Multi-Hypothesis Tracking of Space Objects and Targets

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Abstract

As thousands of satellites are launched each year, tracking the location of objects in space for collision avoidance has become critical. In this work, we develop a new multi-hypothesis tracking algorithm with a novel χ^2-based track scoring metric for tracking objects in a cluttered environment. We find that our method can overcome several challenging scenarios in multi-object tracking.

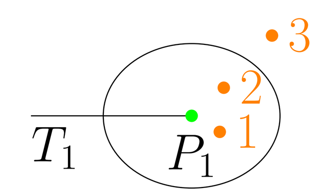
Introduction

Figure 1:GPS satellite (courtesy: The Aerospace Corporation)

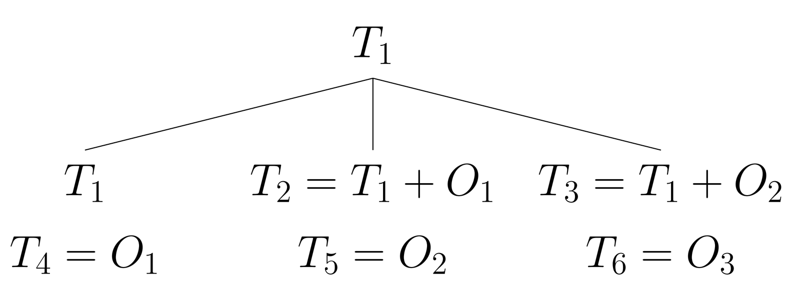
- Thousands of satellites are launched each year, including projects like Starlink internet service.
- To prevent destructive collisions between satellites and space objects, the locations of all objects in Earth's orbit must be tracked.
- The Kalman filter combines measurements from radar and telescopes with knowledge about the object's movement (orbital dynamics).
- However, tracking multiple objects is challenging, because new objects can appear or disappear, and some measurements may be false alarms.
- **Multi-hypothesis tracking** (MHT) is a deferred decision approach to tracking multiple objects in which multiple observation-to-target (O2T) matching possibilities are maintained.
- Since MHT techniques are not well-developed, we evaluate a new method via simulation study.

MHT Algorithm

1. Scan & gate measurements. Eliminate some O2T matchings based on distance, for efficiency.



2. Track creation. Create new tracks for O2T and new object possibilities.

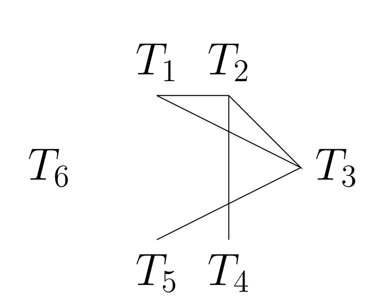


3. Chi-squared track scoring. Find the probability that the measurements seen were generated supposing that predicted trajectory is the truth.

