Virtual Research Presentation Conference

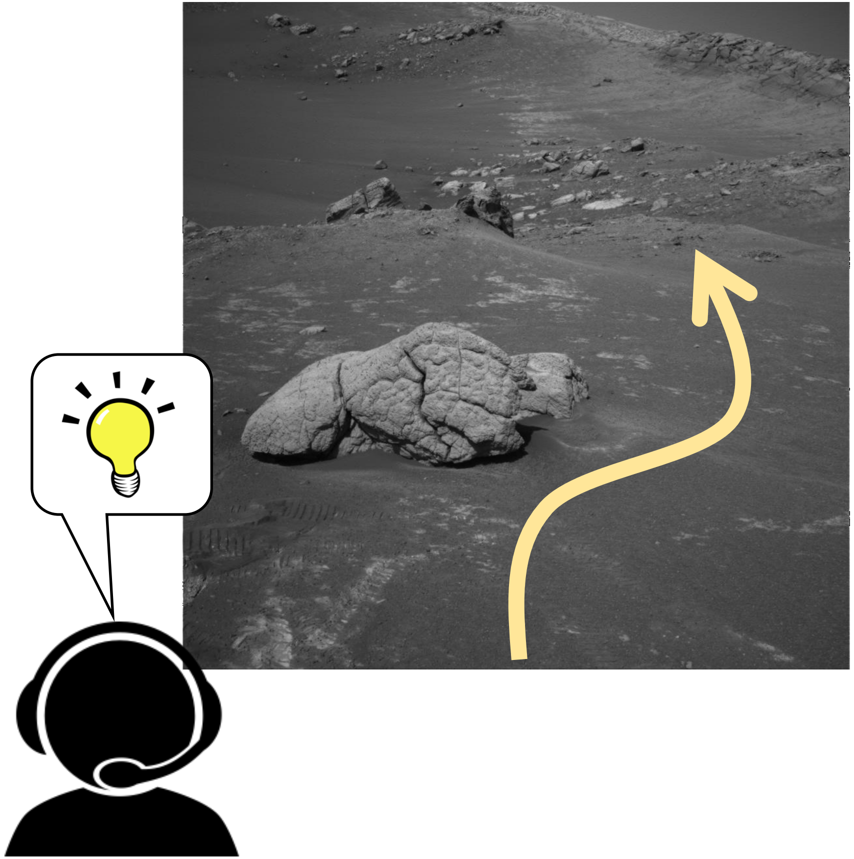
Machine Learning based Path Planning for Improved Rover Navigation

Principal Investigator: Hiro Ono (347)
JPL Co-Is: Neil Abcouwer (347), Shreyansh Daftry (347), Tyler Del Sesto (347), Olivier Toupet (347), Mitch Ingham (3100)
Caltech Co-Is: Yisong Yue (Caltech), Jialin Song (Caltech)
Program: Topic

