EFFICIENT OBJECT MANEUVER CHARACTERIZATION FOR SPACE SITUATIONAL AWARENESS

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ABSTRACT

As the number of objects in space increase exponentially, the need for Space Situational Awareness (SSA) to protect assets from environmental dangers (such as collisions) increases as well. SSA may become a “big data” problem due to the prevalence of low-cost small satellites and proliferation of debris. Additionally, there are multiple, uncoordinated, space observation systems collecting data at varying cadences to create datasets that grow in proportion to the number of telescopes and other sensors. While these datasets are large, they are not persistent or conditioned and are frequently noisy, which makes it challenging to maintain a satellite’s chain of custody and detect out-of-class maneuvers in a timely manner.

Although many SSA operations remain a manual process, Aptima, in partnership with the Air Force Research Labs Space Vehicles Directorate (AFRL/RV), has developed automated satellite maneuver prediction algorithms that learn a satellite’s pattern of life (PoL) and predict when and where future maneuvers will occur. The objective is to incorporate spatio-temporal and relational context to identify maneuvers that are inconsistent with expected, nominal operations. In turn, this approach enables accurate prediction of future states and the rapid identification of deviations from expected behaviors, even in non-persistent environments.

To achieve this, we adapted computationally efficient machine learning algorithms that we originally developed for Activity Based Intelligence (ABI) capabilities in the land, sea and air domains. We have demonstrated high accuracy of probabilistically predicting maneuvers of the Galaxy 15 (NORAD ID: 28884) satellite on noisy, intermittent synthetic datasets. Early results indicate accurate prediction of future maneuvers from a short time history of past observations and lay the groundwork for applications in UCT association, dynamic sensor tasking and patterns of life analysis.

MOTIVATION

A space operations tradecraft consisting of *detect-track-characterize-catalog* is insufficient for maintaining Space Situational Awareness (SSA) as space becomes increasingly congested and contested. Space analysts at the Joint Space Operations Center (JSpOC) need to know where an object will be in the future, what its intent is and what relationships it has to other Resident Space Objects (RSOs). Within the Geospatial-Intelligence (GEOINT) community, Activity Based Intelligence (ABI; Long, 2013) has gained traction for moving away from analyzing features (e.g. individual object tracks). Instead, ABI incorporates context to infer the longer-term, wider ranging activity that an object is engaged in. While ABI has not been widely adopted by the space community; it is a natural fit to address the many of the shared challenges of efficiently processing the variety, veracity and volume of data. Accordingly, in the recent Intelligence Community World Wide Threat Assessment, the Director of National Intelligence, the Honorable James Clapper, has challenged the space community to look outside the domain to seek innovative solutions to SSA (Clapper, 2016).

In this paper, we answer this challenge by applying ABI methodology to a key challenge in SSA: *predicting where and when a satellite may maneuver*. Drawing from approaches in ABI, we seek to probabilistically characterize Patterns of Life (PoL) for the Galaxy 15 Wide Area Augmentation System (WAAS) satellite. PoL are repeatable, predictable behaviors that an object exhibits within a context and is driven by spatio-temporal, relational, environmental and physical constraints. For instance, a satellite's PoL will be determined by its physical properties, orbital dynamics, time of year, and proximity to other Resident Space Objects (RSO), among other Keplerian and non-Keplerian factors. Unexpected dynamic events can be rapidly learned and acted upon once the normal behaviors of an object are understood. While much previous research in PoL has been applied to the land, sea and air domains; space is very well suited to PoL analysis. PoL in space, perhaps even more than in land and sea, are highly normalized based on physics and fuel margins. While shipping corridors and road networks constrain PoL in the maritime and land domains, objects exhibit a higher degree of variability in behavior than possible in space. This is particularly true for satellites in geo-synchronous orbits (GEO) which maintain a narrowly-defined position over earth. Station-keeping maneuvers become generally predictable as the satellite re-positions itself to account for orbital perturbations caused by non-uniform gravitational pull, radiation pressure and atmospheric drag. Therefore, in this paper, we extend previous PoL research to a satellite in GEO by adapting the land/sea-based data elements and physical models to space.