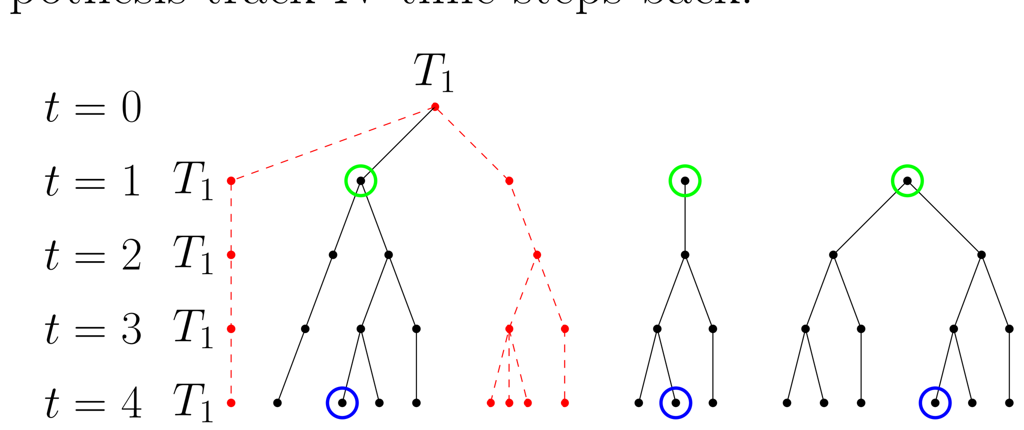
$$\chi^2 = \frac{(n-1)s^2}{\sigma^2}$$

$$s^2 = \text{observed variance in measurements}$$
$$\sigma^2 = \text{expected variance in measurements}$$

4. Hypothesis determination. Form a graph where the nodes are tracks and edges denote incompatibility (sharing measurements). Use the maximum weight independent set algorithm to find best hypothesis.



5. N-scan pruning. Delete any track that doesn't originate from the same track as a best hypothesis track N time steps back.



6. Filter update. Use the Kalman filter to generate predictions for the next time step.

Results

We ran several difficult tracking scenarios with the following simulation parameters: process noise, measurement noise, proportion of measurements that are missed, and average number of false alarms.

Intersecting Paths: When the pruning parameter $N = 0$, the algorithm tends to confuse objects when they intersect.

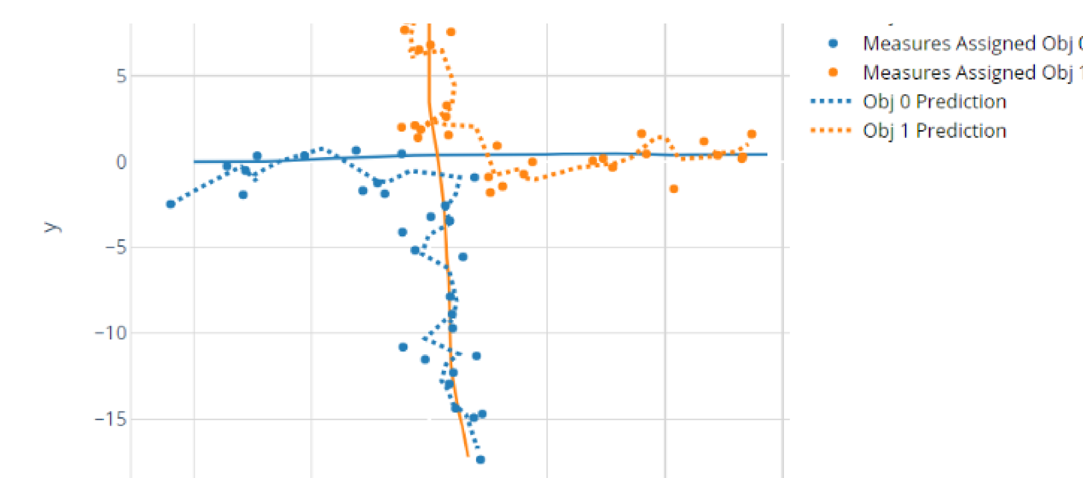


Figure 2:0-scan pruning (single-hypothesis tracking)

However, when $N = 5$, performance is improved.

