



MAARS

Machine learning-based Analytics for Automated Rover Systems

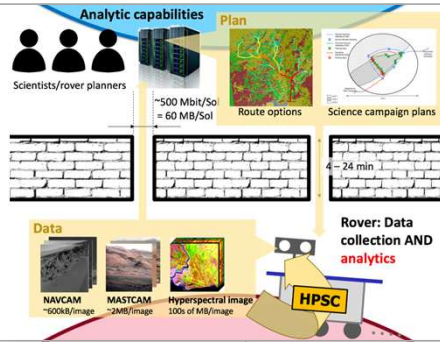
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Project Objective - Develop, test, and benchmark “killer autonomy apps” for future rovers with HPSC (high performance spacecraft computing)

Capability 1: Drive-by Science

- Convert rovers with no scientific instruments (e.g., Sample Fetch Rover) to a science rover by allowing scientists to instruct the rover to find geological features in its navigation camera images
- Overcome comm rate limitation with on-board data interpretation, deep summarization, and triage



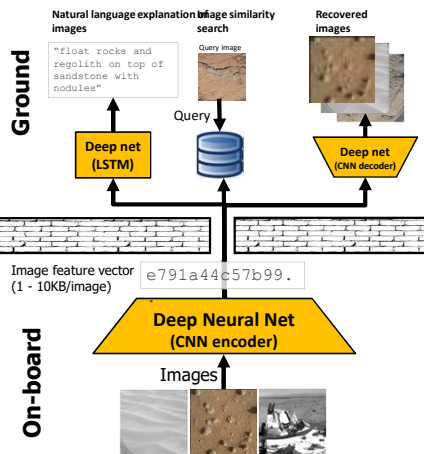
Capability 2: Risk/Resource-aware AutoNav

- Enhanced safety assessment with onboard terrain classification and slip prediction
- Energy-optimal path planning
- Onboard terrain, slip, and driving energy prediction by combining deep learning and terramechanics model

“Interplanetary Google Image”

SCOTI (Science Captioning of Terrain Images) ImageSpace

Makes onboard images searchable by keyword or image similarity *without* downlinking raw data



Deep Learning on HPSC/Snapdragon

- Developed toolchains to run TensorFlow models on HPSC and Snapdragon
 - HPSC: based on TensorFlowLite
 - Snapdragon: based on SNPE (Snapdragon Neural Processing Engine)
- Successfully deployed SPOC terrain classifier (Poster H01)
 - Preliminary benchmark with HPSC Emulator (QEMU) and Snapdragon 820
- Ongoing activities: HPSC Deployment of SCOTI, Benchmark with Snapdragon 855, Network optimization for HPSC

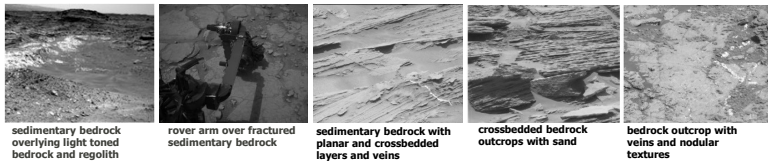
Preliminary benchmark results

Processor	Problem/Model	Model format	Acceleration	Avg. Comp. time [sec]*
Desktop	Terrain classification DeepLabv3	TensorFlow	GPU (Titan X Pascal)	0.023
HPSC QEMU 2.0	Terrain classification DeepLabv3	TensorFlow Lite	CPU-only with SIMD	~80**
	Image classification MobileNetV2			~0.9***
Snapdragon 820	Terrain classification DeepLabv3	DLC	CPU-only	14.5
	DLC Quantized		DSP	0.62

*Per tile, averaged over 176 tiles created from 3 NAVCAM images. A tile is a 513 x 513 image.
 **Computation time on QEMU is significantly slower than real and highly dependent on other processes running on the same machine
 ***The runtime of MobileNetV2 is on a 214 x 214 image