PROBLEM

Modern I&W must predict where and when an unanticipated dynamic event, such as a satellite maneuver, will occur with enough advanced notice to execute a course of action. One particular challenge for the tracking community are high area-to-mass ratio (HAMR) objects. HAMR objects tend to be bits of multi-layer insulation (MLI) that broke off a parent object and drifted into a new, eccentric orbit due to the influence of Solar Radiation Pressure (SRP) (Bradley and Axelrod, 2014). This makes HAMR objects difficult to track and propagate which might provide the opportunity to obscure maneuvers of satellites in close proximity.

Another key challenge in SSA is intermittent coverage of objects that leave "blind" periods during which purposeful maneuvers can go undetected. Geographical, geo-political, and ground-based observation resource limitations all contribute to this challenge. Additionally, there are space-based space surveillance (SBSS) constellations, which provide greater periods of observance, but they are an expensive resource and often require special access to use their data. Therefore, given the limited resources and the potential for unanticipated maneuvers, it is possible to have periods when even high value objects are not observed (Abbott and Wallace, 2007).

Given the challenges of persistent observance, HAMR objects and sheer volume of data, the problem comes down to this: *how do we know a satellite may maneuver if we cannot observe it?* We seek to answer this question by predicting a satellites future maneuvers based on its previous ones. Using only astrometric data in the form of Right Ascension and Declination, we establish a satellite's Patterns of Life (PoL) by finding correlations between maneuvers and temporal intervals. Then, using these patterns we can predict the next maneuver and quickly identify when deviations from this pattern happen. *Deviations are not necessarily threats, but they are unexpected behaviors which can be flagged for space operators to analyze as an early stage of a threat warning and assessment (TWA) system.*

APPROACH

To achieve maneuver prediction, we developed a novel, unsupervised machine learning algorithm, the Interval Similarity Model (ISM). ISM effectively calculates the probability that a satellite is executing a pattern of maneuvers that are similar to historical Patterns of Life (PoL). Inspired by similarity-based clustering (Balcan et al, 2008), ISM's output is a probability density function (PDF) detailing the probability that a maneuver will occur with respect to time. Probability with respect to time is a powerful output as it is easily interpreted but also can be used to calculate additional metrics such as the probability that the next maneuver will happen during any specific time interval. Unlike other clustering approaches, ISM is fast and scalable which is critical given the number of RSOs in the space catalog. It avoids strict clustering in favor of a probabilistic approach; this lends it additional speed and robustness. Additionally, by taking a similarity based approach, ISM can discern the existence of multiple ongoing patterns in a satellite's maneuver history. This is critical because PoL tend to be variable in nature due to the number of context-driven factors influencing their execution. Also, PoL can be "nested" with a larger PoL consisting of smaller, repeating sequences of events which can be considered PoL themselves. For instance, a station-keeping PoL might consist of two thrusting patterns of North-South and East-West control.

ISM stands apart from other machine learning approaches because it allows for learning of patterns from a relatively short time-history of observations. This is critical because machine learning approaches tend to be data hungry, but ISM is able to learn a maneuver pattern from as little as a single exemplar. In general, a pattern learned from a single exemplar will be overfit, but due to the ISM's flexible clustering approach, it would be able to discern variations of that pattern to avoid being overfit. Furthermore, as additional observations become available, the ISM will generalize the maneuver pattern with the new observations. Ability to generalize a pattern from single example is critical in the space domain, where there are few examples of observed complex PoL.

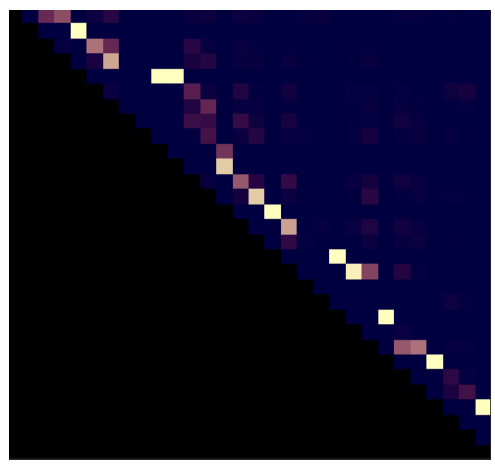

Figure 1: The Similarity Matrix. Each square represents an interval between two maneuvers. The brightness of the square represents the similarity of that interval to the surrounding intervals**.**