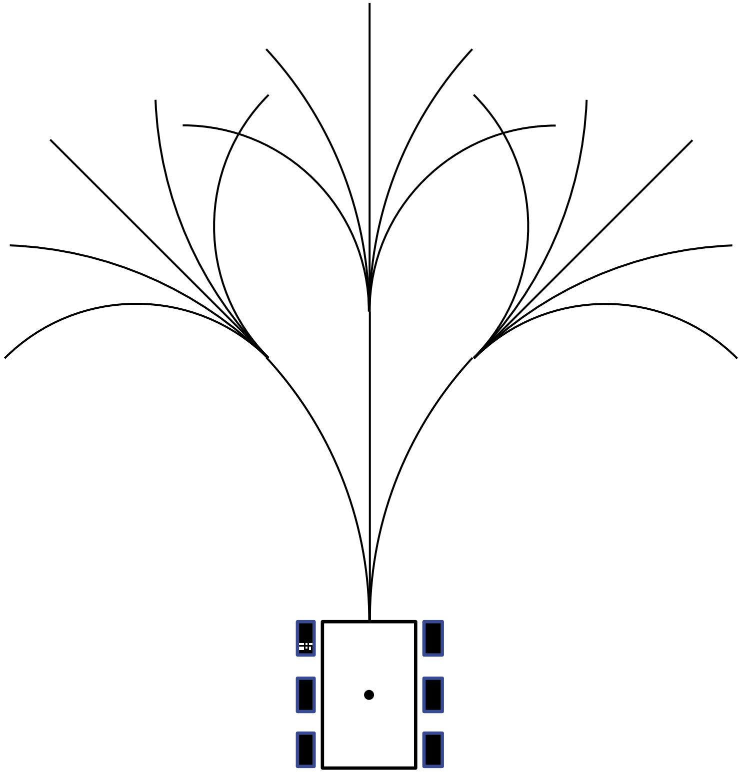
Assigned Presentation # 205

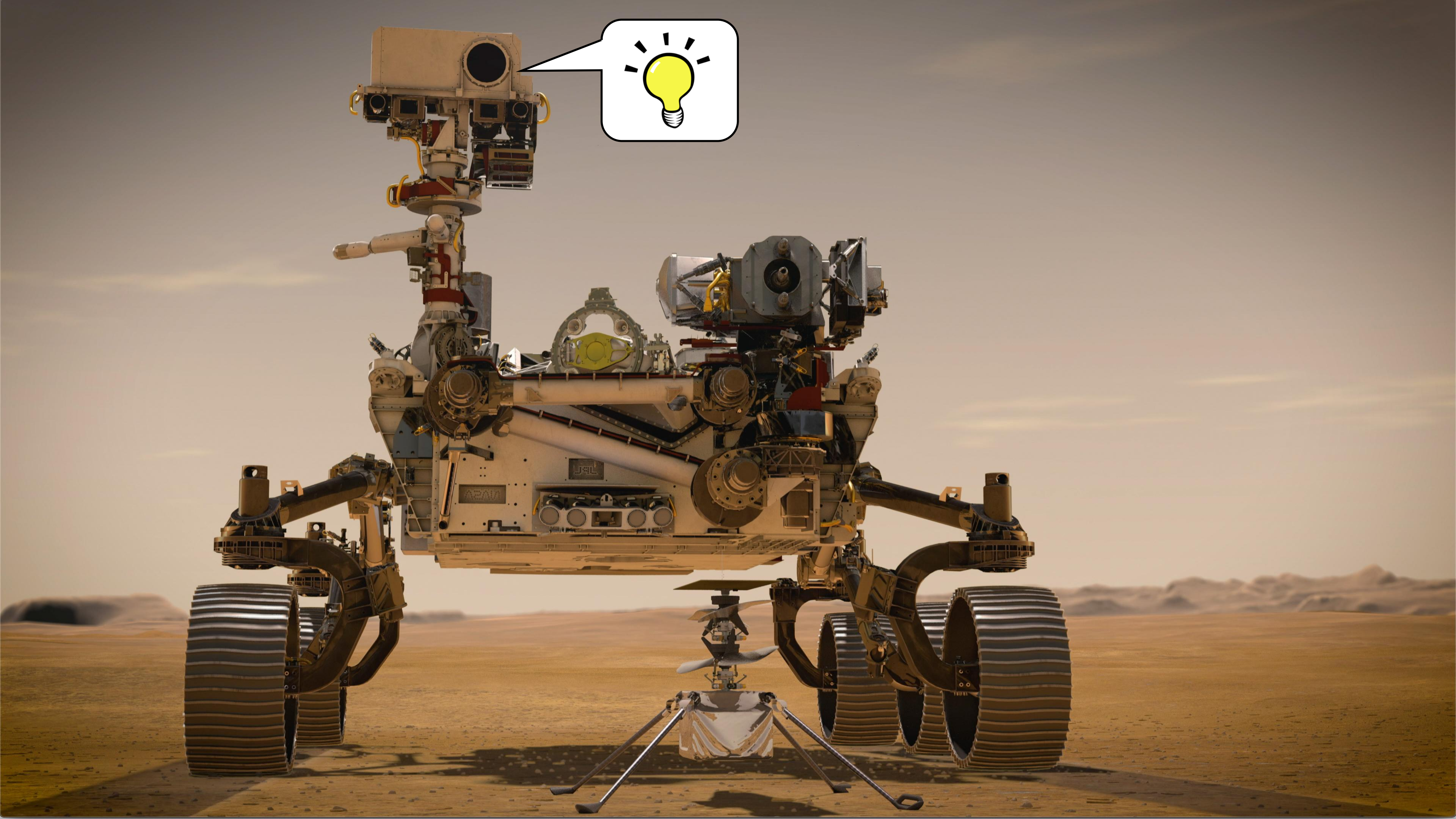
Jet Propulsion Laboratory
California Institute of Technology

