remedy is to allow tracking data to have two IDs, one for the object identified by the site operator or computer and another for reporting a distinct target among concurrently tracked targets.

Difficult Operational Arena

Observation assignment will take place in an operational arena that includes a complex set of target tactics and events, minimally including the following active events:

1. Maneuvers
2. Mother-daughter deployment
3. Proximity operations
4. Formation flying
5. ASAT events
6. Rendezvous
7. Docking and undocking
8. Rephase constellation
9. Breakups
10. New launches

Objects, which use these tactics or suffer these events, are the most critical targets for space surveillance, those that may pose the greatest risk to other objects. Failure to assign observations properly for these tactics and events can result in the object going "lost" or, if it is "found", its identity will be unknown. A Space Catalog assignment algorithm that correctly assigns 100% of all ***inactive*** targets, but fails for any significant number of ***active*** targets, is unacceptable.

Fundamental Tracker Components

We will focus on some basic components to the "tracker": gates, a distance metric, and an assignment matrix. The first two are shown in Figure 1, below, where $\times$'s are the residuals from the new measurements over a prediction interval:

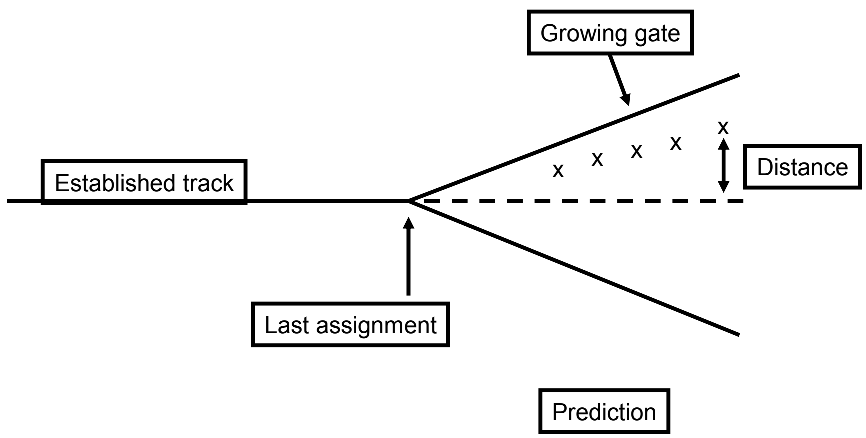

Figure 1 Basic Elements of a "Tracker"

The gate established a boundary beyond which data correlation is highly unlikely. A simple construct is usually used for a gate so that real possibilities can be quickly identified. The distance metric can be as simple as a residual or quite complicated, as discussed below. In any case the distance metric is critical to the assignment process.

We seek a metric where multiple residuals in different dimensions in different units can be converted to a common scalar metric, which simplifies the assignment process. We also seek a metric that reflects the likely error in the orbit.

A Simple Scalar Distance Metric

Correlation algorithms generally reduce all measurements on one target, collected at an instance, to a single scalar metric. A typical unitless scalar metric d can be formed by the array of measurements that make up the residuals:

$$d^2 = Y^T C^{-1} Y$$

where

$$Y^T = \begin{bmatrix} \Delta M_1 & \Delta M_2 & \cdots & \Delta M_N \end{bmatrix}$$

is the residual array and

$$C = HPH^T + R$$

is the track covariance P projected into residual directions by the Jacobian H and R is the covariance matrix of measurement white noise

Note that P should be a realistic[2] characterization of all uncertainties, including position and velocity and relevant biases. In this way the scalar metric can provide a complete characterization of the orbit error, bias error, and measurement residuals.