ISM populates an interval similarity matrix that connects consecutive intervals strongly or weakly based on the similarity between the two intervals. Ultimately this method produces a matrix estimating the probability that each interval is likely to repeat in the future, and this allows for future prediction of maneuvers. Figure 1 shows the similarity matrix for the maneuvers performed by the Galaxy15 satellite in 2012. The axes represent the maneuver numbers (there were 75 maneuvers that year). Each box represents the relationship between two maneuvers. The color (brightness) is the likelihood that the two maneuvers are linked - that they are both part of one repeating pattern, and therefore the pattern is likely to be repeated in the future. The columns of the similarity matrix are generated one at a time, one per each maneuver. Whenever a new maneuver occurs, it creates a new interval between itself and each maneuver that has occurred previously. We are primarily interested in representing how likely it is that that interval will repeat in the future. An interval is likely to repeat if it is part of a pattern of repeating intervals, and intervals in a repeating pattern are likely to be similar.

Formally, suppose we have labeled maneuvers, *i* through *k*, and intervals *ij*, *ik*, and *jk*. Our approach uses Bayesian probability calculation to estimate likelihood that maneuvers are part of a repeating pattern. Equation 1 computes the similarity of interval length where σ is the estimated standard deviation of the interval *ij* duration, and where interval *ij* and interval *jk* are the durations of those intervals. This is the "similarity" part of the interval similarity model, and is the probability that maneuver *k* at time *t* would be observed when the model was given that interval *ij* and interval *jk* are part of the same pattern. Next, we take this similarity indicator and fit use it to estimate how likely it is that that interval will repeat in the future. This estimate is a Bayesian calculation which includes the similarity between intervals *ij* and *jk*, the initial probability that *ij* would repeat, and adaptive priors.

$$P(k\ occurs\ at\ time\ t \mid jk\ is\ a\ repeat\ of\ ij) = \frac{e^{\frac{-(interval1 - interval2)^2}{2\sigma^2}}}{\sigma\sqrt{2\pi}}$$

(Equation 1)

Once the probability of repeat is estimated for each interval, the next step is to use that information to predict when the next interval will occur. A probability distribution for when the next maneuver will occur is generated for every interval. It is weighted by the interval's calculated likelihood of repeat. All of these predicted and weighted probability distributions are combined into one distribution – this is done by further weighting each probability distribution by one minus the cumulative distribution of the other interval predictions (since only one predicted maneuver can be the next maneuver).

EARLY RESULTS

ISM was tested using the maneuver times for the Galaxy 15 (NORAD ID: 28884) geo-synchronous satellite, during a four-year period (2011-2015). The dataset was synthetically generated by AFRL and demonstrated realistic levels of collection cadence (up to six days without observations of object) and noise (up to 90 microradians). This data was astrometric only and had four sources, each collecting at a different cadence and from a different earth-based location. Galaxy 15 was selected for experimentation purposes for three reasons. First, ephemeris data was freely available for use in validation. Second, it demonstrated Patterns of Life (PoL) when performing station-keeping maneuvers. Figure 2 shows PoL in the form of the periodicity of the maneuvers from the inclination history for Galaxy 15 during 2014 and 2015. The repeated patterns across the two years show the regularity of the station-keeping maneuvers. Finally, Galaxy 15 was selected because of anomalous behavior during 2011. In 2010, Intelsat, the operator of Galaxy 15, lost control of the satellite, and it began to drift away from its orbital slot. Intelsat repositioned Galaxy 15 back to its original location on April 4, 2011 (Weeden, 2011). Therefore, while the satellite drifted and repositioned, there was a lot of noise in the data and the ephemeris did not capture all the maneuvers. This is a serves as a test case for detecting deviations from the established PoL.

