Surrogate Physics-Informed Neural Network for Satellite Position and Uncertainty Prediction

BAUDIER Stefan & BONO Alexandre – Thales LAS France, Advanced Radar Concept, Limours, France

Identification of Use Cases

From sensors (radars, optronic sensors, …) to acting systems (weapon ones) various mechanisms process target trajectories of different types: aircraft, missiles or satellites for example. Their objectives are to generate a comprehensive picture of all targets seen by the sensor or to support decision-making, planning, and actions targeting the objects. To achieve this, they rely on the same process: trajectory estimation and prediction. In sensing applications, the measurements must be processed to estimate target's trajectory. Typically, estimation and prediction are closely intertwined, with the prediction mechanism serving as the core element of the estimation pipeline. Moreover, uncertainty estimation and prediction are essential in such frameworks as they enable assessment of data relevance—and, consequently, the relevance of associated decisions. Thus, improving prediction accuracy and/or reducing computational complexity is a critical avenue for enhancement in these systems.

Recently, the French Defense Procurement Agency (DGA) ratified the contract for the future French Space Surveillance and Awareness Radar, named DeepFinder Space. This radar is designed to provide insights into threat identification, collision avoidance, and space operational intelligence. It will replace the GRAVES system, with the goal of better addressing the increasingly complex space environment—particularly the growing threats and the rapid expansion of the orbital population. Balancing the precise description of individual spacecraft with large-scale challenges is required. In this context, prediction algorithms must become more accurate while reducing computational complexity.

The standard tool for satellite trajectory prediction are numerical propagators. Because they are based on numerical integration (e.g., Runge-Kutta or Euler methods) of physical laws, they can lead to a computational bottleneck when the system is overloaded with targets. Furthermore, the uncertainty of such trajectories does not conform to the Gaussian distribution - a common hypothesis in estimation-prediction setups (e.g., Kalman filters). This necessitates the use of computationally expensive algorithms (e.g., Monte Carlo) to represent this banana shape distribution. Finally, assessing the epistemic uncertainty of these propagators often relies on manual engineering tunning. These issues have been investigated in the literature, but only separately.

Proposed Technical Approach

The contribution of our work is to address the three aforementioned prediction challenges by enhancing and integrating selected state-of-the-art methods, primarily by leveraging a surrogate Physics-Informed Neural Network (PINN) as a core tool. We based our experiments on the LEOMSAT dataset [1], which consists of synthetic satellite trajectories scenarios in Low Earth Orbit (LEO). We focused on the trajectories without maneuvers and with low drag friction. The goal is to reduce the complexity of the problem to facilitate the verification of the proposed approach, without distorting the core challenge.

The work described in [2] adapts the well-known analytical propagator SGP4 into a Pytorch version called dSGP4, aiming to make it usable in a deep learning pipeline, enable parallelization and facilitate gradient computation via auto-differentiation. The ML-dSGP4 model proposed in [2] improved the accuracy of the dSGP4 propagator by wrapping it in two Multi-Layer Perceptron (MLP). We proposed a version based on a Transformer model that replace the second MLP. It improves the accuracy of the propagation, leading to delay the moment where the propagator error crosses the 1km symbolic threshold about 3 hours and the threshold of 2 km error about 12 hours, compared to the MLP version. As a result, the error remains below the threshold for up to 5.5 days and 9.1 days respectively. In such a system the revisit time of a satellite (e.g., the interval between to crossing in the radar field of view) is strongly linked to the Keplerian period, ranging between 90 and 120 minutes in LEO. This improvement is thus substantial regarding in comparison to the problem characteristic time period.

The proposed Transformer-dSGP4 model is also well-suited to the two identified uncertainties processing methods. For instance, propagating uncertainty using Monte Carlo algorithms requires approximately 3,000 particles to adequately represent the banana-shaped uncertainty distribution. The PUZZLE algorithm [3] tackles the issue of uncertainty propagation for spacecraft orbit, particularly by hybridizing Unscented Transforms (UT) and Gaussian Mixture Models (GMM). Our tests, based on this framework, demonstrate that about 20 kernels are needed in the GMM to obtain a probability density that closely matches this distribution—particularly to replicate empirical results comparable to the 68–95–99.7 rule of Gaussian distributions. When coupled with UT, propagating 15 particles per Gaussian kernel results in a total of 300 particles—ten times fewer than required by the Monte Carlo method. Furthermore, the deep learning framework is highly conducive to parallelizing these propagations. Given that the selected PINN model is significantly faster than the numerical models typically used in Monte Carlo simulations, this approach yields a much more efficient method for propagating uncertainty while preserving the banana-shaped distribution.

Finally, the model is also well-adapted to deep ensemble training, as it primarily depends on the dSGP4 core, rendering the Transformer component both efficient and lightweight. The deep learning model's epistemic uncertainty in a general application is computed in [4] through a deep ensemble model setup. Training multiple variants of this model—as required in this framework—does not introduce a computational bottleneck. As recommended in [4], we trained an ensemble of 5 models, which effectively assesses the model's epistemic uncertainty. This approach enables automated computation of this critical metric without significantly increasing computational costs.

In summary, this proof of concept addresses all key prediction challenges—namely, accuracy, uncertainty propagation, and epistemic uncertainty assessment—thereby making it suitable for applications in other domains. We constrained the selected solutions to reduce complexity and computation time while maintaining a high-performance pipeline. Future work should investigate the relaxed assumptions regarding drag and maneuvers to fully address the complexities in LEO.

References

[1] S. Baudier, S. Velasco-Forero, F. Jean, D. Brooks, et J. Angulo, « Synthetic Dataset of Maneuvering Low Earth Orbit Satellite Trajectories for AI Analysis », oct. 2024, doi: 10.5281/ZENODO.13885585.

[2] G. Acciarini, A. G. Baydin, et D. Izzo, « Closing the gap between SGP4 and high-precision propagation via differentiable programming », *Acta Astronaut.*, vol. 226, p. 694-701, janv. 2025, doi: 10.1016/j.actaastro.2024.10.063.

[3] R. Detomaso, A. Muciaccia, et C. Colombo, « Hybrid Gaussian mixture model and unscented transformation algorithm for uncertainty propagation within the PUZZLE software », *Adv. Space Res.*, vol. 75, nº 10, p. 7226-7241, mai 2025, doi: 10.1016/j.asr.2025.03.026.

[4] B. Lakshminarayanan, A. Pritzel, et C. Blundell, « Simple and Scalable Predictive Uncertainty Estimation using Deep Ensembles », 4 novembre 2017, *arXiv*: arXiv:1612.01474. doi: 10.48550/arXiv.1612.01474.