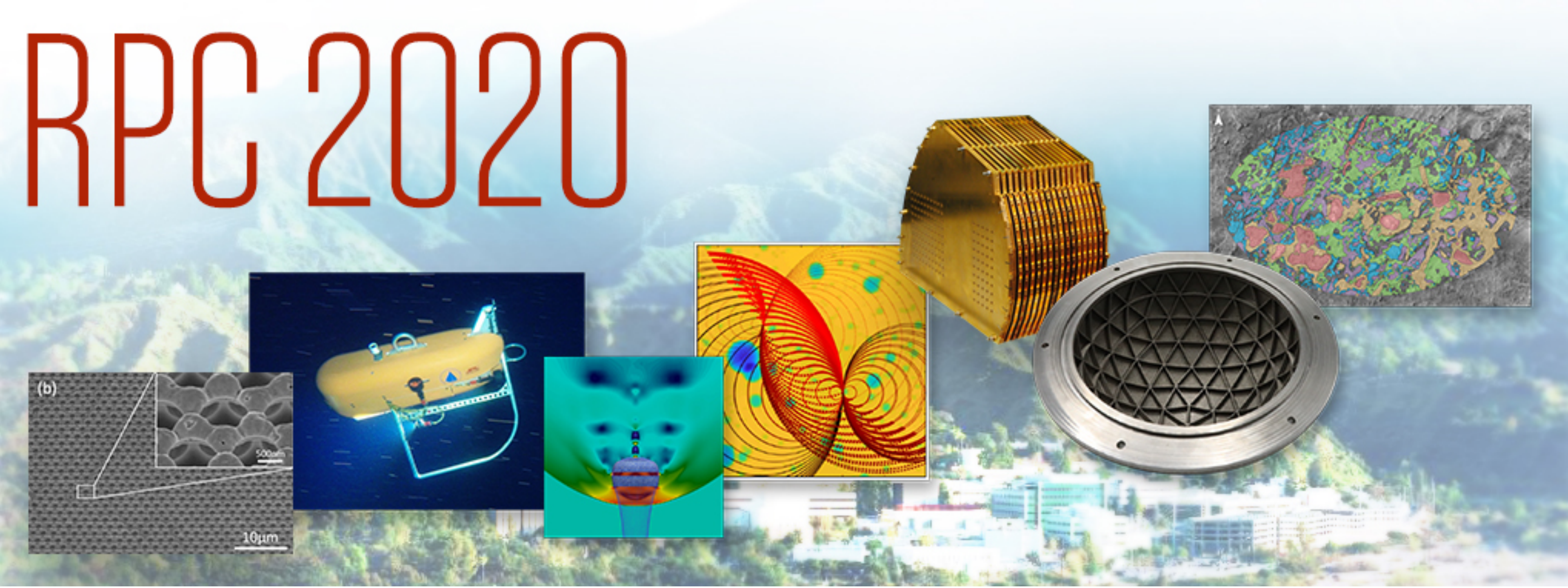


Virtual Research Presentation Conference

Barefoot Rover: a Sensor-Embedded Rover Wheel Demonstrating In-Situ Engineering and Science Extractions using Machine Learning

Jack Lightholder (398)
Yuliya Marchetti (398), Eric Junkins (347), Thomas Schibler (397), Paul Springer (398), Devon Yates (393), Jimmie Young (398), Matthew Cross (Western University), Lukas Mandrake (398)
Strategic Initiative

Jet Propulsion Laboratory
California Institute of Technology

RPC-251

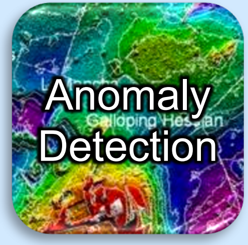
Motivation and Relevance

Combine in-situ sensors on a wheel and machine learning (ML) to:

- Add a sense of touch to the visual odometry.
- Deploy onboard in near-real time to generate important engineering and science products.
- Provide feedback to autonomous systems in evolving environments:
  - Work in no-light conditions.
  - Anomaly detection, monitoring for states which haven’t been observed before.
  - Data prioritized for transmission to operators.