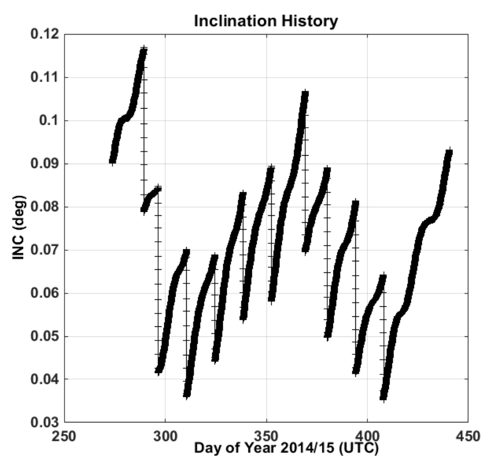

Figure 2: Galaxy 15 PoL from 2014-2015 shown as periodicity of the maneuvers from the inclination history.

For each year during the four year timespan of the data, ISM was started fresh and learned the on-going patterns of the satellite. Effectively, this allows for PoL to be dynamically learned and refined. After each maneuver was fed to the algorithm, it produced a prediction for the next maneuver that was compared to the actual next maneuver time. We evaluated maneuver prediction using standard metrics including the log-likelihood – a measure of the probability that the maneuvers would occur when they did, given the computed Probabilistic Density Function (PDF). The more accurate the prediction model, the higher value the PDF will have at the time of maneuver. This average can be calculated using both arithmetic and geometric means – a perfect PDF will optimize the geometric mean. The log of the geometric mean is the 'average log-likelihood' – a common metric for evaluating probabilistic models. We also computed the Average Integral of PDF Near Maneuver Metric. For a certain time interval around the next maneuver, we want to know the total predicted probability that a maneuver would occur in that interval. This metric is similar to the previous metric, but it levels the playing field between very peaky and smoother distributions. For instance, if the time interval is one day's length, then this metric is saying on average, what was the probability that the maneuver would occur on the day that it did. Multiple time intervals could be used, such as daily and hourly. Figure 3 shows a predicted maneuver for Galaxy 15 in 2012. The left graph shows that there was a predicted maneuver (blue) with a high probability on day 209 that coincided with the time of an actual maneuver (red) from the ephemeris data. The right graph shows the corresponding Cumulative Distributive Function (CDF), which is the cumulative probability, of the next predicted maneuver.

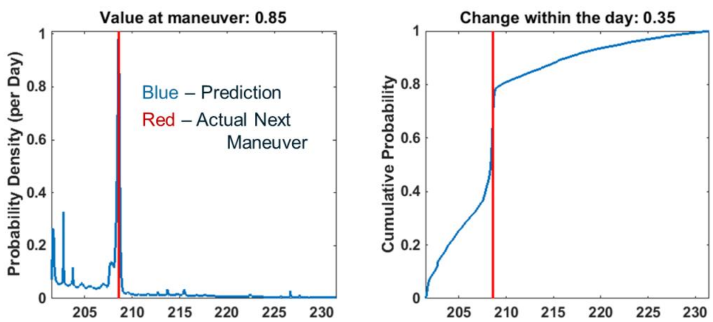

Figure 3: ISM correctly predicts a maneuver for Galaxy 15 in 2012 with high probability and PDF.

We compared the maneuver prediction performance with a baseline, which assumes that maneuver times are generated by a Poisson process using an exponential decay mechanism. For evaluation, we also computed an add-on category by accounting for the similarity of phase of orbit in addition to similarity of interval. Given the oddities of Galaxy 15 in 2011, we broke that data apart from other years (2012-2015) and report the results separately. Table 1 shows the Galaxy 15 2011 results and Table 2 shows the averaged results across the other years of the Galaxy 15 data. In both set of results, ISM performed much better than the baseline, achieving improvements in all metrics. Including the information on orbit phase was able to effectively double the improvement over the baseline, which is strong motivation to expand ISM to include other types of information in future work.

	Baseline (Poisson)	ISM	ISM + Orbit Phase
Instantaneous Log-Likelihood	-2.39	-1.97	-1.43
Daily Log-Likelihood	-2.43	-2.12	-2.18
Arithmetic Mean of PDF at Maneuver	0.194	0.364	1.34
Arithmetic Mean of Daily Probability	0.179	0.182	0.180

Table 2: Results on Galaxy 15 from 2011 only. ISM out performs baseline and adding in orbit phase further improves results. Results are lower than those in Table 2 because of irregular PoL in 2011.

