Satellite Radar Cross Section Regression: A Case Study for Deploying Artificial Intelligence in the Space Force

Phantom Impact Paper
Artificial Intelligence Review Journal

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The Phantom Fellowship is a rigorous five-month career-enhancing opportunity for high-performing Department of Defense professionals to assess, develop, and gain exposure to Artificial Intelligence (AI) and Machine Learning (ML) technologies. During the program, enlisted, officer, and government civilian personnel (Phantoms) embed directly with the Department of the Air Force (DAF) & Massachusetts Institute of Technology (MIT) AI Accelerator (AIA), a cutting-edge organization with the mission of advancing AI/ML technologies for the DOD while also addressing broader societal and ethical issues related to AI/ML.

During their Fellowship, Phantoms are required to apply their newly acquired AI/ML foundational knowledge to produce a short-form research paper (Impact Paper) that seeks to address an AI/ML problem related to their home unit and/or career field.

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Abstract—**Radar cross section is a correlation criterion for space operators identifying satellites. Sometimes, through maneuver or natural movement, a satellite's radar cross section may change over time. This change may be predicted with machine learning regression to help space operators correlate objects. Radar cross section prediction is implemented at ground based radars to warn space operators of changes. This advanced warning reduces uncorrelated targets and assists with object identification, saving time and manpower across multiple Space Force units. This capability was delivered in four months by utilizing agile and commercial development operations practices. This avoids the arduous processes common in transition pathways such as creating a program of record. By artificial intelligence technologies to Space Force Combat Development Teams for development, supra coders, software factories, and contractors can transform fundamental research into incremental capabilities for the space warfighter.**

Keywords—satellite, radar cross section, ground based radar, space domain awareness, artificial intelligence, machine learning, deep neural network, deep learning, supervised learning.

I. Introduction

Ground based radars (GBRs), primarily operated by the US Space Force, assist with Space Domain Awareness (SDA) by tracking objects in orbit. These radars automatically detect and report metrics to space operators. Sometimes, through some adjustment of rotation, angle, or maneuvers, a satellite's radar cross section (RCS) may change over time. The radar's system typically automatically updates an object's RCS upon detection. However, extreme dips in RCS can sometimes cause the automated system to mark an object as an uncorrelated target (UCT). Space operators, upon seeing a UCT, must report to the 18th Space Defense Squadron (18 SDS) potentially causing a cascade of actions at the 18 SDS, The National Space Defense Center, and Combined Space Operations Center. Tactics could be adjusted in mission planning beforehand to correctly correlate the target if there were a way to anticipate this problem. RCS prediction may also help operators better suggest identification to the 18 SDS upon seeing a UCT. With additional data collection, RCS can be predicted with artificial intelligence (AI) regression techniques enabling advanced warning of this anomaly.

A simple software solution could rectify this issue; however, security reviews, lengthy Authority to Operate (ATO) approvals, and funding concerns often make small software deployments infeasible. Leveraging software factories and existing pipelines lends itself to timely incremental capability delivery. By utilizing Space Force organizations such as Combat Developments Teams (CDTs) and software factories, advanced AI research, such as that from the Department of the Air Force Massachusetts Institute of Technology AI Accelerator (DAF-MIT AIA), can be transformed into capabilities quickly and securely by deploying through software and pipelines with continuous ATO.

A. Background

SDA is accomplished through the Space Surveillance Network (SSN), a global network of radars, optical telescopes, and space based sensors. The goal of the SSN is to keep reliable and current information on objects in space [1]. Sensors are divided into three categories: dedicated sensors solely supporting the SSN mission, collateral sensors with a primary mission other than space surveillance, and contributing sensors owned by other agencies that provide support upon request. The SSN is commanded and controlled by the 18 SDS. SDA is the mission and responsibility of Space Delta 2 to enable space battle management and support ground operations. Space Command's catalog of artificial objects in orbit around earth lists 54,200 objects including 14,102 satellites as of 2022.

