How and Why to Conduct On-Orbit Space Domain Awareness Using Computational Methods to Supplement Human Operators

Contents

Abstract

Space is an exciting environment attracting enough players to soon exceed the ability to effectively track objects manually. We will need to update our space traffic systems to use artificial intelligence as supplements or replacements for human operators to achieve continued steady access to space. Computer vision will be a crucial component of sensing assets for space domain awareness conducted in orbit. We can extend this space traffic control network for planetary defense against near-earth objects that could pose impact risks. Besides tracking satellites and debris in Earth orbits, it can also provide traffic information for cislunar assets.

If the Space Force operates these assets, they can also be used as early warning sensors for terrestrial actions that would be harder to detect if only looking for infrared flashes. Using computer vision space domain awareness algorithms as a base, we can add additional algorithmic models suggesting recommended maneuvers to operators. With further development, these algorithms can conduct maneuvers themselves. They can also run sub-missions for the Space Force. As we design these systems, we must avoid common ethical traps and decisions that would erode trust in the algorithms among operators and civilian regulators or oversight authorities.

Background

With the proliferation of space objects in Earth's orbit,[1] we will soon exceed the ability to effectively track objects manually. We will eventually reach a point where space traffic control will require automated maneuvering to avoid collisions. Further, continued automation will be necessary for planetary defense, early warning for terrestrial and aerial assets, and making decisions for orbital actions. The challenges associated with Earth orbits will compound as we enter cislunar space with many unstable orbits and distances so vast that tracking objects becomes even more complex.[2] Some of these tasks can be handled by scripts and standard automation. However, because of the inherently dynamic nature of space, some of this will need to be handled by intelligent machinery trained on general data but free to act as it sees fit (within acceptable parameters).[3], [4]

Computer vision for object recognition and classifying new objects are examples of tasks that cannot be merely scripted. In the space environment, many objects can be classified based on common characteristics. However, debris and new objects without previous reference imagery will require a certain level of inference based on previous information. Humans are very good at performing abstract recognition like this. However, because of the speed and volume with which debris fields may manifest in Kessler-Syndrome-like manners,[5] human operators will be unable to keep pace with the conditions if unaided by machines. Plausible machine-assisted methods include supervised or unsupervised machine learning and other methods, which will be discussed in this paper. Regardless of the methods used, the algorithms employed will need to be speedy, reliable, and trustable. Furthermore, in many cases, the decisions made by those algorithms need to be explained in a way that will allow a human operator to understand if an algorithm is acting based on junk data. The algorithms must also be transparent enough to enable an operator to know if it is going outside the bounds of the law or what is desired within the diplomacy, information, military, and economy realms of the decision-making framework.[6], [7]

Image Recognition and Computer Vision

How Image Recognition and Computer Vision Operate

Image recognition has commercial applications today in optical character recognition for scanning documents[8] and translating signs.[9] It works as facial recognition for tagging people in social media posts[10] and object recognition to determine what is in a picture.[11] It also gives situational awareness information in the still-developing field of self-driving cars.[12]–[16]

Image recognition and, more broadly, computer vision operate by various mechanisms, depending on the system. The most common methods with high accuracy involve training an algorithm with pre-existing datasets. The algorithm types with the most promise for space-based space domain awareness include image segmentation, object detection, edge detection, pattern detection, image classification, and feature matching.[14] Exactly how each of those algorithms operates is beyond the scope of this article but may be studied more in future articles.

Some challenges for space-based computer vision include solar glare, atmospheric distortion, distance, irregularly shaped objects, and new objects with no prior reference.[2] If an object is silhouetted against the sun or Moon, that will form a different visual signature. If an object reflects sunlight directly into the sensor, it can overexpose the sensor and potentially damage it. If looking for activity within the atmosphere, lensing, Rayleigh Scattering, clouds, and shimmer can affect signal processing image quality. Because most space objects will experience negligible atmospheric drag, they are typically designed in ways that present significantly different profiles depending on their orientations relative to an observer. These changing profiles can make classification challenging. In orbit, most objects will be thousands of kilometers apart. As we extend into cislunar space, the distance involved increases by one to two orders of magnitude. If we operate these sensors for planetary defense, we move into the billions of kilometers, looking at between 1 and ≈150 AU.[17]–[20]

Satellites

One use of computer vision and image recognition is for satellite space traffic control. These are the most straightforward objects to detect, by nature of their length in the 10 cm to 109 m range.[21], [22] Commercial and science payloads typically have multiple reference photos that can be fed into an algorithm to detect the satellite on sight. Military and reconnaissance payloads by nature of their secrecy would necessitate an adaptive supervised learning method of image recognition that is regularly updated and verified with a human.

