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

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Outline

• Motivation

• Summary of methods

• Hardware and sensors

• Machine learning:
  – Sensor data extractions
  – Featurization
  – Results
  – Terrain detection

• Summary and future directions
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
The main methods and goals of Barefoot Rover:

• Use hardware to collect data from in-situ sensors for various configurations of terrain, materials, slip, hydration, composition.

• 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 and terrain types multi-class classifier
  – Hydration multi-class classifier

Various data collection experiments: rocks, pebbles, sharp landforms, dunes, various compositions.
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
Contact area time series is one of the two extractions from the raw pressure sensor data:

- Contact area is the number of pixels in the area that is touching the ground.
- Obtained with thresholding via Interquartile Range (IQR) of the pressure values for each reading of the pressure sensor.
- Can differentiate among terrain types.

Moderate slip

Higher overall contact area

Rock

Rock present
Pressure grid “unwrap” images are the second pressure sensor extraction:

- They represent the spatial and time dimension of the wheel.

- The rows of pixels around Inertial Measurement Unit (IMU) are stacked as vectors for each time step.

- Unique visual signatures for various terrain states.

From left to right and top to bottom: images of rock, dunes, slip, flat experiments. The rows of the pressure sensor are stacked as one vector on the y-axis, with 0 corresponding to the row that aligns with the IMU reading at that point in time.
**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: slip and rock

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

Low slip image

High slip image

Test error for various slip configurations

Higher likelihoods of buried rock

Density distribution for different rock categories:
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.
Unsupervised terrain detection

Monitor time series to determine high-level terrain state and changes:

- Are we seeing something we’ve seen before or **is this new**?
- **Prioritize** data/findings for onboard applications.
- Computationally **fast** and requires only a small amount of data to be held in memory.

Simulated 4 time series states (colored)
• 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.

Summary and future directions

• Implementation of developed software as part of an onboard system.

• A new, better tactile wheel and hardware that can represent deployment in real terrain.

• Various novel applications and infusions, e.g. ice roads/beachfront driving, Lunar/Martian wheels, new sensors (neutron spectrometer).