Radar cross section is a measure of how detectable an object is by radar; it is typically measured in square meters or decibels relative to square meters corresponding to the angle, size of the object, material of the object, and polarization of the radiation. Because RCS is a property of an object's reflectivity, the strength of the radar emitter and distance to the object do not affect the RCS [2]. Satellites can have a wide range of radar cross sections, from small CubeSats with cross sections on the order of a few tenths of a square meter, to large communication or reconnaissance satellites with cross sections on the order of tens or hundreds of square meters.[1] The RCS of a satellite is constantly changing by a small amount as the angle from the sensor to the satellite changes with the satellite's orbit.

Many satellites need to have their payloads, such as sensors and antenna, continuously pointed towards earth. Over time, external forces will require the satellite to actively stabilize to maintain correct orientation. This process is referred to as attitude control. Satellites without attitude control are often inactive or malfunctioning. Maneuvering in space requires fuel, a finite resource for satellites in orbit. Because of these restrictions in orientation and movement, active satellites with drastically changing radar cross sections are relatively uncommon.

[1] The ISS has an RCS of about 402 sqm or 26 dbsm.

B. Problem

A few years ago, space operators manning the PAVE[2] Phased Array Warning System Radar at the 6th Space Warning Squadron (6 SWS), Cape Cod, created a digital version of their mission planning board, POSNEG[3], in Microsoft Access. Microsoft Access logged information on their satellite contacts to a database. With this newly stored data, they noticed that a specific satellite would go undetected every few weeks. The weapons and tactics officers found that the RCS of the satellite would decrease with each pass until it was missed, then it would reappear with its RCS increasing with each pass. They deduced that the satellite was rotating in a way that gradually presented a growing and shrinking RCS. At some point the RCS would be significantly smaller than expected causing the radar system to miscorrelate the satellite. With new knowledge and advanced warning of this phenomenon, the radar operators were able to maintain accountability of the satellite by resetting the expected RCS value on the radar's system. While this tactic proved to be successful, the procedure described is not done for every satellite tracked at the space warning squadron; there is not enough manpower to examine every satellite of interest at each GBR nor across the Space Force.

This issue was disclosed to Delta 4's Combat Developments Team (4 CDT) during regular discovery interviews. 4 CDT proposed utilizing AI to enable advanced warning of the anomaly before the satellite passes. With the goal of reducing and better identifying UCTs, 4 CDT worked to research and develop a ML solution.

II. Research and Development

A. Desired AI Behavior and Approach

The weapons and tactics shop described a gradual change in RCS suggesting that a prediction on the next pass' RCS could be made by regression. Regression is a common AI behavior used to predict a quantity for a given input, in this case the input will be time and the prediction will be RCS. With enough historical RCS data the model can be trained using a labeled dataset of true examples, otherwise known as supervised learning.

B. Simulated Data

Due to the lack of pre-existing real world data and restrictions on RCS information, simulated data was used to train proof of concept models. Simulations were performed in Systems Tool Kit, a multi-physics digital mission engineering software.

The simulation places a generic phased array radar located in Cambridge, MA pointing east. For a more accurate simulation, parameters matching a specific radar can be added.

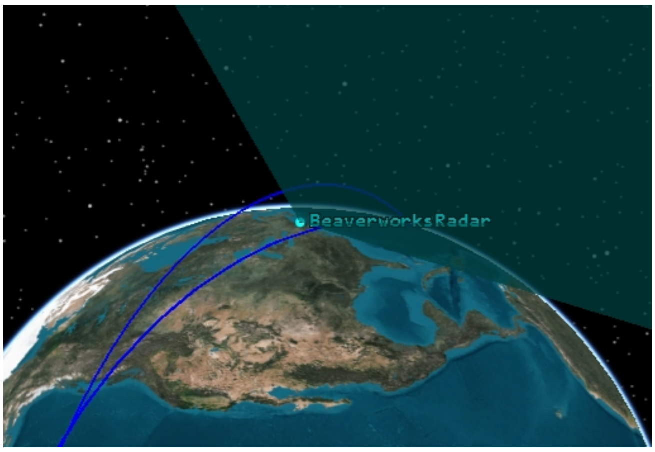

Figure 1: Simulation showing field of view of radar with track of the ISS.