Other Distance Metrics

There are many possible metrics and many are extensions of the simple metric given above. For example, consider the problem where a target is marginally detectable, it is possible to scale the metric with a function of the probability of detection and / or the probability of false alarm:

$$d^2 = Y^T C^{-1} Y * F(p_D, p_{FA})$$

Similarly, if the covariance is very large (a very poorly known track) this simple distance metric can be artificially small and the poor track can "steal" tracking data from a good track. A classical way to compensate for large covariances is to modify the metric by the log of the determinant of the covariance:

$$d^2 = Y^T C^{-1} Y + \ln(|C|)$$

Finally, if a sequence of observations is processed to construct a 6-parameter position and velocity estimate (X), then the covariance on X can be used to define a scalar metric:

$$d^2 = Y(X)^T P_{Y(X)}^{-1} Y(X)$$

Y(X) can be any representation of the differences, perhaps in orbital elements or some other suitable frame.

The Assignment Matrix

The assignment matrix is a construction of known tracks and detected observations; it is non-trivial when there are closely spaced objects. For example, consider the case where a sensor detects three objects and has three established tracks to work with, as in Figure 2 below:

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[2] A realistic covariance is required to make this formulation of the miss-distance metric to work properly. "How realistic" is not a matter of debate. Generally one or two significant digits of accuracy is sufficient for correlation. A realistic covariance is achievable, if one abandons least squares orbit determination for a sequential filter, and then properly implements process noise models derived from errors physical errors.

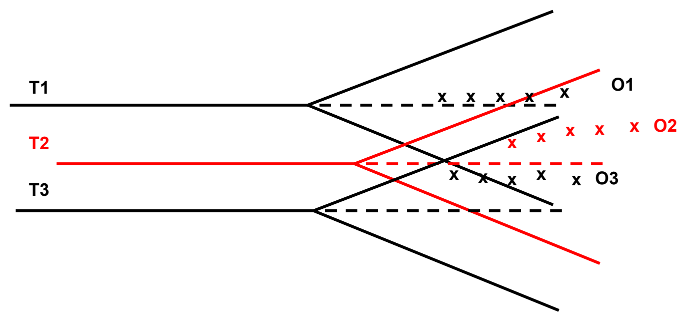

Figure 2 Three Tracks Competing For Observations

Formally, the process of assigning observations to closely spaced tracks is represented by a matrix of distances, where the distance metric for each pair-wise combination of track and observations is listed. Then the rules for observation assignment are applied. Table 1 was generated to represent the situation in Figure 2 at an instant (or for one "frame")[3]. The distance values are invented for illustration, but approximate the situation graphed.

	O1	O2	O3
T1	2	4	8
T2	8	5	3
T3	14	10	7

Table 1 Assignment Matrix for Figure 2

This is a classical Assignment Matrix, and it is the basis for all assignment algorithms, whether it is formally constructed or not. If the metric includes a realistic covariance for the track, as defined above, then this assignment table completely characterizes the instantaneous decision problem, a fact we will refer to later.

[3] A "frame" is the collection of all observations made within the sensor's field of view (F.O.V.) or field of regard (F.O.R.), such that they constitute a set of distinct objects, due to being seen separately and simultaneously, or at least within one unique scan of the F.O.R. of the sensor.

Three Assignment Methods

The purpose of this discussion is to expose strengths and weaknesses of three classical assignment algorithms, so that we can make an informed decision when specifying an improved tracker for an improved Space Catalog.

Many references can be found in the tracking literature to the three assignment methods described below. The first two, the Greedy Method and the Global Nearest Neighbor method, are basic "text-book" solutions, widely used, easy to understand, easy to implement, and therefore the first choice for many applications. Both of these algorithms assign one observation to just one track, seeking to make the best assignment possible. The Greedy Method can misassign observations when objects are closely spaced and both of these algorithms can misassign observations when observations are missing (MDTs are present). The third algorithm is the Multiple Hypothesis method; it is also a "text-book" method, characterized as a brute-force, "keep all possibilities" approach that guarantees that the correct solution is maintained, albeit at a cost of keeping a lot of feasible-but-incorrect solutions too. A Multiple Hypothesis algorithm can assign the same observation to multiple tracks.

The Greedy Assignment Method

The "Greedy Method" of observation-to-track assignment is exactly as it sounds. Given a metric to define the "distance" between the track and the observation, the track with the smallest distance wins the assignment without regard for the benefit to or penalty on other tracks. An observation is assigned to one and only one track. This is the simplest assignment algorithm with the smallest computational burden.