Experienced human driver



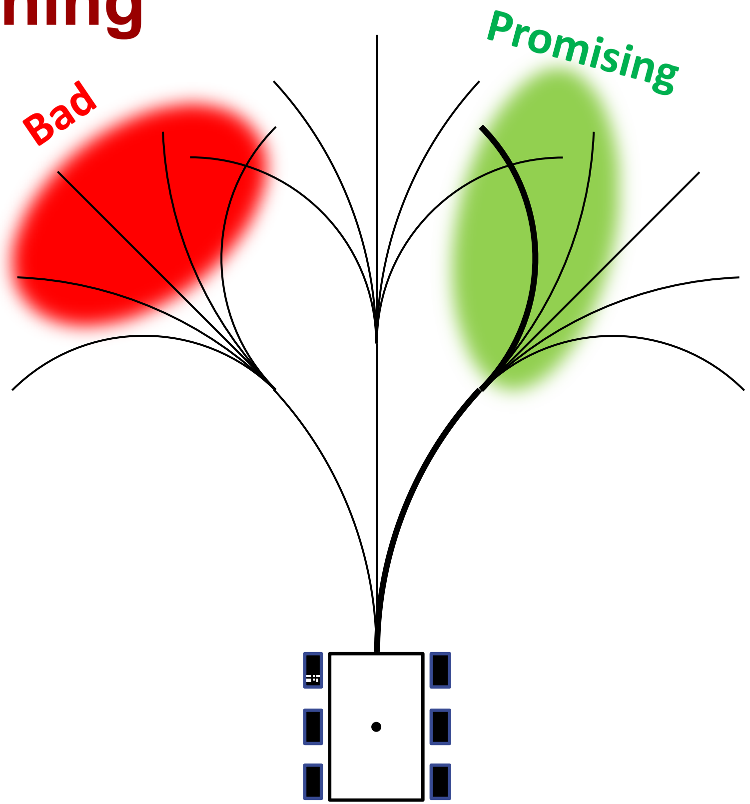
ENav Algorithm

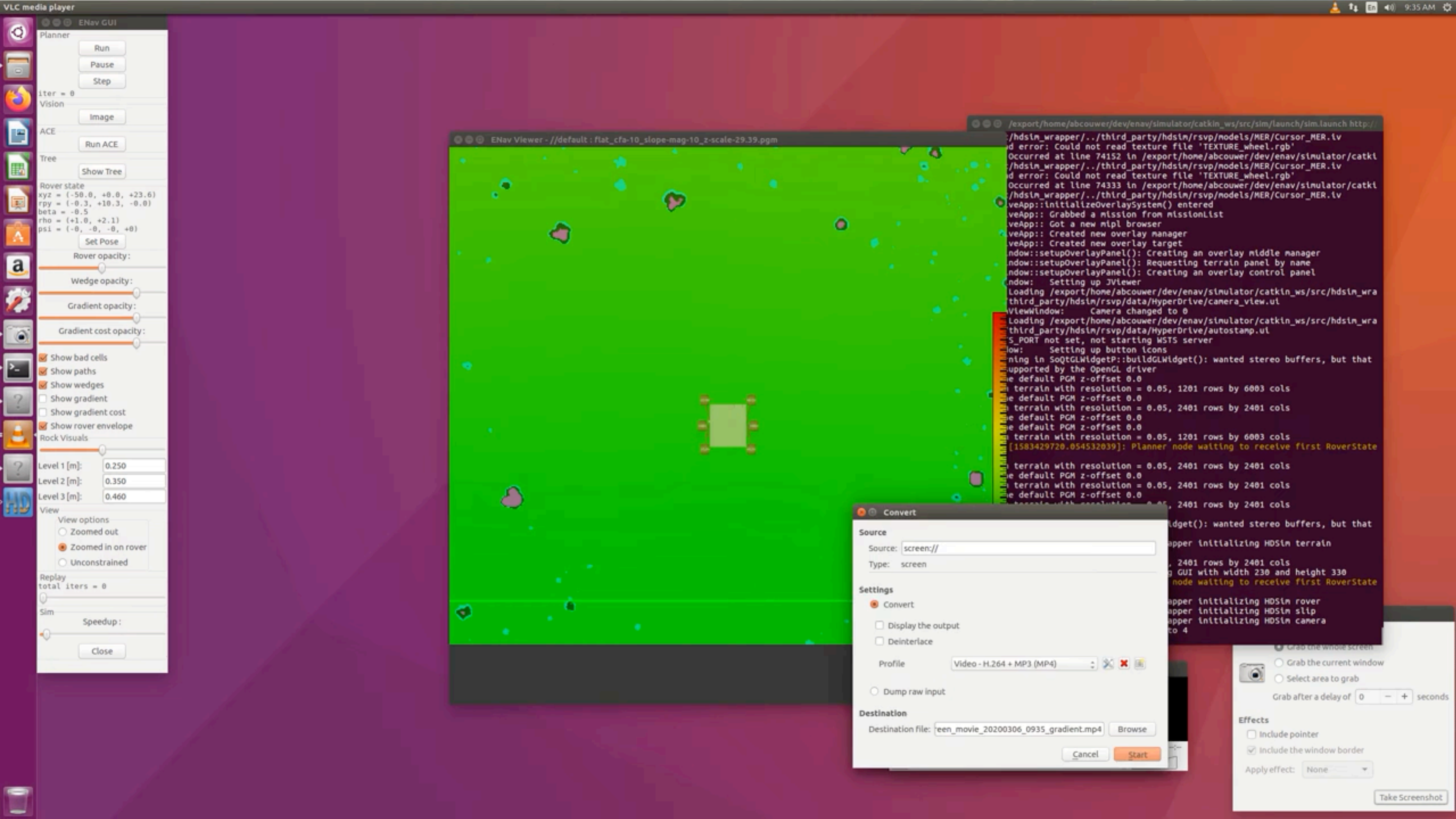




Heuristics for ENav Path Planning

- Two heuristics developed in FY20
  - **Human-designed** heuristic, designed by domain experts
  - **Machine-learned** heuristic, automatically learned from numerous runs of ENav in simulation
- Heuristics guide path planner towards promising direction
- Reduce the number of computationally expensive collision checking (ACE)




VLC media player
9:35 AM
ENav GUI
Planner
Run
Pause
Step
iter = 0
Vision
Image
ACE
Run ACE
Tree
Show Tree
Rover state
xyz = (-50.0, +0.0, +23.6)
rpy = (-0.3, +10.3, -0.0)
beta = -0.5
rho = (+1.0, +2.1)
psi = (-0, -0, -0, +0)
Set Pose
Rover opacity:
Wedge opacity:
Gradient opacity:
Gradient cost opacity:
Show bad cells
Show paths
Show wedges
Show gradient
Show gradient cost
Show rover envelope
Rock Visuals
Level 1 [m]: 0.250
Level 2 [m]: 0.350
Level 3 [m]: 0.460
View
View options
Zoomed out
Zoomed in on rover
Unconstrained
Replay
total iters = 0
Sim
Speedup:
Close
ENav Viewer - //default : flat_cfa-10_slope-mag-10_z-scale-29.39.pgm
/export/home/abcouwer/dev/enav/simulator/catkin_ws/src/sim/launch/sim.launch http://
/hdsim_wrapper/../third_party/hdsim/rsvp/models/MER/Cursor_MER.iv
d error: Could not read texture file 'TEXTURE_wheel.rgb'
Occurred at line 74152 in /export/home/abcouwer/dev/enav/simulator/catki
/hdsim_wrapper/../third_party/hdsim/rsvp/models/MER/Cursor_MER.iv
d error: Could not read texture file 'TEXTURE_wheel.rgb'
Occurred at line 74333 in /export/home/abcouwer/dev/enav/simulator/catki
/hdsim_wrapper/../third_party/hdsim/rsvp/models/MER/Cursor_MER.iv
veApp::initializeOverlaySystem() entered
veApp:: Grabbed a mission from missionList
veApp:: Got a new mipl browser
veApp:: Created new overlay manager
veApp:: Created new overlay target