Because RCS is aspect-dependent, information about the RCS of each angle of the object must be uploaded. Real world RCS measurements are expensive and time consuming so this simulation resorts to approximate RCS model calculations. These measurements will be taken from a simplified model of a National Reconnaissance Office Lacrosse satellite, also known as Onyx [3]. The Onyx's RCS file in the simulation contains the RCS measurement of 25 equally spaced points in a spherical coordinate system around the satellite; values between those 25 points are interpolated.

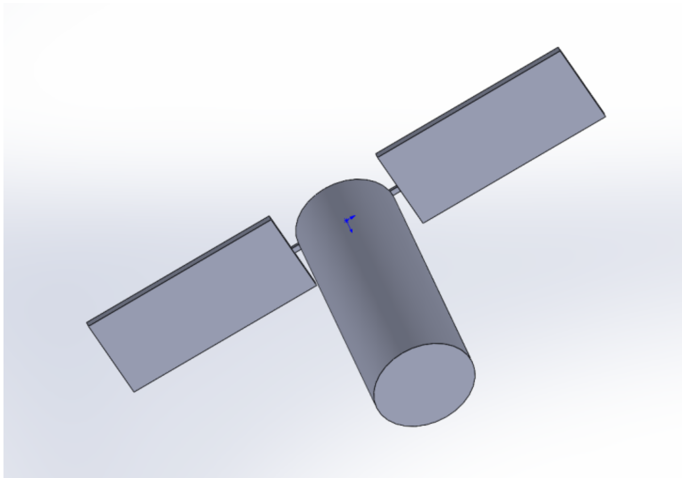

Figure 2: Simplified 3D model of NRO Lacrosse satellite used for RCS simulation. Model recreated for this project by Liam Dunphy.

The satellite in the simulation is poised to pass the radar's field of view every 90 minutes. Playing the scenario and using the radar to track the satellite it can be seen that the average RCS of an attitude controlled satellite is stable. The satellite's attitude can be adjusted in the software to simulate a less stable RCS from that of a rotating or tumbling satellite.

C. Real World Data

Since the POSNEG has not been fully adopted by GBRs, there is no current database of pass-by-pass RCS. With the help of space operators, the RCS data used to calibrate the model was collected by hand for this project.[4]

[2] PAVE is a United States Air Force program identifier relating to electronic systems.

[3] POSNEG is a shorthand for positive negative acquisition, used to describe a mission planning board listing expected passes and taskings.

[4] RCS data is controlled unclassified information. To see figures of changing RCS from the dataset, including from

Frequently in the dataset, groups of passes follow a predictable curve. There is a jump in RCS when the satellite's orbit takes it out of the field of view of the radar for multiple passes. An initial model will be trained on each grouping of passes since it seems to exhibit the most obvious pattern. A future model may predict the RCS over longer periods with more data but for the scope of this paper the model will focus on one grouping at a time.

D. *Predictive AI Model*

The deep neural network architecture consists of an input layer, three hidden dense layers, and a single unit output layer. Since there is only one input variable, the common rule of thumb is to use few hidden layers. One hidden layer can approximate functions for less complex data such as simple mappings from one space to another [4]. The model does not currently predict when the satellite will be out of view of the radar entirely. In actual implementation, the algorithm will only be run during times where the GBR anticipates it will observe the satellite.

III. Implementation and Deployment

A. *The POSNEG's Environment*

In late 2022, a new digital POSNEG was built by Space DEL 4 CDT available as a web app on SIPR through the Delta Analysis Reporting and Tracking System (DARTS). DARTS is a website hosting multiple mission related apps for Space Delta 4. As the new POSNEG is currently in beta testing; this upcoming software modernization gives an opportunity to integrate a solution directly to the mission planning software.