Formally, the process of assigning observations to closely spaced tracks is represented by a matrix of distances, called the Assignment Matrix, where the distance metric for each pair-wise combination of track and observations is listed. Then the rules for observation assignment are applied. The following table was generated to represent the situation in Figure 2. The distance values are invented for illustration, but approximate the situation graphed.

	O1	O2	O3
T1	2	4	8
T2	8	5	3
T3	14	10	7

Table 2 Greedy Algorithm Assignment Matrix for Figure 2

The Greedy Method would assign each of the observation sequences to the tracks that have the best distance as indicated in red. O1 will be correctly assigned, but O2 and O3 would be misassigned and T3 would erroneously go without any new observations. As a consequence the orbit determination for T1 will probably suffer a high level of data rejection and be flagged for manual attention. An analyst would be required to sort out the mess. Further T2 will probably continue to steal future T3 observations and T3 might go "lost" or might "adopt" subsequently-detected T2 observations, in which case T2 and T3 will swap identities.

This demonstrates why Greedy Method assignment algorithms used in the current Space Catalog have difficulties with closely spaced objects.

The Global Nearest Neighbor Assignment Method

The next simplest track assignment algorithm is called the Global Nearest Neighbor (GNN). Given the matrix in Table 2, this method seeks to choose an overall (global) assignment that minimizes the sum of the distances (also called the "lowest cost" solution), while assigning obviously distinct observations to distinct tracks. In this case the lowest cost solution (total = 14) is given by the red entries in Table 3:

	O1	O2	O3
T1	2	4	8
T2	8	5	3
T3	14	10	7

Table 3 GNN Assignment Matrix for Figure 2

The GNN algorithm would assign each of the observation sequences to the tracks correctly, since the lowest total score would be achieved with T2 choosing the second best observation sequence. If all objects are always detectable, the GNN algorithm is a fairly robust tracking algorithm.

But GNN can make serious misassignments if O2 is not observed (O2 is a MDT and that column is blank). In this case the minimum cost (sum = 5) incorrectly assigns O3 to T2. This illustrates a weakness in the GNN method.

If targets are widely spaced and there are no alternative assignments to consider, then the assignment matrix is trivial and the GNN method is the same as the Greedy Method.

GNN methods would improve Space Catalog reliability for closely spaced detectable targets, whether it is sufficient for 100,000 objects remains to be seen.

Evaluating the GNN Assignment Matrix

It should be pointed out that there are computationally efficient text-book methods for evaluating the assignment table to find the minimum cost. A brute force search of the assignment matrix requires approximately N^4 operations.

In 1957 James R. Munkres[2] applied a method of steepest descent and reduced the processing requirement to roughly N^3 calculations. The Munkres method is an optimal method in the sense that it always finds the absolute minimum cost.

Several developments converged in 1992 to create a new approach, called the JVC. Principle contributors were Jonker and Volgenant[3] (1987) and Castanon[4] (1992). The JVC method employs a mathematical technique called "relaxation" to reduce the problem and then follows that with Munkres method applied to the reduced problem. Relaxation is a method of finding a minimum cost for a constrained search (constraints couched as inequalities) over a bounded range. Relaxation is a useful tool for integer, mixed integer, large scale, and non-linear programming applications[12]. The JVC algorithm has been used extensively in assignment problems for the past 15 years. It does not guarantee optimality, but it always converges to something very close to the optimal solution. More importantly the JVC algorithm is faster than Munkres method and has replaced Munkres in most recent applications.

Higher order search, optimization, and relaxation algorithms abound in books and journals for mathematics, signal processing, etc. When choosing higher order algorithms the question is whether they provide a "better" solution or provide a solution at lower computational cost.