Maintaining separate training, validation, and test sets will be both challenging and yet vital to allowing image recognition to work in this environment.[23] These data sets and models generated from them will need to be updated frequently to prevent model drift.[24] Each new launch represents a new payload (or typically multiple payloads)[25], [26] necessitating the update of the catalog and image recognition models. These updates are essential after collisions, discarded staging, and other debris enter orbit.

While image recognition will be a powerful tool for identifying objects, it can also determine their trajectories to update the satellite catalog maintained by the 18th Space Control Squadron.[27] One easy way to do this is to calculate the object's parallax against the celestial background over a few recording frames.[28] For objects in low Earth orbit, parallax may be possible through stereoscopic imaging in a single satellite. Cislunar space may require multiple spacecraft for effective stereoscopy. Comparison references can be made using either parallax method, but against the Earth or Moon for orientation.

Depending on the field of view and other objects in the frame, distance could also be measured through parallax. That can be assisted by the use of additional ranging sensors for accuracy. Such sensors include LIDAR and microwave radar, although power requirements and time delays become technical hurdles at cislunar distances and beyond.[2]

Debris

While satellites typically refer to intentionally launched and orbiting spacecraft, the term technically encompasses all objects orbiting a body[29] and includes debris. However, practically speaking, space debris is a collective term referencing orbital objects that serve no functional purpose. This includes lost tool bags, rocket bodies, paint chips, decommissioned satellites, pieces from satellite break-ups, and meteoroids.[30], [31]

By their nature, debris will have irregular shapes that will likely not have perfect matches in any database. Further, many objects will be so small that they cannot be effectively tracked by ground-based radar.[32] Debris-tracking is an area where on-orbit optical tracking and mmWave radar can significantly improve space domain awareness. In addition to size and shape disparities, debris dispersion patterns and satellite maneuvering could result in multiple blind spots where objects hide behind each other relative to the sensor (ground-based or orbital). This can be mitigated through continuous observation and overlapping lanes of coverage from a variety of orbits.

Early Warning

Satellites have historically been used for and continue to be used for multiple early warning systems directed at the ground.[33], [34] While intercontinental ballistic missiles and other rockets have been the primary detection mission for these satellites, there are additional possibilities with improved automation.

Hypersonic Aircraft and Projectiles

As our sensors continue to improve, detecting hypersonic aircraft should be the easiest since they still require considerable thrust, which will be hot and reasonably obvious with existing infrared detection systems.[35] However, their proposed low-altitude flight profile could represent a challenge cleaning the heat signature from the rapidly moving background of the ground below. That would be a task well-suited to a variety of artificial intelligence computer vision systems. This is also a task that could potentially be accomplished with orbital radar. However, this would likely require significantly more power than merely passive detection. It would still require considerable signal processing to remove the ground below to a degree much higher than with infrared sensing, where propulsion systems produce far more heat than background targets.[36]–[39]

A slightly more challenging but still important task would be to track hypersonic projectiles, such as those generated from railguns and coilguns. Per publicly available test data, such projectiles can travel up to 100 miles without any additional propulsion.[40] This means there could be minimal warning for ground assets without persistent overhead imaging. Further, since these projectiles are not actively propelled in-flight, their infrared signatures will be negligible. The air will still be heated around them if they travel fast enough, but detecting them would require much more advanced signal processing than is required to detect missile launches. Using orbital mmWave radar sensors could be a way to see through clouds.[41] However, we would still have to perform a large amount of signal processing to remove background noise produced by radar reflections off ground features and slower-moving objects.

