Demonstrating Onboard Inference for Earth Science Applications with Spectral Algorithms and Deep Learning

Itai Zilberstein*[1], Alberto Candela[1], Steve Chien[1], David Rijlaarsdam[2], Tom Hendrix[2], Léonie Buckley[2], and Aubrey Dunne[2]

[1]Jet Propulsion Laboratory, California Institute of Technology, CA, USA
[2]Ubotica Technologies, Ireland

1 Introduction

The capabilities of in-orbit assets to perform Earth science has skyrocketed in recent years. New space providers are deploying satellites that possess state-of-the-art multi- and hyperspectral instruments along with processors that raise the ceiling for onboard computation. CogniSAT-6/HAMMER (CS-6) is one such spacecraft that has a visible and near infrared range hyperspectral instrument and neural network acceleration hardware, enabling advanced edge data analysis [7].

Analyzing data onboard serves several key functionalities including rapid response to detected phenomena and reducing data volume by identifying unusable data. The former relies on inferring properties of a data acquisition. Performing this computation at the edge is key to enabling new, time-sensitive measurements of rare Earth phenomena. This realizes a key component of NASA's New Observing Strategies (NOS) program.

We focus on the development and deployment of onboard algorithms to perform this inference for both spectral signature detection and image analysis in the visible and near infrared spectral ranges. We target numerous Earth science applications ranging from the detection of clouds and volcanic activity to flood and surface water mapping as well as land-use classification. This ongoing effort consists of composing datasets using automated labeling techniques, designing and implementing algorithms within the constraints of flight hardware including training machine learning models, validating inference and execution, and a flight demonstration.

2 Approach

Spectral analysis is used for mineral and vegetation mapping; it includes common methods like spectral angle mapper, match filters, and the Reed-Xiaoli anomaly detector; as well as spectral unmixing using deep learning [2]. Image analysis consists of semantic segmentation using the U-Net [8] deep CNN architecture. The trained models identify clouds, surface water extent (flooding), thermal events (e.g., volcanoes, wildfires), and land surface type (e.g., city, forest, water, cropland,...).

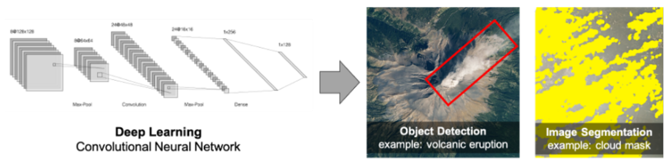

Figure 1: CNNs will be used for the onboard analysis of many science events.

CS-6 data is limited due to its recent launch (March 2024). For spectral analysis, we leverage data from the USGS spectral library [5]. Our image datasets are composed of 190 scenes from the Menut satellite operated by Open Cosmos and several hundred scenes from Planetscope data. We use the red, blue, green, and near-infrared bands from these data products. Using statistical techniques, we derive a band mapping from specific CS-6 bands to equivalent Menut bands so that CS-6 inputs are compatible with models trained on the latter.

We derive automated labeling techniques from the Haze Optimized Transform method for clouds [9], Normalized Difference Water Index method for surface water [4], band thresholds for thermal activity [6], and ESA's WorldCover maps for land use [1].

Development begins with training of deep learning models. These models are then tested on Myriad X Neural Compute Stick(s). Finally, the models are executed on a flatsat testbed at Ubotica before upload and use onboard CS-6.

3 Results and Conclusion

Leveraging edge computing for onboard data analysis is an exciting new capability of Earth-observing assets that opens the door for new Earth science [3]. We hope to advance the technology readiness level of this capability to enable deployment to future Earth-science missions.

*Contact: itai.m.zilberstein@jpl.nasa.gov. Full paper appears in the proceedings of the International Symposium on Artificial Intelligence, Robotics and Automation in Space (i-SAIRAS) 2024.

Acknowledgements

Portions of this work were performed by the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration (80NM0018D0004). This work was supported by the NASA Earth Science and Technology Office (ESTO). Government sponsorship acknowledged.

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