Multiple Hypothesis Assignment Method

Multiple Hypothesis assignment is a "brute force" algorithm that is designed to keep all possible combinations of assignments and follow the tracks until they prove to be false hypotheses. Revisit Figure 2:

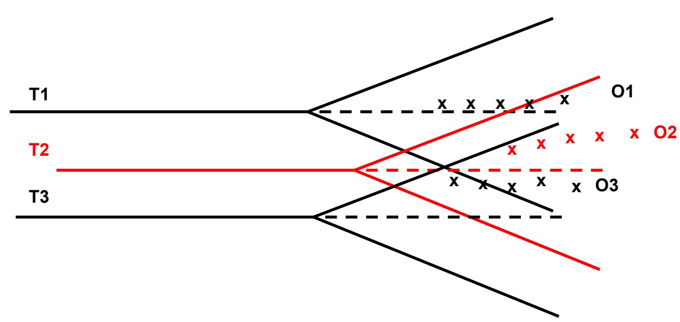

Figure 3 Three Tracks Competing For Observations

A Multiple Hypothesis assignment will result in a growing number of tracks when there are multiple feasible possibilities, as in Figure 4, below:

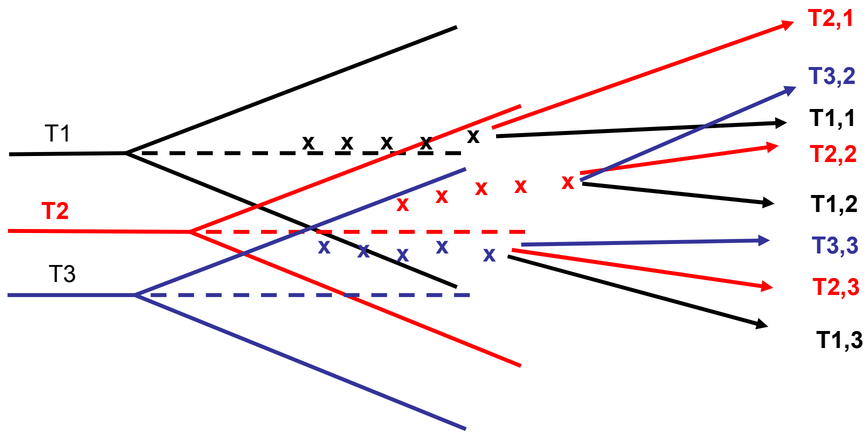

Figure 4 Multiple Hypotheses for 3x3 Problem

The matrix can become more complicated if there are new targets detected, because all possibilities have to be accounted for. Then you have new potential hypotheses formed by each observation sequence.

It is fairly obvious that MHT is a "brute force" approach and the creation of an ever increasing number of hypotheses will soon swamp any computer architecture. Hence, a method of "pruning" unlikely tracks becomes critically important.

Pruning decisions based on whether the object is subsequently detected and confirmed are fairly standard. However one has to be sure that an attempt was made to track the target before declaring a failure of the hypothesis. If the sensor is a continuously operating "fence" and reports all detections, then the pruning algorithm simply waits passively for confirmation of a hypothesis, while maintaining a count of the number of expected fence penetrations. On the other hand, most sensors only track a target if expressly directed to do so (or "tasked" to track the target), in which case it is necessary to direct the sensors to track each hypothesis, which will increase the work load for each sensor substantially.

In summary, MHT is a "brute force" technique, keeping all feasible hypotheses until they prove to be false. The advantage to MHT techniques is that the correct assignment is almost always made. The disadvantages are in the potential multiplicity of false assignments that are made and the potential impact to computer resources and to sensor resources. Clearly we only want to invoke MHT methods if there is a substantial performance improvement over the simpler techniques.

How to Select an Assignment Algorithm

For the space surveillance problem with 100,000 or even 150,000 objects, we need to choose an observation correlation algorithm. We are fairly sure that the Greedy Method is insufficient, especially for closely spaced targets, since it has proven to be insufficient for 18,000 objects. There is a great temptation to choose the most complex algorithm, the MHT, because of the apparent complexity of the problem. However, the potential cost of MHT also creates a great temptation to avoid MHT.