B. *Feature in Production*

The DEL 4 CDT utilized the RCS prediction algorithm to build an alert feature in the POSNEG. If the object's RCS values are unstable, the POSNEG displays a warning in the dashboard highlighting details of the incoming satellite. Hovering the cursor over the alert displays more information on previous RCS values and the predicted RCS of the upcoming pass. This feature is being used in mission planning as a part of the POSNEG beta testing at various space warning squadrons in DEL 4.

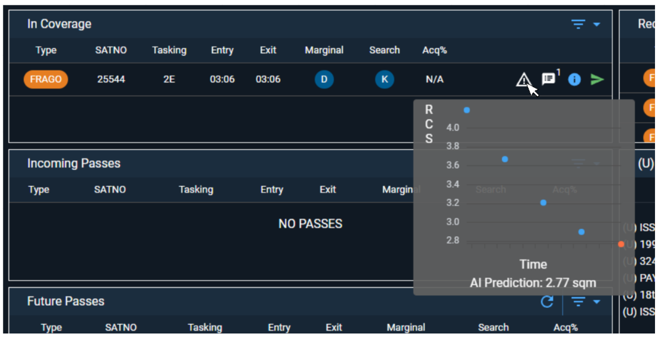

Figure 3: Screenshot of the alert feature in the POSNEG with mock data.

C. *Evaluate and Iterate*

Iteration and incremental delivery is essential to the agile process [5]. The RCS prediction feature was delivered in line with the agile principle of early value delivery. It can be anticipated that the training data may not be consistent with the entire range of real world circumstances. A common issue that may be encountered is the discrepancy between training and real world data. This issue may be pronounced in the case of models trained on unclassified or simulated data but operating on real world classified data once deployed. As of the writing of this paper the feedback process is ongoing. DEL 4 CDT will build upon the feature incrementally by examining evolutions in data and collecting feedback from users.

satellites with above average maneuver capability, contact the author.

IV. Recommendations for Transitioning AI Research

A successful transition expects the AI to be implemented and operationally in use. The stated mission of the AIA is to "create a(n)… end-to-end… pipeline for AI technology." AI/ML applications and case studies must overcome a proverbial valley of death[5] where matured science may fail to become a competitive advantage for the military if they are not transitioned.

A. *Pathways*

The AIA highlights four pathways for transition of developed technologies adapted from a Government Accountability Office analysis of the Defense Advanced Research Projects Agency [6]:

1. AIA Program Insertion: AIA technologies are re-used in another AIA program or a follow on program is created.
2. Direct to operations: The AIA transfers technology directly to an end user organization for operations and missions.
3. Program of Record: AIA technology is transferred for further development in a program of record.
4. Follow-on Development: Another DOD component funds continued development, use, or implementation of the technology during or following completion of the AIA program.

A combination of direct to operations and follow-on development may be possible in the Space Force because the service has a strong digital culture with many organizations developing software such as CDTs, software factories, contractors, or supra coders embedded in operational units. The early value delivery with incremental change can lead to increased interim capability with stakeholders fighting for small-scale solutions and their operational impact.

B. *Developers, Platforms, and Pipelines*

Development can be done through supra coders, internal development teams, software factories, or contractors. Space Force software development is typically done through software factories though it is increasingly common to see ad-hoc teams of supra coders or CDTs deploy software. The RCS prediction feature was developed with the Delta 4 CDT internal software development team and with the help of volunteer supra coders from various units with relevant experience.

Internally developed applications are commonly web based because supra coders are most familiar with web tech

[5] The Valley of Death is a commonly used phrase to describe a difficult phase to overcome such as the leap from launch to revenue generation or prototype to DOD contract [7].

stacks. Web apps are particularly advantageous because web browsers are already vetted to run on government computers. Deploying through the web also lends well to agile practice because new versions are immediately available online without installing updates.

Software factories and their preferred platforms each have their own pipelines and requirements for a certificate to field (CtF) to deploy to DOD networks. When building a stand alone application, repositories, containers, pipelines, and hosting must be funded and sustained. To avoid this difficulty, one can release changes to a general platform that serves multiple functions like DARTS with a CtF and sustainment plan already in place. Or, one can also implement a user ready solution on data platforms like Warp Core, a data as a service platform that has the ability to integrate python code and create dashboards, as seen in [8].