	Baseline (Poisson)	ISM	ISM + Orbit Phase
Instantaneous Log-Likelihood	-2.53	-1.17	-0.31
Daily Log-Likelihood	-2.53	-1.90	-1.51
Arithmetic Mean of PDF at Maneuver	0.09	0.84	2.56
Arithmetic Mean of Daily Probability	0.08	0.19	0.35

Table 3: Results on Galaxy 15 aggregated over data from 2012-2015. ISM out performs baseline and adding in orbit phase further improves results. These results show maneuvers were predicted on the correct days and with high confidence.

The difference in results between Table 1 and Table 2 demonstrate the importance of establishing PoL in the data. Figure 4 contrasts the regularity of station-keeping maneuvers in 2014 (right graph) with the irregularity of recovery maneuvers during 2011 (left graph). In 2011 there was a period of very frequent maneuvers (36 maneuvers in 42 days) which was followed by a long stretch of no maneuvers (0 maneuvers in 41 days). In 2011, the PoL were established on the period of frequent maneuvers so when the behaviors deviated, the accuracy of predicted maneuvers went down. ***Setting aside evaluation metrics, detecting deviations from the established PoL is a critical need for SSA.*** Space operators would be interested to know when a maneuver is predicted based on historical patterns, but not observed. In the case of Galaxy 15 during 2011, the low accuracy results are a flag that the behavior is unexpected as compared to the other years of Galaxy 15.

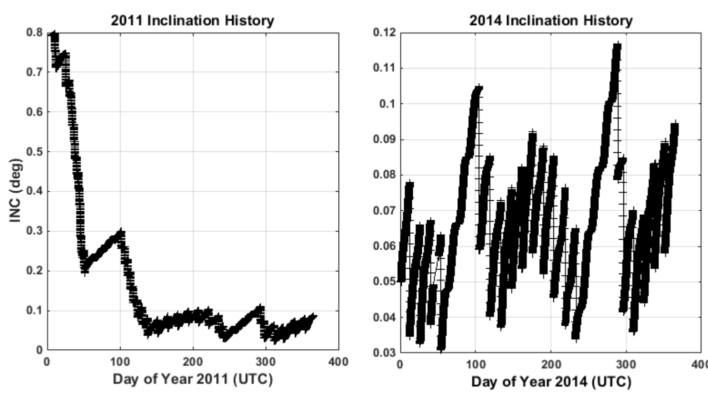

Figure 4: Comparison of the Galaxy 15 maneuvers in 2011 (left) and 2014 (right). 2014 demonstrated regular station-keeping maneuvers while 2011 demonstrated irregular slot recovery maneuvers.

CONCLUSIONS

Maneuver prediction moves beyond the *detect-track-characterize* tradecraft to an ABI-inspired methodology that incorporates spatio-temporal context. The ultimate goal of our research is to identify and characterize unusual behavior of an object and predict future states that are associated with the inferred pattern of life (PoL). In this paper, we presented the foundation of our vision which currently consists of the probabilistic Maneuver Prediction algorithm called the Interval Similarity Model (ISM). Early results from the ISM model have demonstrated that efficient maneuver prediction can be performed on noisy data with intermittent temporal gaps. We have demonstrated when there are repeated PoL, such as seen in Galaxy 15 in 2012, the ISM is able to predict future maneuvers. When an object's PoL is irregular, as seen in Galaxy 15 in 2011, the ISM is not able to accurately predict future maneuvers. ***However, it is able to flag deviations from anticipated behavior in order to alert space operators for their assessment.*** We believe that alone provides value to the Space Protection enterprise.

The application of this work extends beyond maneuver prediction. It can be incorporated into data association tasks for Uncorrelated Track (UCT) correlation. It can be used to dynamically task a constellation of sensors to decrease observation gaps. And it can be used for left-of-event prediction of large scale, long term patterns of life, such as a satellite end-of-life maneuvers into a disposal orbit. Future work is planned for validation on larger datasets, additional objects and ISM model extensions.

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