We will not make a recommendation at this time between single assignment methods or multiple hypothesis methods.

A thorough analysis of the correlation problem for 100,000 – 150,000 objects has not been performed. Although the total size of the Space Catalog will be large, there is no evidence yet for how much that will translate into observation misassignments. Due to the apparent complexity of the problem, users fear that an Assignment Matrix might be very complicated, for example:

	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	O12	O13	O14
T1	40	55	5	20	58	79	23	35	44	68	99	74	89	45
T2	1	54	6	34	200	109	56	10	57	67	52	58	14	98
T3	87	11	88	10	9	8	7	564	39	46	6	5	4	97
T4	92	56	8	12	45	2	87	15	54	456	12	48	49	98
T5	96	234	76	345	457	43	5	1	435	34	33	46	52	26
T6	34	56	36	92	47	67	45	23	3	567	4	454	67	2
T7	54	37	94	93	37	291	89	478	2	59	33	83	84	66
T8	8	18	76	49	53	67	102	57	88	59	7	86	11	88
T9	98	76	11	78	9	50	60	70	80	8	90	99	68	97
T10	57	69	4	97	2	77	88	96	44	86	57	84	48	88
T11	94	64	88	56	78	8	45	54	55	95	66	12	69	96
T12	59	77	68	94	68	5	54	69	38	15	74	69	56	38
T13	78	89	54	58	67	3	46	6	61	78	8	57	9	83
T14	48	84	57	75	89	98	76	66	98	48	68	76	54	5

Table 4 Notional Complex 15×15 Assignment Matrix

Even when there are a large number of targets simultaneously in the Field of Regard of a sensor, they may still be separated sufficiently to make many combinations unlikely (grey squares), which will reduce the complexity to the point where GNN methods might work well:

	O1	O2	O3	O4	O5	O6	O7	O8	O9	O10	O11	O12	O13	O14
T1			5	20										
T2	1		6					10					14	
T3		11		10	9	8	7				6	5	4	
T4			8	12		2		15			12			
T5							5	1						
T6									3		4			2
T7									2					
T8	8	18									7		11	
T9			11		9					8				
T10			4		2									
T11						8						12		
T12						5				15				
T13						3		6			8		9	
T14														5

Table 5 Notional Simplified Assignment Matrix

We recommend that we first quantify the problem and justify selection or rejection of single assignment or multiple hypothesis methods. The approach is to determine the failure rate for single assignment algorithms. The Assignment Matrix will be constructed at regular intervals for each sensor for a large scale simulated catalog. If we simulate the satellite population, consistent with current ESA or NASA population models, include such effects as variable cross-section of targets, and simulate sensor Field of Regard, Field of View, and detection thresholds of each sensor, then we can construct a reasonable time history of all targets versus all sensors.

The assignment matrix completely characterizes the correlation problem at any time, and knowledge of Truth allows us to measure the misassignment rate for any algorithm. A time history of Assignment Matrices can be used to develop a large statistical sample of frequency of misassignment, lost tracks, and MDT issues. It may also be useful to examine sequences of Assignment Matrices to determine if a misassignment of one observation is rectified in subsequent frames. That could lead to a modification of the GNN method to consider multiple frames before making a single assignment decision.

Ultimately the failure rate of GNN methods will determine whether MHT methods are required.

Final Remarks

The prospect of correlating observations to a 100,000 or 150,000-object catalog has frightened some analysts and there has been some discussion about adopting the most complex correlation methods without evaluating the problem from first principles. There has even been discussion about "new science" being required to perform this correlation correctly. We do not believe this problem to be that difficult, and encourage a methodical approach as outlined above. We should define the correlation failure rate for 100,000 objects using the Assignment Matrices to drive our algorithm selection process.

Finally, although we have not done the analysis and have not selected an algorithm, we would be surprised if MHT methods are required to maintain a 100,000-object catalog. MHT methods might be required to initialize such a catalog, to start with the current 18,000 objects and add 80,000 to 120,000 new objects overnight. But MHT may not be required to maintain the larger catalog.

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