Planetary Defense

Another huge benefit for orbital assets is planetary defense. We have a lot of blind spots using only ground-based sensors. If we place radio and optical telescopes at various stable Lagrange points, we can substantially increase the area we cover in tracking near-earth asteroids.[17], [42]

After placing the observatories, we then have to filter all the objects we track. We have to classify them by type, distance, and classic orbital elements, along with their risk of impact. Because of the sheer volume of comets and asteroids in our solar system (> 1.1 million),[43] we need to classify these objects using some form of artificial intelligence. Otherwise, it will take far too long and be prohibitively expensive to catalog all items that could one day pose an existential threat to life on Earth.[44]

Planetary defense is once again a great place for computer vision systems. The time scale involved allows for more options here than with satellite traffic, including handling algorithms on the ground where it is much easier to upgrade computing power and algorithm accuracy.

Object Avoidance

Artificial intelligence will shine with object avoidance. Because space is a complicated environment full of moving objects, a well-trained artificial intelligence algorithm can take all known data about space traffic and conduct analyses of multiple course-correction options within a fraction of a second. This data includes calculations that would take a human minutes to calculate by hand for a single possible path.[45] Once the calculations are made, alongside probabilities of success and second-order collisions, there are two possibilities. The algorithm can issue maneuver recommendations or conduct autonomous actions. Both options will increase the amount of orbital traffic that can be safely handled, increasing the amount of possible activity in the commercial, exploration, and national security sectors.

Maneuver Recommendations

If the algorithm is used to issue maneuver recommendations, it can issue a top-three recommendation with success probabilities for each action. These recommendations can be presented by text, as graphical overlays on its path highlighting the threat, a combination of both, or in a different method. There are already a multitude of automated warning systems in use in non-space environments.

Cars have blind-spot monitoring systems that issue audible or visible warnings when drivers try to merge with a car in their path.[46] Most commercial jets have terrain avoidance and warning systems that issue audio alerts and a recommended action, “WHOOP WHOOP PULL UP,” as an example.[47]

We can design something similar in our space environment. A visual alert with recommendations, like many video games use in tutorials or during specific sections of gameplay, could form the basis of this design.[48] Recommended path corridors could take a similar form to synthetic vision setups in commercial aviation glass cockpits, identifying flight-path markers, danger areas, and recommended actions.[49] Before deciding on an exact form, current system operators, user experience designers, graphics designers, and data visualization experts should all be consulted. These consultations will ensure the resulting software solution is usable, looks good, and communicates the necessary information quickly and effectively.

Autonomous Action

Artificial intelligence can do a lot more than simply suggest possible actions. Properly trained algorithms can take action on their own. This would decrease reaction time[50], [51] and allow for the most efficient use of orbital slots. This also opens up many opportunities requiring short evaluation and reaction times. However, there are also limits to what can be accomplished autonomously. Amazon and Tesla are two companies that have heavily relied on automation but also found limits to what the machines can accomplish relative to humans.[52] The exact split in capabilities and duties between automation and humans will vary considerably depending on what is technologically possible at any given time.

Maneuver

The most obvious place to start is with autonomous maneuvering. Since artificial intelligence can already conduct analyses to choose the best options by the probability of success, why not allow that algorithm to execute the best option on its own? Computers can execute maneuvers with minimal delay or reaction time. This allows for satellites to be considerably closer together. SpaceX has already equipped its Starlink system with automated collision avoidance maneuvering capabilities.[53] Autonomous collision avoidance is a feature that will need to become standard as we launch more and more objects into space, with estimates projecting over 100,000 satellites being launched within the next decade.[54]

As we design systems that autonomously maneuver, we need to design them with “rules of the space lanes” similar to rules of the road and right of way on the seas and in the air. However, space inherently has several key differences. First, many objects are effectively “dead in the water.” Second, a single change will affect many objects in a ripple effect. Third, while some satellites can maneuver with ease, others maneuver slowly. Finally, orbits do not behave like terrestrial pathways due to orbital perturbations and a lack of air resistance.[55] These factors need to be considered when crafting both rules of the roads and autonomously maneuvering satellites.