In this project, DARTS was utilized to quickly field a solution instead of creating a standalone application. The POSNEG and other apps utilize DARTS' CtF to perpetually deploy changes and new microservices through Platform One and ODIN. DARTS was updated for this project to run TensorFlow through TensorFlow.js. DARTS has extra containers available for running other popular python AI libraries such as PyTorch.[6] Any future development on DARTS will be able to leverage these libraries for implementing AI.

C. Combat Developments Teams

CDTs have experience working with software factories and contractors through their role as innovation shops for their respective deltas. Each delta is assigned one mission area creating a well defined correlation to a research area. The CDTs with their relevant mission, expertise, and innovation role should serve as a "customer champion" to ensure solutions are finalized into capabilities.

V. Conclusion

AI regression can be used to predict future satellite RCS values. This prediction can assist with mission planning to better identify and reduce UCTs. This AI capability was rapidly fielded to space operators by transitioning technology through a CDT. The CDT utilized an internal development team and supra coders to deploy on an existing microservice host platform.

Most guardians experience space through the medium of software. As a digital service, adopting advances in AI is integral to maintaining a competitive edge in the space domain. With questions rising on how to best transition technology, incremental development is supported by virtue of the Space Force's propensity towards agile practices.

Acknowledgment

This project would not have been possible without the support of guardians around the country. I'd like to thank Education with Industry Intel Corp Fellow TSgt Raymond Kell for his expertise and contribution to the project's AI codebase, Anchor Developer Specialist Cybyl Hancock for her help with releasing the feature onto DARTS, DOK Space Operator Lieutenant Anna Pinkerton for her insights on RCS data, Supra Coder Councilman Captain Scott Hubert for his help in the discovery effort, and DEL 4 CDT Director Captain Whitney Hessler for her overall support in this endeavor.

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Appendix: Description of Organizations

Combat Developments Teams: Formerly known as Combat Developments Divisions (CDDs), this type of organization was borrowed from US Army Special Operations Command. A CDD may enable procurement of specialized hardware or the development of specific software. CDDs were adopted and later renamed to Combat Developments Teams to better reflect their smaller size in the Space Force. CDTs are sometimes staffed with their own internal development teams or more ordinarily a few Supra Coders. DEL 4 CDT has its own internal software development team with Supra Coders, contractors, and reservists working on multiple projects in various stages of application lifecycle.

SpOC and Deltas: Space Force operations are centralized under Space Operations Command (SpOC). Below SpOC there are 9 Space Mission Deltas each with their own function. Of particular interest to this project is Space Delta 4 (DEL 4) responsible for missile warning. DEL 4 is the parent organization of the space warning squadrons operating all ground based radars with the exception of the GBR at Eglin. The space warning squadrons' primary mission is to watch for ICBMs; however, the radars often have the bandwidth to perform their collateral mission of SDA associated with Space Delta 2.

Software Factories: The Air Force has multiple software factories providing continuous integration and delivery (CI/CD) of applications. Software factories that commonly work with the Space Force include Kessel Run, Section 31 Kobayashi Maru, and Space Camp. Each of these software factories leverage different pipelines and hosting environments for a continuous authority to operate. These CI/CD pipelines allow for secure and perpetual changes to the code. Software factories commonly retain their own teams but they also work closely with CDTs. To illustrate this relationship, DEL 4 CDT is counted as a product team developing two apps with Space Camp and maintains an additional app on Kessel Run's pipeline.

[6] Other software without containers prepared to run python may incur additional cost and review to deploy a new container depending on the platform.

Department of the Air Force Massachusetts Institute of Technology Artificial Intelligence Accelerator: The DAF-MIT AI Accelerator, consists of military and government personnel working in conjunction with Lincoln Laboratory (LL) and MIT to perform fundamental AI research in a broad range of areas to improve DAF operations. AIA Projects typically have MIT principal investigators, LL leads, and AIA government liaisons. A phantom fellow may also be attached to a project to support project management, assist with research, and provide operational expertise.