Auto-generated image captions by SCOTI on validation set

- Network trained with ~3,000 annotated images created by a geologist
- Training & validation sets contain NAVCAM and MASTCAM images from MSL



Benefits to NASA and JPL (or significance of results):

- Ground-based search with SCOTI and image similarity immediately deployable on PDS
- Potential infusion of ground-based energy optimal route planning into M2020 extended mission
- On-board infusion to future rovers with HPSC for drastically extending driving distance without risking safety or missing science opportunities
- Make high data rate instruments realistic, such as hyperspectral imagers
- Potential enabler for radically new missions such as driving up to the Southern Highland or go through the layered ice deposit on South Polar Cap

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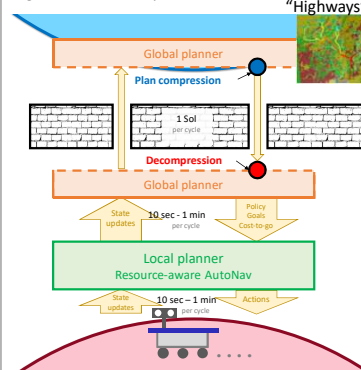
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Onboard strategic planning

RAND (resource-aware, non-stop driving)

- Ground: Plan optimal routes/schedules to goals from *anywhere* on HIRISE map
- Compress plans and send to rover
- Strategic plans recovered onboard
- Allows quick onboard *replanning* without ground-in-the-loop



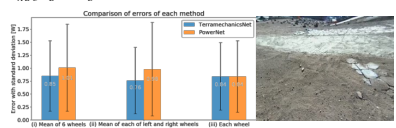
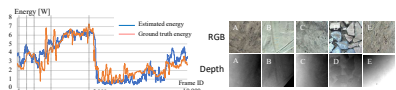
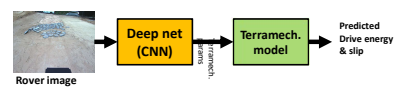
Highway-based plan compression

- Landing sites often have natural “highways” due to non-uniform traversability
- Rover typically ends up with one of highways wherever it starts
- Main idea:** Send plans only on highways, compute the rest onboard
- Prelim result: ~250 KB for 1 km drive (original size: 260 MB)

Energy-optimal AutoNav

VeeGer (vision-based estimation of expending and generating energy for rovers)

- Makes onboard prediction of driving energy and slip on the surface ahead of the rover
- Used as a cost map for enabling energy-optimal path planning
- Semi-model-based approach:
 - Front end: Deep net (CNN) for estimating terramechanics parameters from images
 - Back end: Terramechanics model for estimating slip and driving energy
- Tested on Athena Rover in the Mars Yard



Setting	(a) VeeGer-TerramechanicsNet	Mean and standard deviation of the difference between estimated power by VeeGer and ground truth; (i) mean of 6 wheels, (ii) mean of each of left and right wheels, (iii) each wheel.
mean	0.85	0.68
stddev	0.76	0.64
	0.84	0.65

Publications:

Journal

- Higa, S., Iwashita, Y., Otsu, K., Ono, M., Lamarre, O., Didier, A., Hoffmann, M. To appear in Robotics and Automation Letters (RA-L) and IROS, 2019

Conference

- M. Ono, B. Rothrock, C. Mattmann, T. Islam, A. Didier, V. Sun, D. Qiu, P. Ramirez, K. Grimes, G. Hedrick, and C. Laporte, “Make Planetary Images Searchable: Content-based search for PDS and On-Board Datasets,” LPSC, 2019
- M. Ono et al., MAARS: Machine learning-based Analytics for Rover Systems, to be presented in IEEE Aerospace, 2020

Invited talks

- B. Rothrock “Making Planetary Images Searchable,” AI4Science Workshop, Feb 2019
- M. Ono “Extraterrestrial Autonomous Driving,” NAE Frontier of Engineering, Sep 2019
- M. Ono “Robots in Space: How JPL uses Ai & Machine Learning for Space Exploration,” Innovate@UCLA: Fall Day of Innovation, Oct 2019

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