WHITE PAPER

Machine Learning for Space Missions: A Game Changer for Vision-Based Sensing

Vision-based sensing systems are enabling increased levels of autonomy and precision in navigation for space missions. With high-precision relative and optical navigation, vision-based sensing systems are playing a critical role in:

- Rendezvous and proximity operations (RPO)
- Entry, descent, and landing (EDL)
- Robotic exploration of the solar system

Today's increasingly ambitious mission requirements, along with an energized and innovative private sector, are motivating a surge of research in vision-based sensing and perception techniques that use artificial intelligence with machine learning.

Traditional Development of Vision-Based Systems

Despite the increasing popularity of vision-based sensing systems, developing them has been costly and resource intensive. The algorithms used to translate a raw image into data that can be used for vehicle control are developed by a niche group of engineers with specialized expertise. Verification and validation of these algorithms can involve complex physical testbeds with robots moving on tracks toward physical-scale models of approach targets such as spacecraft and asteroids. In some cases, the testbeds are even flown in orbit before the technology is deployed on its intended mission.

Once the algorithms are developed and validated by test, implementation onto production hardware is complicated by the need to optimize the available on-board processing resources, which are often limited by the availability of computing hardware that can survive the hostile radiation environment of space. As part of this optimization, it is common for portions of the algorithms to be distributed between FPGAs and computer processors. However, this split can increase both design complexity and the number of engineering specializations required.

NASA's Raven deployed on the International Space Station. Raven is an on-orbit testbed for developing vision-based sensing systems for relative navigation. Image courtesy NASA.

Accelerating Development with MATLAB and Simulink

Change is brewing. The ongoing private space race, which is disrupting many space-related technologies, is also driving down the cost of developing relative navigation capabilities. Competitions such as the ***Google Lunar XPRIZE*** have motivated new companies to develop extraterrestrial landing technology at substantially lower cost than was previously possible.

How are they doing this? Companies are using higher-level languages such as ***MATLAB***® and ***Simulink***® for algorithm development. This approach enables their algorithm design engineers to focus on developing the high-level application rather than spending time reinventing lower-level image processing routines, which are now available off the shelf. MATLAB and Simulink also enable rapid prototyping of candidate algorithms, which can be integrated with existing guidance, navigation, and controls models for early system-level validation. Using ***Model-Based Design*** with MATLAB and Simulink also enables software and hardware development engineers to automatically generate code for embedded deployment on both processors and FPGAs and to create test benches for system verification.