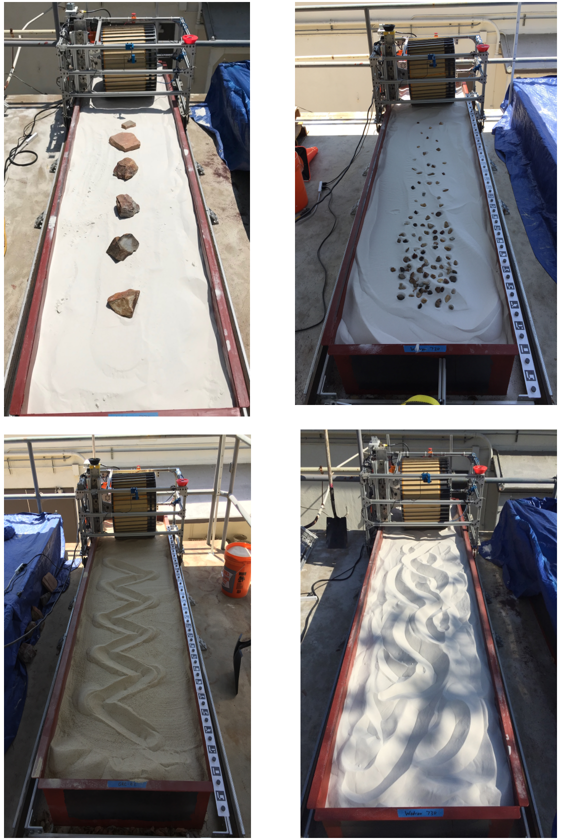
Engineering, safety, stability products

Science and high-level products



Methodology

- Use hardware to collect data from in-situ sensors for various configurations of terrain, materials, slip, hydration.
- Pre-process the collected data to extract meaningful representations, e.g. images.
- Build and train machine learning models using metrics/features computed based on the representations:
    - Slip regression
    - Rock binary classifier
    - Hydration multi-class classifier



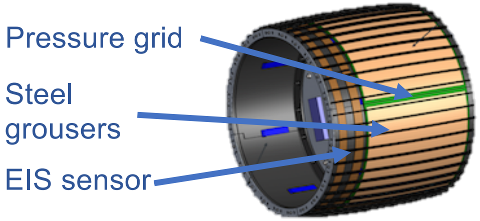
Various data collection experiments: rocks, pebbles, sharp landforms, dunes.

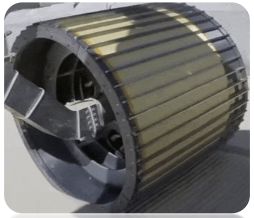
Methodology

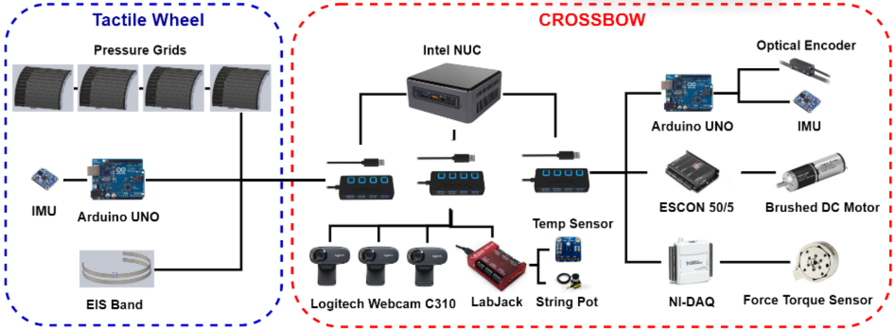
Main Barefoot Rover hardware components:

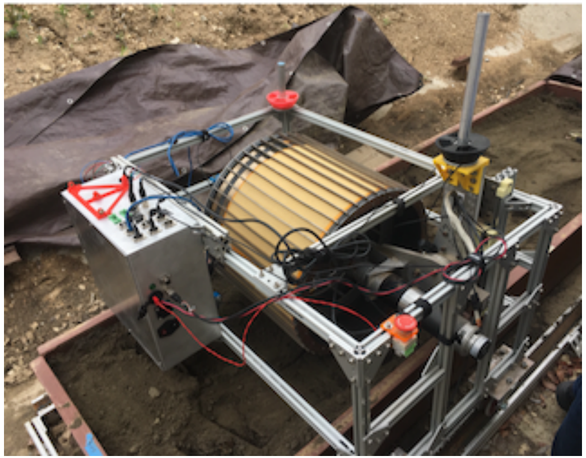
1) **Tactile wheel** carries two main in-situ sensors:
   - 2D Xiroku pressure sensor (PS)
   - Electrochemical Impedance Spectroscopy (EIS) sensor

2) **CROSSBOW test cart** allows mobility and data taking:
   - Motor, force/torque, string potentiometer