ndow::setupOverlayPanel(): Creating an overlay middle manager
ndow::setupOverlayPanel(): Requesting terrain panel by name
ndow::setupOverlayPanel(): Creating an overlay control panel
ndow: Setting up JViewer
Loading /export/home/abcouwer/dev/enav/simulator/catkin_ws/src/hdsim_wra
third_party/hdsim/rsvp/data/HyperDrive/camera_view.ui
ViewWindow: Camera changed to 0
Loading /export/home/abcouwer/dev/enav/simulator/catkin_ws/src/hdsim_wra
third_party/hdsim/rsvp/data/HyperDrive/autostamp.ui
S_PORT not set, not starting WSTS server
ow: Setting up button icons
ning in SoQtGLWidgetP::buildGLWidget(): wanted stereo buffers, but that
upported by the OpenGL driver
e default PGM z-offset 0.0
terrain with resolution = 0.05, 1201 rows by 6003 cols
e default PGM z-offset 0.0
terrain with resolution = 0.05, 2401 rows by 2401 cols
e default PGM z-offset 0.0
e default PGM z-offset 0.0
terrain with resolution = 0.05, 1201 rows by 6003 cols
[1583429720.054532039]: Planner node waiting to receive first RoverState
terrain with resolution = 0.05, 2401 rows by 2401 cols
e default PGM z-offset 0.0
terrain with resolution = 0.05, 2401 rows by 2401 cols
e default PGM z-offset 0.0
2401 rows by 2401 cols
dget(): wanted stereo buffers, but that
apper initializing HDSim terrain
2401 rows by 2401 cols
GUI with width 230 and height 330
node waiting to receive first RoverState
apper initializing HDSim rover
apper initializing HDSim slip
apper initializing HDSim camera
to 4
Convert
Source
Source: screen://
Type: screen
Settings
Convert
Display the output
Deinterlace
Profile
Video - H.264 + MP3 (MP4)
Dump raw input
Destination
Destination file: een_movie_20200306_0935_gradient.mp4
Browse
Cancel
Start
Grab the current window
Select area to grab
Grab after a delay of 0 seconds
Effects
Include pointer
Include the window border
Apply effect: None
Take Screenshot