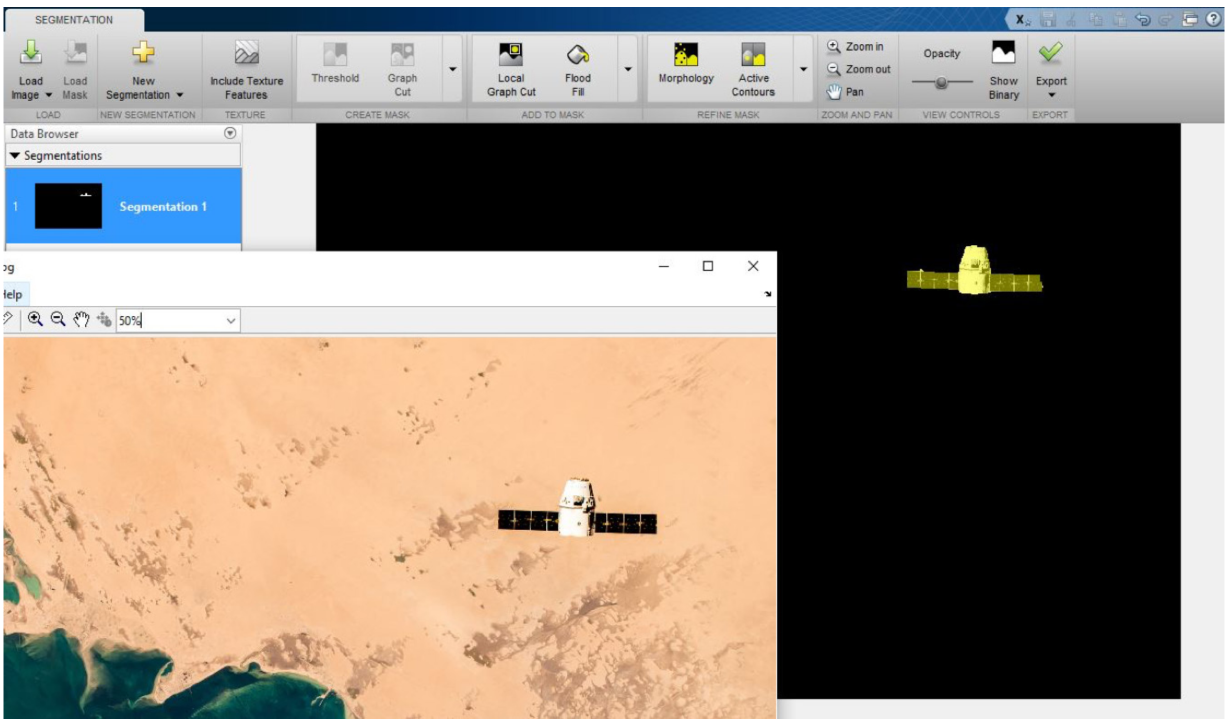


Image processing with MATLAB. Techniques such as segmentation can be done in MATLAB without reinventing established methods. Space vehicle image courtesy NASA.

Machine Learning: A Game Changer

While vehicle design workflows in the space industry have seen incremental changes, other industries, most notably automotive, have completely transformed their approach by using recent advances in ***machine learning*** to develop their autonomous systems. Taking advantage of large amounts of collected data, they are using ***deep learning*** to train systems to detect and recognize objects to enable autonomous operations.

The space industry has taken note of these advances. While space-based deployment of machine learning for computer vision is in the experimental stage, organizations are already adopting machine learning techniques in production systems on the ground segment. The primary use cases are ground-based spacecraft health monitoring and geospatial analytics.

The use of machine learning for space vehicle health monitoring is driven by interest from large satellite fleet operators in reducing operation costs. These operators monitor dozens of satellites from a single control center, with engineering staff on hand to respond to faults and failures if needed. The engineers are also responsible for monitoring and trending the health of the fleet—a task that is now aided by machine learning. Low risk levels are maintained by using machine learning models to complement, rather than replace, engineers in the control center, who maintain responsibility for acting on the new information provided. The algorithms are trained using the vast amount of spacecraft telemetry data that operators already have sitting in their data centers; in some cases, these algorithms are able to detect anomalous trends before their human counterparts, reducing the need for human eyes on the real-time telemetry data. The applied techniques and lessons learned are improving the acceptance of machine learning within the space industry, and will potentially also apply to future uses of machine learning on-board highly autonomous spacecraft.

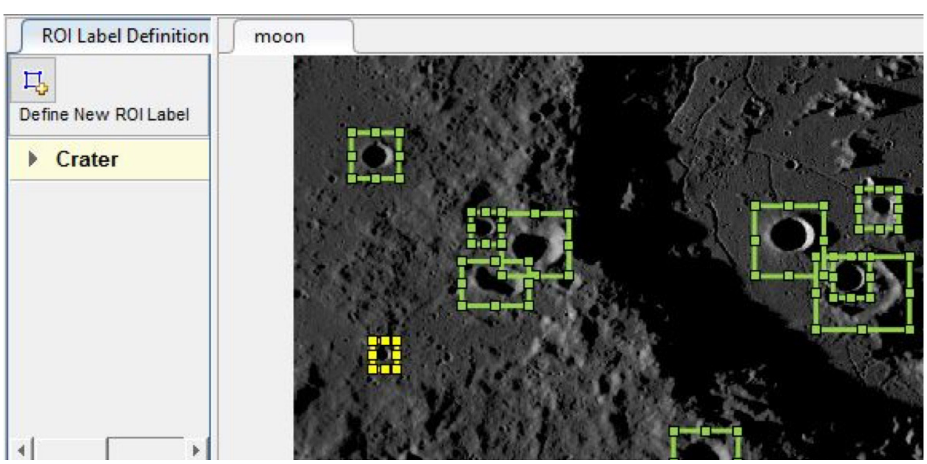
Geospatial analytics refers to processing Earth-sensing data provided by imaging satellites. Because it uses optical imagery, this use case is a natural precursor to vision-based sensing in space. Machine learning in geospatial analytics is motivated by the sheer amount of data collected by today's satellite systems, which makes it infeasible to analyze manually. In many cases, coding algorithms by hand to perform the wide range of desired processing is also prohibitively difficult. Machine learning is well suited for precisely these situations: large amounts of data that is complicated to process. Machine learning models are used for a variety of use cases in Earth-sensing, such as classifying agricultural landscapes to plan crop yields, detecting and classifying cars in mall parking lots, and predicting stock market performance.