Generative Adversarial Networks (GANs)[56] within a digital twin[57] framework would likely be the best training ground for developing algorithms capable of choosing and executing the best maneuvers. Specifically for applications such as precision station-keeping, satellite chasing, collision avoidance, docking, and quickly charting paths through cislunar space with its bizarre gravitational effects.[2] After the framework is developed, an outgrowth of that algorithm should be built to handle computer vision to know its actual environment and natural language processing to effectively interpret desired end-states from constellation operators. That is correct, *constellation* operators. Humans will not be operating individual satellites on the scale that humanity is moving towards, except in rare circumstances. Most interactions will be with constellations or clusters of satellites since the algorithms can do the heavy lifting of the actual maneuvers.

Repair

What happens when a satellite breaks down on-orbit, in cislunar space, or beyond? How can it be returned to operational status? The traditional method has been to send humans to conduct spacewalks to repair the malfunctioning satellite — if it is in low earth orbit.[58] Beyond that, if the operators cannot affect a repair remotely, it becomes a dead object. Further, human astronauts cost a considerable sum of money to place correctly for a repair. For example, the Hubble Space Telescope repair estimate in 1999 was $205 million.[59] If we want efficient repairs, we need to remove humans from the equation.

The most recently demonstrated remote repair capability is from the Space Logistics MEV-2, where MEV-2 maneuvered onto Intelsat 10-02, allowing itself to serve as a maneuvering unit, extending the Intelsat 10-02's service life by five years.[60] As technology advances, repair missions like this can become commonplace, eventually handled entirely by artificial intelligence algorithms. Further, some automated repair mechanisms can be built into the satellite before launch, allowing the satellite to service itself for minor repairs as needed and instructed by the governing algorithm.

Defense

Space is a contested environment.[61] It is easy enough to recognize a need to avoid accidentally hitting other operational satellites and debris. However, what happens if someone actively fires on our systems? Anti-satellite activity can take the shape of kinetic attacks from Earth (land, sea, or air-launched), kinetic attacks from orbit (throwing projectiles), signal jamming, sensor blinding, maneuvering to a satellite to rip it apart with a robotic arm, or even ramming one satellite into another.[62]

Protecting against aggressive action is a necessary component of keeping national defense assets operational. Protection could be handled by humans but would become costly and prone to error. With our goal to be a lean and agile force,[63] this needs to be handled computationally. Orbital defense is a prime environment to use a GAN algorithm. We can put in as much information as we have and have algorithms fight each other to learn from the fight and become even better so that when something occurs on-orbit, they can immediately execute the best defense. While GANs immediately stand out, other reinforcement learning models could also achieve the same objectives.

Using a system like this will save time and money and be a valuable force multiplier. Further, because such algorithms can be self-contained within an orbital asset, it improves survivability, even if the satellite is under electronic attack or a controlling ground station is incapacitated. That means that the combination of quicker reaction times and self-contained programming will allow the asset to stay active much longer in a degraded environment.

Offense

Offense has no place in the areas of commercial space or space exploration. However, this is an arena in which the Space Force must be prepared to operate. While we would prefer to deter aggressive action in space, should conflict break out, a key component of maneuver warfare is offensive action against designated enemy targets, in accordance with the laws of armed conflict.[64], [65]

The same features that make GAN algorithms attractive for defense make them equally attractive for offense. Other reinforcement learning methods could also work. For example, deep learning, like was used for AlphaGo, is another possibility.[66] Algorithms need to account for orbital maneuvering in evasive action, possible sensor blinding efforts,[67] and distraction countermeasures like chaff[68] in addition to any possible direct actions or counter actions occurring from the object being targeted for offensive action.

Ethics

Automation raises many ethical questions. For centuries, humans have been concerned about how automation may negatively impact jobs.[69] While some jobs are susceptible to automation replacing them, many times, the same automation that usurped a job created new categories of jobs or changed the way the old job functioned. For example, when automated teller machines (ATMs) were introduced in the 1980s, the number of human tellers did not decrease. The number *increased*. However, the human teller's job changed from counting cash to being a customer service representative and salesperson.[69, pp. 6–7]

Besides the obvious ethical questions related to jobs, there are further questions about algorithmic bias and decision making. The trolley problem is a classic ethical allegory for comparing ethical standards.[70] Many variations on the theme exist. For simplicity, assume a trolley is on a track headed toward several workers who cannot escape. You can switch the trolley to the only alternate track, thereby killing only one worker, or do nothing and allow the trolley to kill several workers. Your ethical framework determines the solution you choose and your rationale for that choice. Two example frameworks are whether you consider a net human gain to be best or doing no active harm to be best.