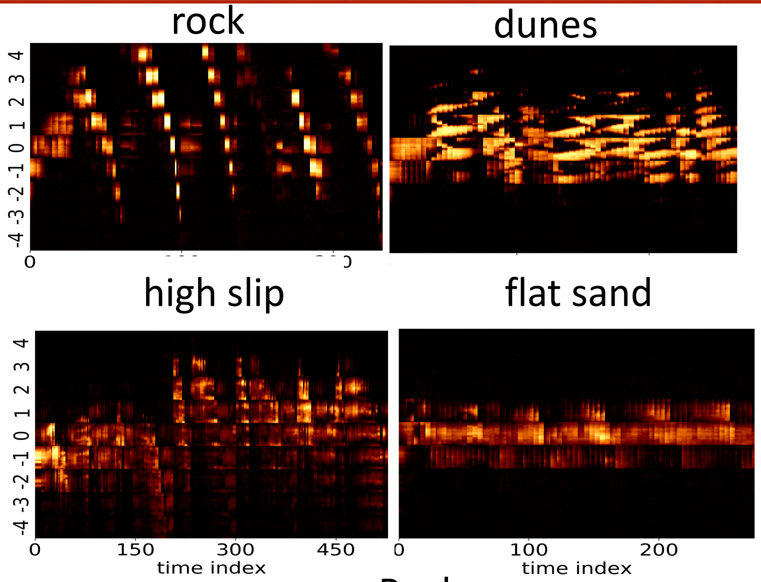


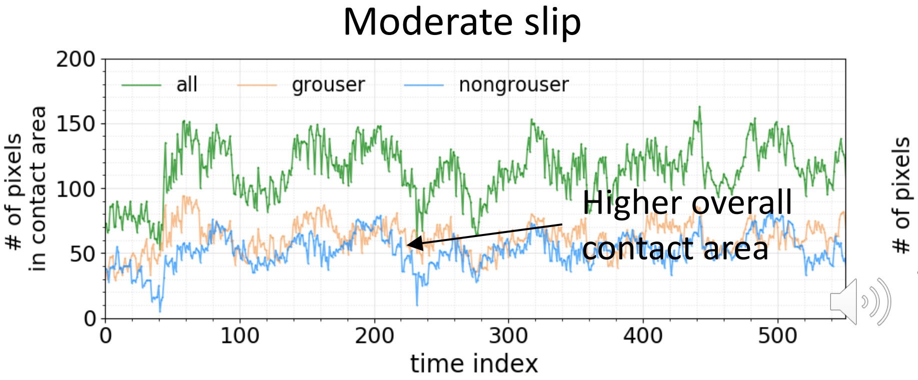
Tactile wheel is mounted on the CROSSBOW cart to be used in experiments

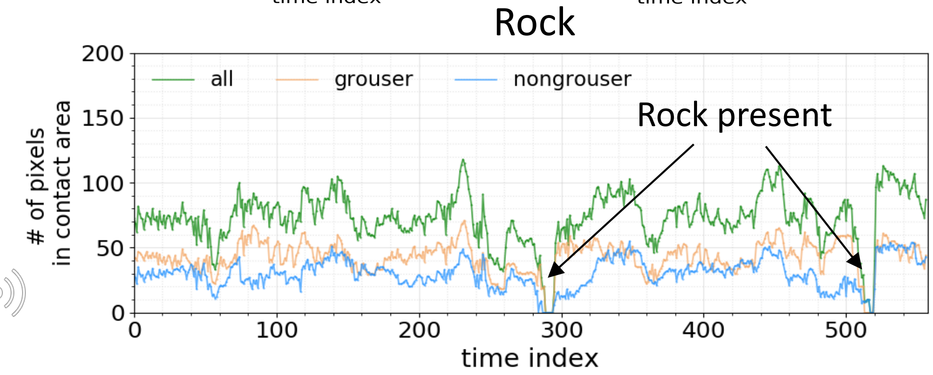
Methodology

The main two types of extractions:

- Contact area time series (bottom):
  - The number of pixels touching the ground in the area
- Pressure grid images (right):
  - Represent the spatial and time dimension of the wheel