Can machine learning techniques also be applied to on-board relative navigation systems to overcome cost and resource challenges while also improving the capabilities of the system? A fundamental challenge to this approach is the traditional conservatism of the industry. The space industry has historically favored reliability and testability over performance. In today's development processes and best practices, the developed algorithms are expected to be simple enough to be reviewed by humans, as well as to exhibit deterministic behavior, where a given input to the algorithm always produces the same, known output. Neither of these are true for deep learning networks, where the algorithms are essentially impossible for humans to understand, and often produce outputs that are difficult to fully predict. Even if the expectations were to shift, the amount of training data available from space is highly limited compared with the data available from the world's millions of miles of roadways.

Monitoring deep learning training progress in MATLAB.

Incremental Adoption of Machine Learning

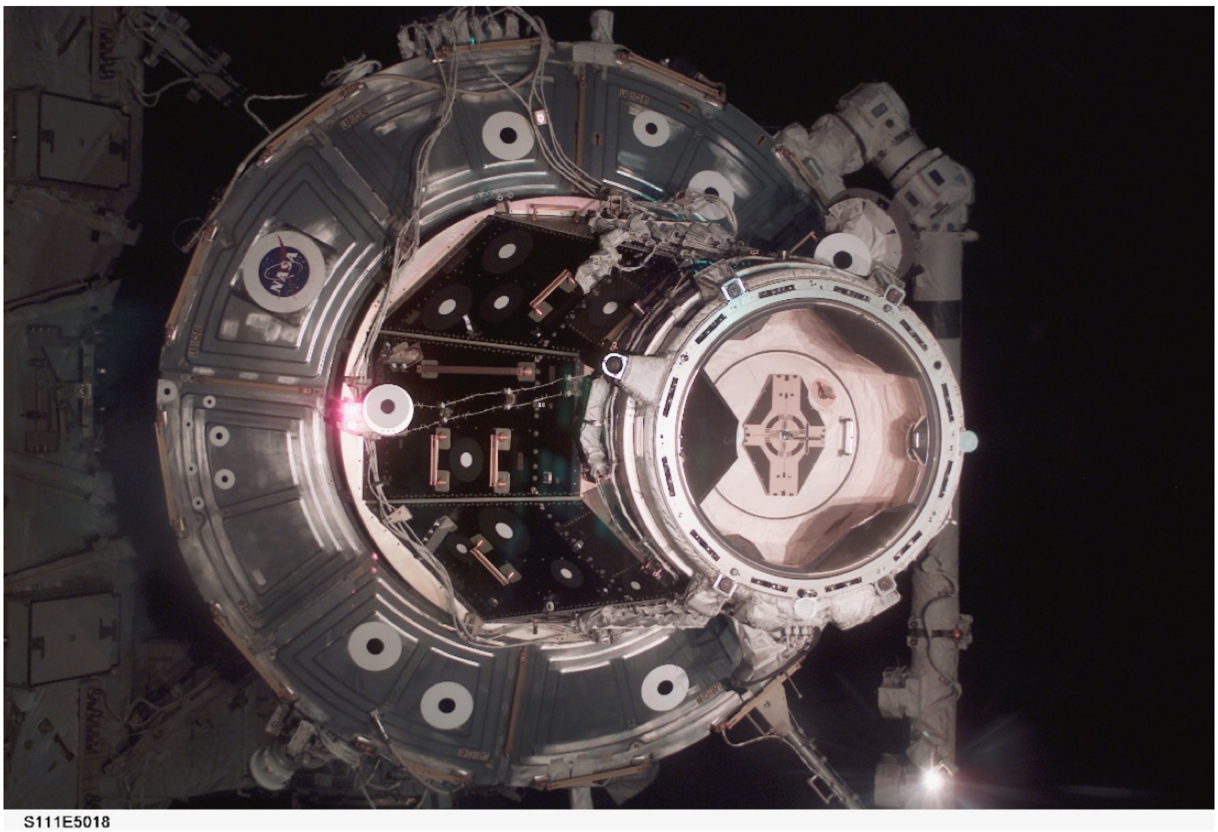
As the current trend in mission complexity continues, spacecraft will increasingly explore unknown terrain and encounter unpredictable situations, often at distances from Earth that make real-time ground control impractical. To solve this problem, the industry is discovering a use for applications that do not require fully predetermined behavior, or even a real-time operating system. As already demonstrated on the ground segment, problems using electro-optically sensed data such as visual camera images, and time-series data such as vehicle telemetry, are well suited for machine learning. Machine learning techniques will likely first be used to transform raw sensed data into state estimates informing higher-level logic, such as to initiate a specific scientific task like selecting a target to image, probe, or sample. As confidence in this approach increases, machine learning can also be applied to more critical problems, such as teaching a spacecraft to detect a safe landing zone by avoiding hazards such as boulders or small craters.