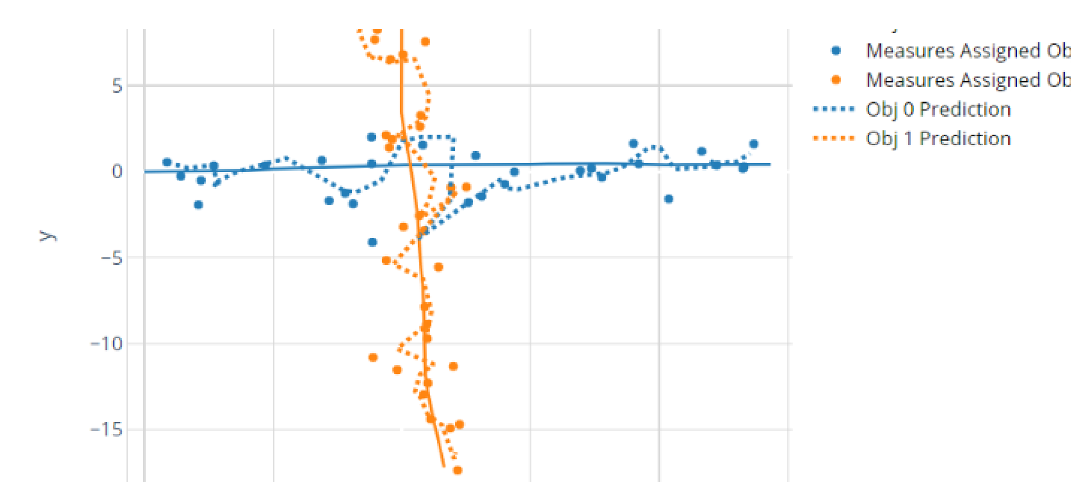


Figure 3:Intersecting paths with $N = 5$

Parallel Paths: When looking at the best hypothesis, the algorithm does a fair job of keeping the objects separate, even with false alarms.

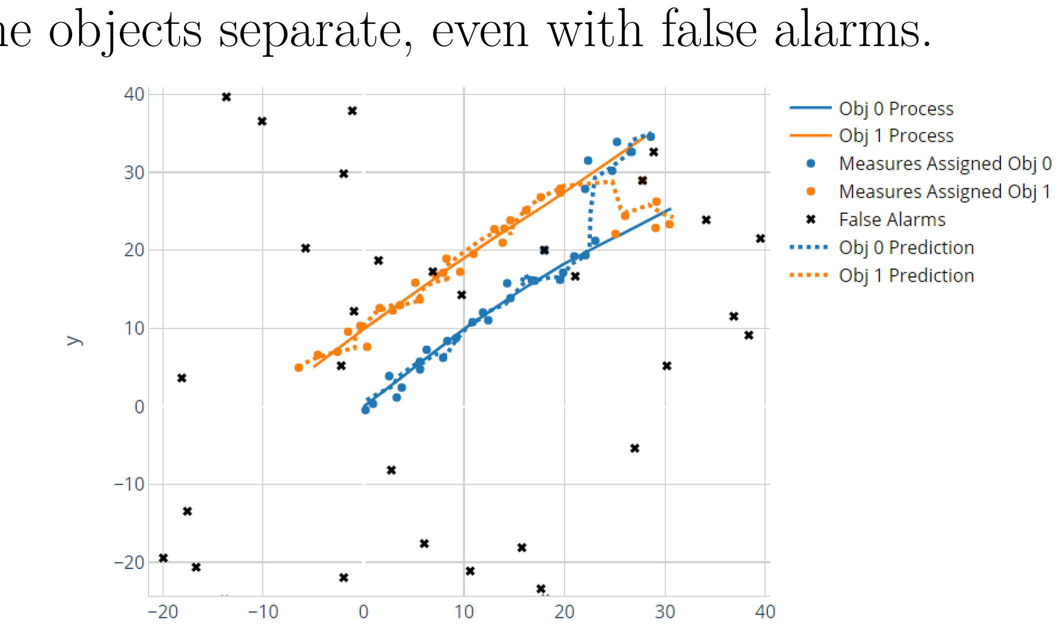


Figure 4:Parallel objects and false alarms

Discussion

In this project, we empirically tested the strengths and weaknesses of the MHT algorithm.

Strengths:

- Resolves uncertain paths
- Performs well in divergent cases
- Is able to detect object births relatively well

Weaknesses:

- Difficult to score scenarios with missed measurements (especially in parallel)
- Excessive track creation in object birth/death
- Computational issues

Future Research:

- Score hypotheses rather than individual tracks
- Develop new hypothesis computation algorithm to leverage probabilities
- Add additional error metrics; rates for false alarms, object swaps, etc

References

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