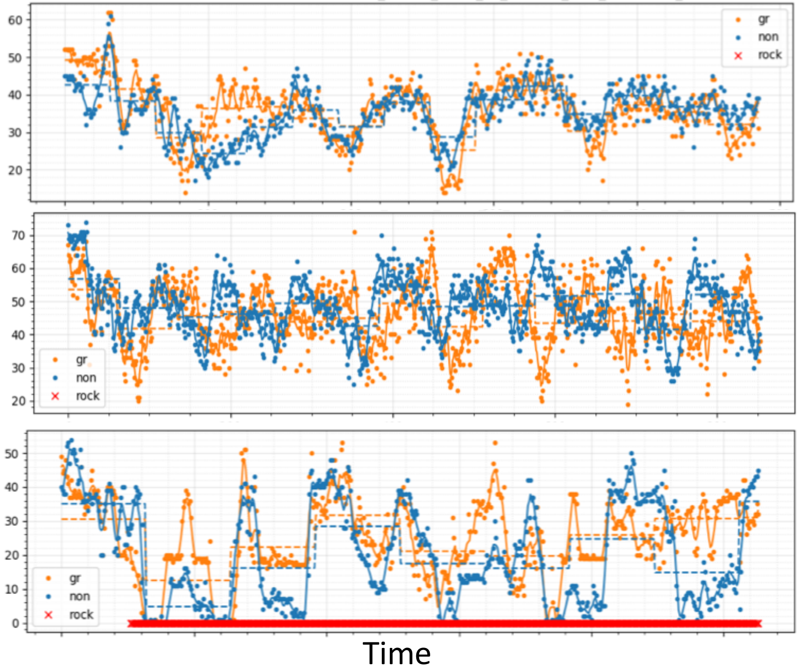




Methodology

Features are extracted to be the input into the ML models:

- Sliding window for streaming implementation.
- Contact area times series:
  - Signal processing, e.g. wavelets, rolling statistics
  - Time series metrics
- Pressure grid images:
  - Statistics in the spatial dimension of the wheel
  - Geometric features from derived image objects
- Grouser and non-grouser pixels carry additional information.



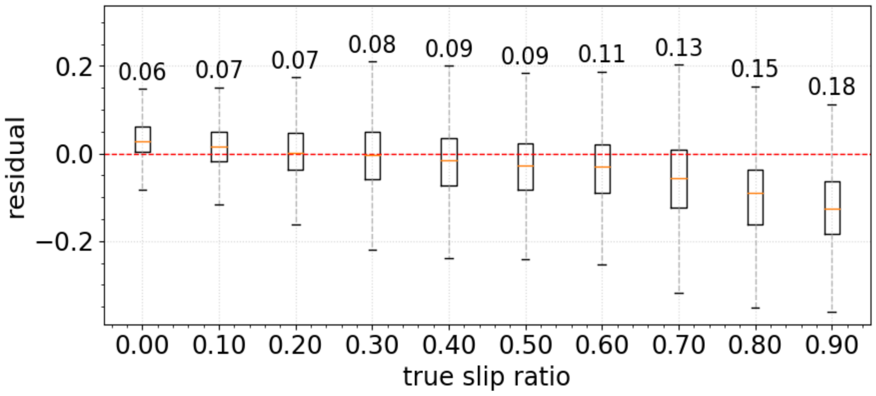
Contact area time series for **low slip/flat**, **high slip, rock** (top to bottom) contact area with wavelet and mean filter smoothing. Each type of experiment has a unique signature.

Results

Two main ML models trained with Gradient Boosted Trees are:

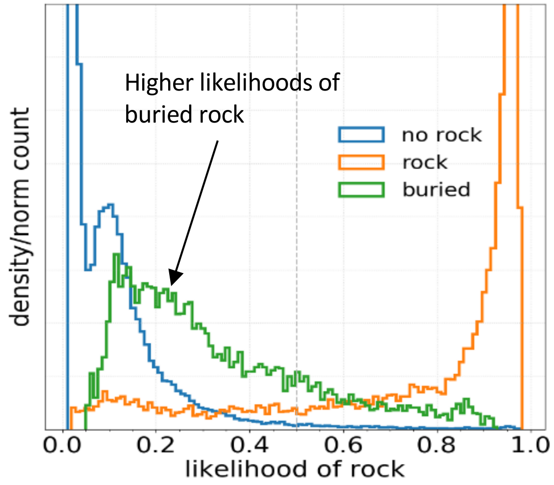
Slip regression model:

- Test root mean squares error (RMSE) -- **8.5%**
- Bias for higher slip values
- Better than current post-hoc estimates with 10% error



Rock binary classification model:

- Overall test accuracy -- **99%**
- Rock accuracy -- **85%**
- Buried rock accuracy -- **7%** but obtained rock likelihoods are larger than for the flat experiments