The trolley problem is hard enough for humans to solve. A prominent artificial intelligence YouTuber taught an algorithm how to solve the trolley problem.[71] In the process, she uncovered a complicated web of how the biases of training sets and the unconscious biases of programmers influence the final result.[71, Secs. 10 & 12] This has implications on-orbit for algorithmic defensive and offensive operations. When defending an asset, the algorithm needs to correctly identify threats. When counter-attacking or directly attacking, targets need to be correctly chosen. Mis-identification can cause grave damage to national security in a space battle if it results in a friendly-fire incident. It even has the potential to go beyond merely damaging assets and move to illegal territory that could be considered a war crime if the algorithm chooses to engage a target that is not a legitimate military objective. That itself opens another layer of ethical questions in determining who to hold to account for such actions.

The trolley problem, the importance of classification accuracy, biases, unintended consequences, algorithmic accountability, and more all underpin the growing field of ethics research in artificial intelligence. These questions are so important that the first United States Chief Data Scientist wrote and published an entire book on the subject.[72], [73] He also intentionally priced it as free to distribute to as many people as possible.[74] A key takeaway from his book is the importance of developing an ethics checklist tailored to each industry and company, or organization. This checklist should be used when developing and updating all artificial intelligence algorithms. The levels of ethical thought required vary according to the level of war being fought. Strategic levels require the most thought, and tactical levels require only rough rubrics. Even outside of algorithms, the importance of ethical thought is being strongly considered within the armed forces.[75]

Further, the Department of Defense has thought through and published five guiding principles for artificial intelligence in combat and non-combat roles.[76] When designing an artificial intelligence system, we must be responsible, equitable, use traceable techniques, create reliable systems, and deploy properly governable systems.[76] Therefore, developing these systems must follow appropriate rules from the Department of Defense, in addition to any space domain-specific rules the Space Force develops.

Algorithmic Checks and Balances

Related to the ethics of ensuring algorithms are making the correct decisions is verifying those assurances. Verification can take several forms. The first form is regular validation testing to ensure the models have not drifted.[77] That means testing the models with a recent sample of real-world data to ensure that the statistical decisions match what was achieved in training. Machine learning engineers will need to regularly perform validation testing to prevent undesirable model drift.

Another idea is to regularly perform competitions between different algorithms and human operators to see who performs the best and why. Competitions could take the form of a regular portion of Space Flag exercises. From those results, the existing systems can be updated with lessons learned.

Humans have displayed algorithm aversion in many situations.[78] This takes the form of preferring humans over algorithms, even when algorithms perform better than humans. A key component to making computational supplements to humans work is getting those humans to trust the computer's decisions. For humans to trust an algorithm, they need to be confident that the algorithm has the same information as the human, the same goals, and a compatible decision matrix, in addition to a high statistical likelihood of success.

One facet of this discussion is the concept of algorithmic black boxes that absorb information and then spit out decisions in a way that makes no sense to humans.[79] While this approach is common in machine learning environments, it has significant risks to operational success.[80] Many people operating in the space of artificial intelligence operate under a "Bigger is better" mentality, meaning that the more complicated the model, the better it will perform.[80] However, that assumption is not necessarily valid. Models designed with inherent interpretability perform within a margin of error of black-box type systems.[80], [81] Because their performance is so close to large black-box models, small and interpretable systems should be the default. Smaller interpretable systems can more readily have their processing handled onboard an orbiting system (reducing reaction times) and significantly increase trust for operators and civilian oversight of any military operations using these systems.

Conclusion

Image recognition and computer vision have many applications for orbital assets in commercial and national security environments. These systems can be used to inform human operators, provide early warning, and issue maneuver recommendations. They can also function as modular algorithms, feeding into larger algorithms for autonomous object avoidance, autonomous repair, and even conducting some level of autonomous defensive and offensive actions on-orbit. The sensors and information needed for success vary depending on the orbital regime, expected threats and targets, and expected actions. Developing these systems requires an interdisciplinary team of statisticians, machine learning engineers, ethicists, lawyers, and satellite operators. Once these systems are operational, they open the door for an exponential increase in human activity on-orbit and beyond Earth's gravitational influence.

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