Gradient Convolution Heuristic

Given a terrain heightmap around a rover, the gradient convolution heuristic is calculated as follows:

1) Convolve the heightmap with normalized 3x3 Sobel operators to find the x and y gradient

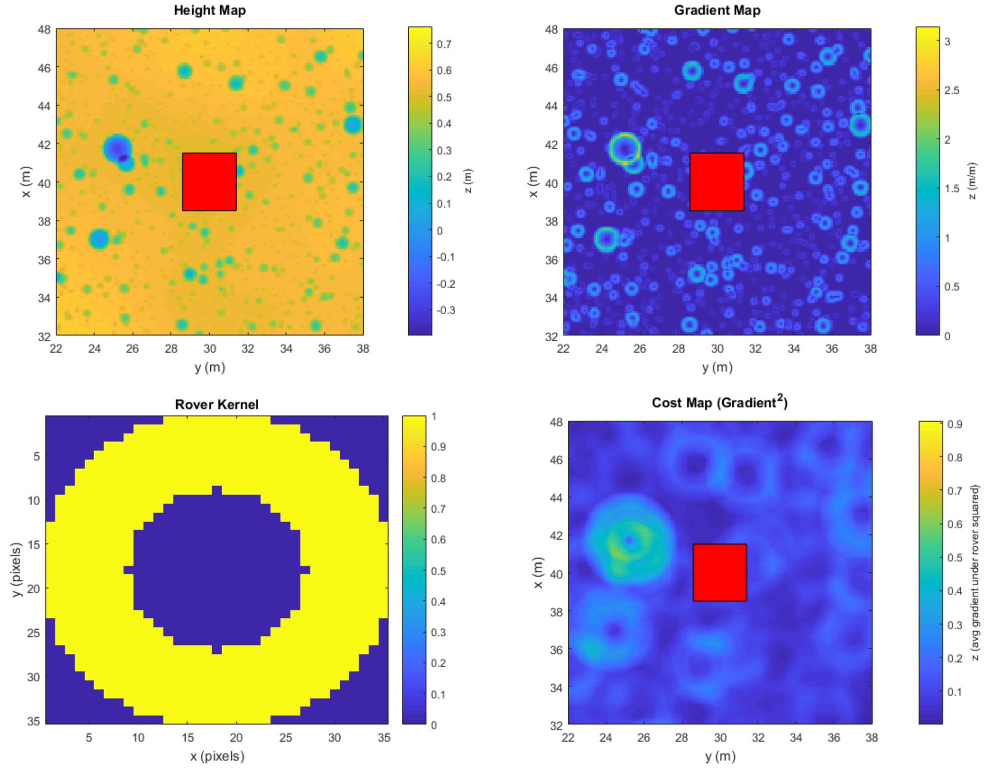
$$\mathbf{G_x} = \frac{1}{2r}\frac{1}{4}\begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * \mathbf{A} \qquad \mathbf{G_y} = \frac{1}{2r}\frac{1}{4}\begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * \mathbf{A}$$

2) Find the squared gradient as the element-wise multiplication of the x and y gradient:

$$\mathbf{G_{sq}} = \mathbf{G_x} \circ \mathbf{G_x} + \mathbf{G_y} \circ \mathbf{G_y}$$

3) Convolve the gradient map with an annulus-shaped kernel representing the footprint of the rover:

$$\mathbf{G_c} = \frac{k}{\sum \mathbf{R}_i}\mathbf{R} * \mathbf{G_{sq}}$$

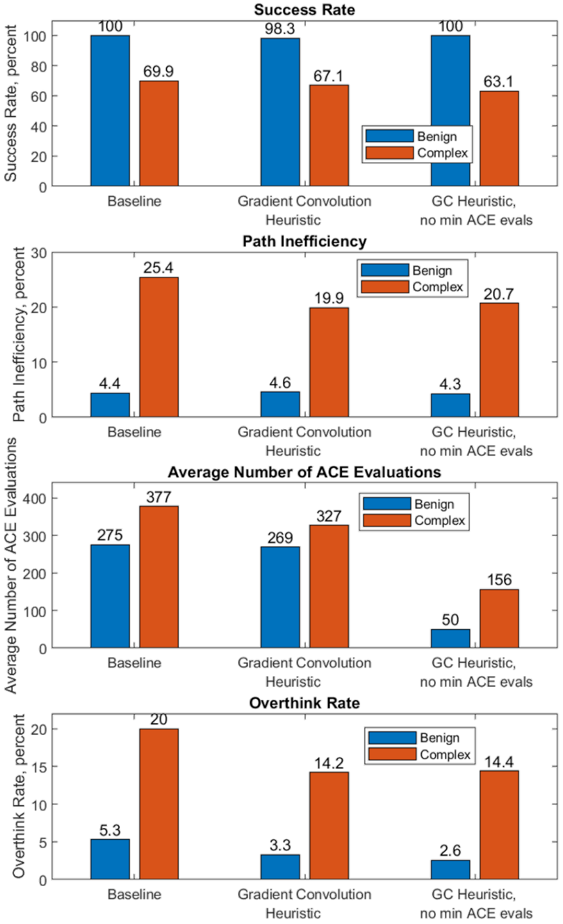


Work by Neil Abcouwer and Tyler Del Sesto

Gradient Convolution Heuristic – Monte Carlo Simulation Results

Tests with the Gradient Convolution Heuristic integrated into ENAV showed:

+ Reduced path inefficiency in complex terrain by up to 22%
+ Substantial reduction in the number of ACE evaluations, by up to 59%
- Small reduction in success rate in complex terrain
+ **Heuristics have potential to increase computational efficiency.**



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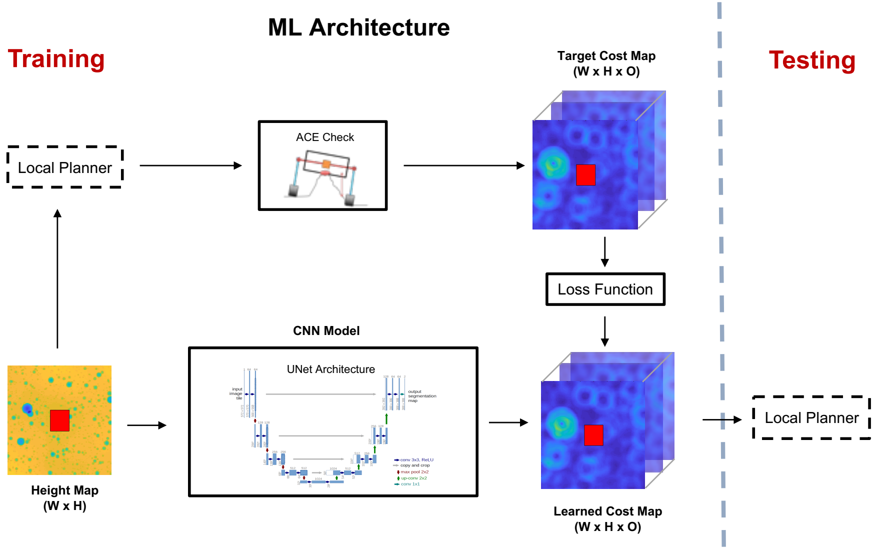
Machine Learned Heuristic

Architecture:

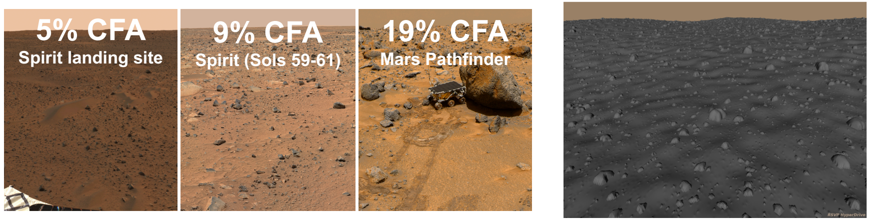
- Data-driven framework to automatically learn the heuristic
- Uses an encoder-decoder style Convolutional Neural Network based on U-Net to predict the outcome of the of ACE algorithm for a given terrain map
- Using this prediction, ENav can reduce its search space by more optimally sorting its initial list of potential paths
- ACE Check is still done on the final selected path before execution, ensuring classical safety guarantees.



Dataset Generation and Training:

- Training data was generated using a ROS-based ENav simulation environment with a wide-range of terrain properties (CFA: 7-15%, Slope: 0-20 degrees)