Labeling hazards (craters) on the lunar surface with MATLAB. Moon image courtesy NASA.

Availability of Training Data

Although insufficient training data exists for many applications, significant data from Earth, the moon, and Mars is already available for machine learning applications. Also, it is likely that sophisticated scene generators already in use for algorithm verification and validation purposes, such as the European PANGU, could be used to provide additional training imagery for deep learning. For satellites, existing images taken during ground processing can likewise be complemented with artificial scene generation. For RPO applications, a satellite can then be taught to recognize a feature of interest and plan a path to it while avoiding obstacles such as radiators and solar arrays.



Night-time view of the forward docking station of the International Space Station during rendezvous operations. Views like this can be complemented with generated imagery to achieve the full envelope of lighting and other mission conditions. Image courtesy NASA.

The Future of Space-Rated Hardware

Looking slightly further into the future, it is only a matter of time before space-rated graphics processing units (GPUs) become a reality, radically improving the processing power available on a spacecraft. When that happens, it is conceivable that an autonomous spacecraft could take the next evolutionary step: continuously learn from its environment using deep learning techniques and then apply that learning to fulfill its mission.

A Road Map for Vision-Based Sensing

The space industry is just starting to adopt the advances in vision-based sensing pioneered by automotive and other industries to develop increasingly autonomous spacecraft. In this first phase, Model-Based Design with MATLAB and Simulink are improving design efficiency and affordability of electro-optical systems. The next phase will deploy machine learning algorithms to selective, low-risk space missions, forcing a fundamental shift in the way the industry defines requirements and verifies algorithms that would allow for the inclusion of non-deterministic software. This, in turn, will ultimately enable the final stage: spacecraft teaching themselves how to explore previously uncharted territory.

About the Author

Ossi Saarela is the space segment manager at MathWorks, where he works with space programs around the world on applying modern engineering tools and practices. Ossi has almost two decades of engineering experience in the space industry, serving as a flight controller for the International Space Station, supervisory logic designer for satellites, and lead systems engineer on an electro-optical sensing system for rendezvous and proximity operations. He holds a B.S. in physics from UCLA and an M.S. in astronautical engineering from the University of Southern California.

Learn More

For additional resources on MATLAB and the space industry, visit:

- ***MATLAB and Simulink for Space Systems***
- ***What is machine learning? 3 things you need to know***
- ***Machine learning examples, articles, and tutorials with MATLAB***