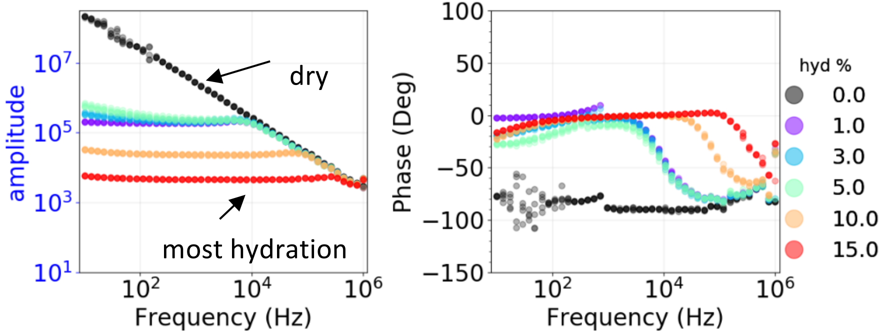


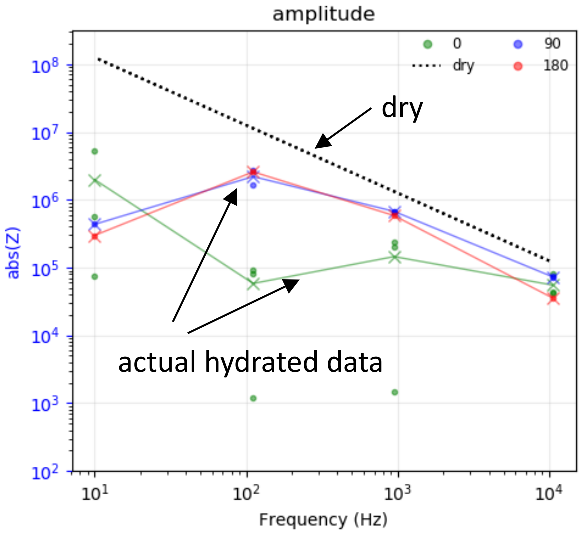
Results

Hydration classification is performed based on EIS sensor, which produces amplitude and phase of a signal:

- Data was collected in lab conditions, with static wheel experiments
- Discrete hydration levels set: 0, 1, 3, 5, 10, 15%
- Hydration accuracy -- **87-99%**

Hydration levels are clearly separated:

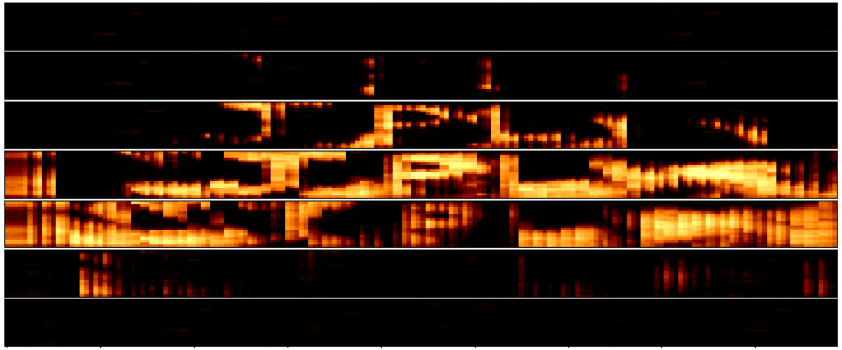




In-motion EIS experiment with **10%** hydration shows distinct moisture signature, however, data appears to be very noisy in general and requires good contact with the ground.

Results

- A low resolution 2D pressure sensor allows extraction of valuable information regarding the terrain.
- Simple and fast time series methods can capture the features of the terrain and the state of the wheel.
- Hydration levels can be detected, including while wheel is in motion with the EIS sensor.
- Developed a prototype of streaming terrain change detection that can enhance autonomous driving.
- Implemented ML algorithms in HPSC and EMU flight software architectures.
- Future work would implement and rigorously test the methods on a real rover wheel in true-to-life conditions.



Publications and References

Yuliya Marchetti et al. “Barefoot Rover: a Sensor-Embedded Rover Wheel Demonstrating In-Situ Engineering and Science Extractions using Machine Learning”. In:2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE. 2020.

Paul Springer et al. “Machine Learning Algorithm Performance on the Lucata Computer”. In:2020 IEEE High Performance Extreme Conference (HPEC). IEEE. 2020.