Dataset Generation



Example generated terrain

Work by Shreyansh Daftry, Neil Abcouwer, Siddarth Venkatraman

Machine Learned Heuristic

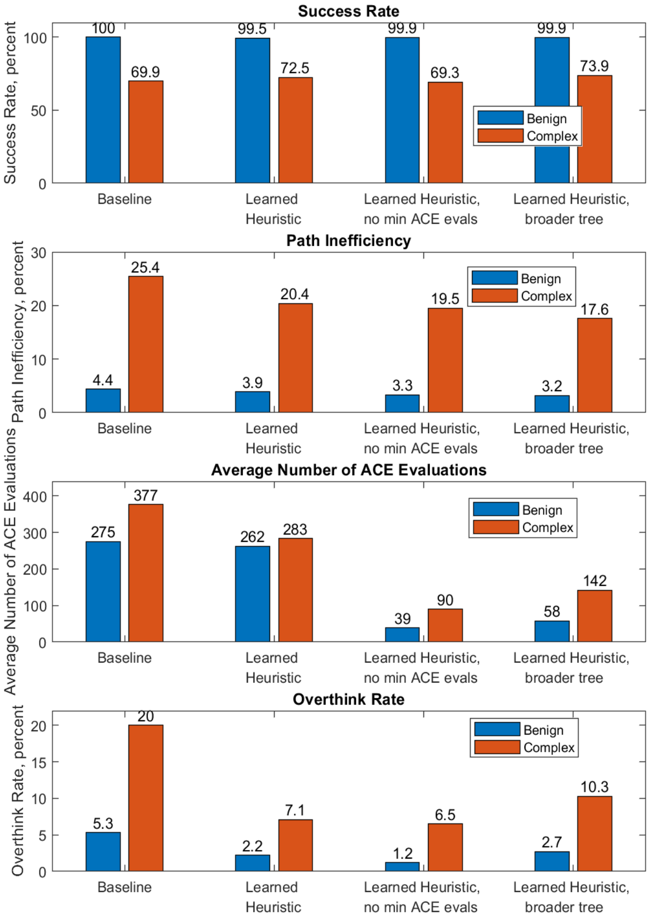
Performance of CNN Model in Learning Heuristic:

- Training Accuracy: 97.8%, Validation Accuracy: 95%

Input Heightmap **Ground Truth** **Prediction**

Tests with the Learned Heuristic integrated into ENAV showed:

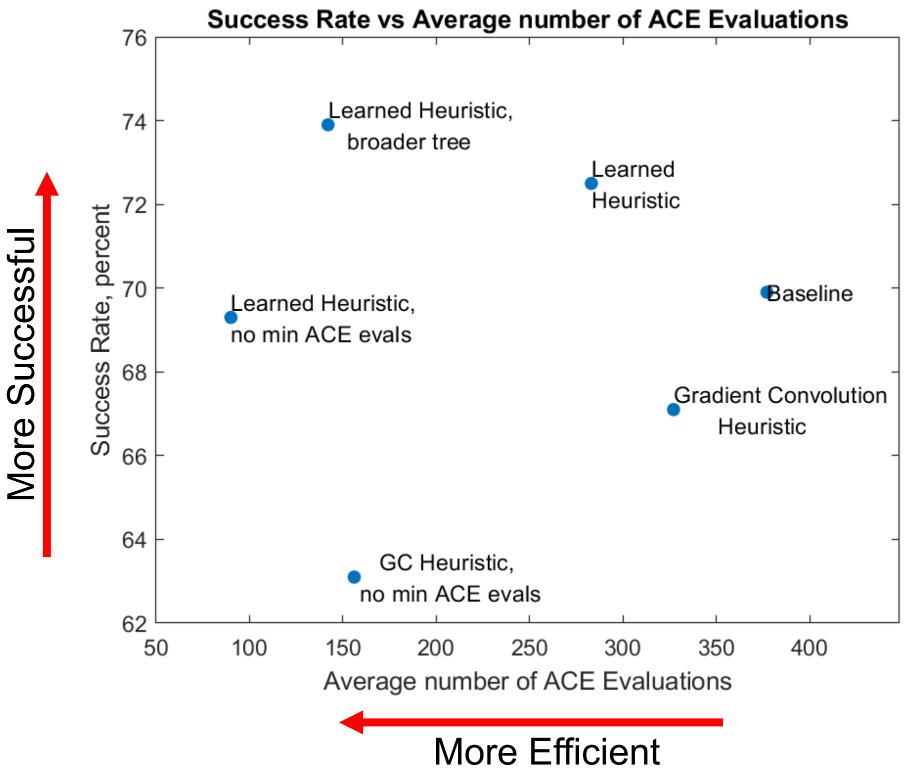
- 31% Improved path efficiency in complex terrain
- 76% reduction in the number of ACE evaluations
- Learned Heuristics have potential to significantly increase computational efficiency.



Work by Shreyansh Daftry, Neil Abcouwer, Siddarth Venkatrman

Overall Monte Carlo Simulation Results

- The learned heuristic proved broadly superior to the hand-designed Gradient Convolution Heurisitc
  - Greater success rates
  - Fewer ACE evaluations
- Both heuristics worth testing on representative hardware.



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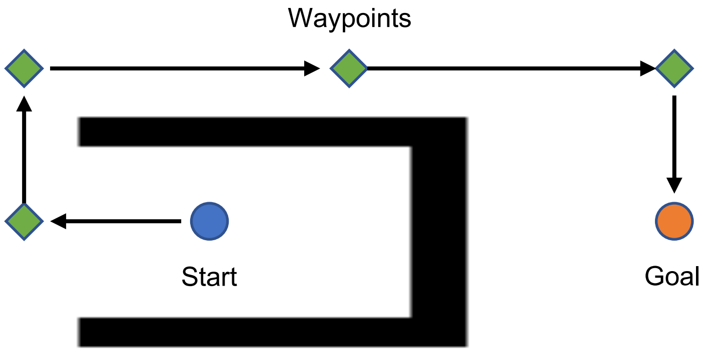
Hierarchical Path Planning



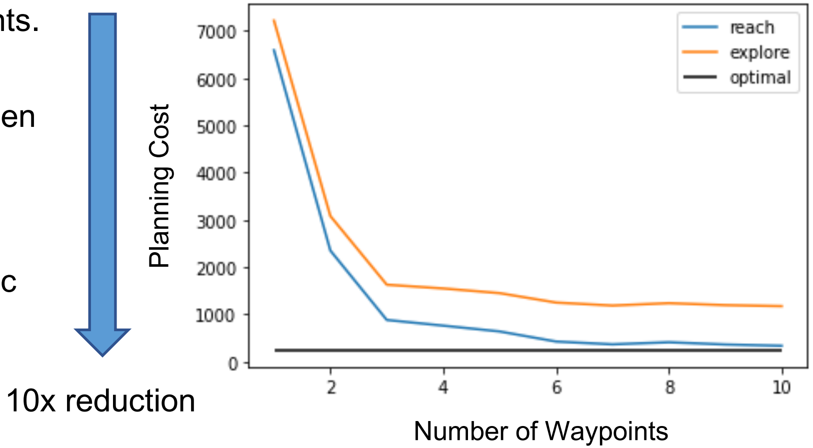
Long distance planning is challenging for the existing planner which mainly relies on local information.

We propose to utilize hierarchy in planning tasks:

1) Use global information to define sub-problems for planning in the form of waypoints.
2) Use the existing planner to complete plans connecting waypoints.

Preliminary experiments show a 10x reduction in planning cost when used with the A* algorithm if an expert places the waypoints manually, compared with planning with no waypoints.

Work is underway to design machine learning models for automatic waypoint placements from global map information.



Work by Jialin Song

FY20 Accomplishments

- Development and implementation of the hand-designed and machine-learned heuristics
- Integration of the heuristics with ENav FSW; evaluation with Enav Monte Carlo Sim
- Two conference paper drafts
  - Machine Learning-Based Path Planning for Improved Rover Navigation. N. Abcouwer, S. Daftry, S. Venkatraman, T. del Sesto, R. Lanka, O. Toupet, M. Ono, J. Song, and Y. Yue. Abstract accepted to *IEEE Aerospace Conference*, 2021
  - Learned Heuristics for Safe and Efficient Path Planning, S. Daftry, N. Abcouwer, S. Venkatraman, T. Sesto, J. Song, O. Toupet, M. Ingham, R. Lanka, Y. Yue, H. Ono. To be submitted to *ICRA 2021*

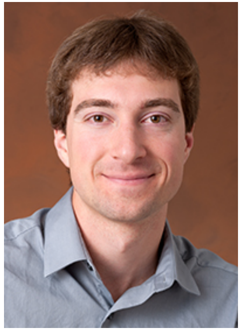
FY21 Goals

- Maturation of the machine-learning-based heuristic
- Deployment on a processor that is analogous to future on-board computers (e.g, Qualcomm's Snapdragon) for validation and benchmarking
- Advance the technology to TRL 4

Research Presentation Conference 2020

Neil Abcouwer
347

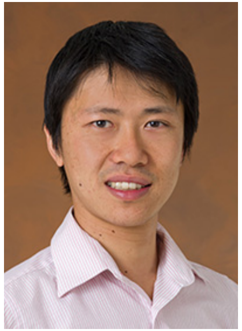
Shreyansh Daftry
347



Tyler Del Sesto
347

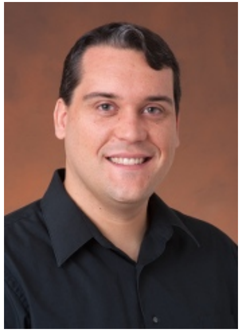
Mitch Ingham
310

Ravi Lanka
Former 398

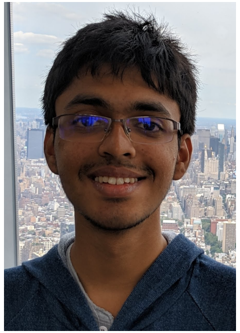


Hiro Ono
PI, 347

Jialin Song
Caltech



Olivier Toupet
347



Siddarth Venkatraman
347-Intern

Yisong Yue
Caltech PI