Experimental Learning for Traversability Estimation and Stochastic Motion Planning on a Planetary Rover

Thierry Peynot, Ken Ho, Angela Lui, Rowan McAllister, Robert Fitch and Salah Sukkarieh
Uncertainty

- Localisation
- Perception (incomplete & uncertain maps) \(\rightarrow\) Traversability
- Control (uncertain outcomes) \(\rightarrow\) Planning

Anticipate (impact of) terrain deformation

Outline:

1. Traversability estimation from incomplete exteroceptive sensing data via experimental learning
2. Motion planning and stochastic control with mobility prediction model learnt from experience
Traversability Estimation for a Planetary Rover via Experimental Kernel Learning in a Gaussian Process Framework

Ken Ho
Thierry Peynot
Salah Sukkarieh

[ICRA 2013]
• **Objective:** Estimate attitude and configuration for a rover
  – Indication of traversability
• **Heterogeneous terrain**
• **Occlusion/missing data in perception**
  – Field of view/sensor placement
Previous work

DEM-Kin

DEM → Vehicle Kinematics → Incomplete Map of Vehicle Config.

• Kinematic modeling on geometric terrain model (Lacroix et. al.)
  – Dependent on geometry of vehicle and terrain
  – All 6 wheels contact ground
    • Need data on all 6 wheels
Previous work (cont.)

- Classifying terrain types and predicting slip based on terramechanic model (Iagnemma et. al., Helmick et. al.)
- Improving geometric terrain model (Vasudevan et. al.)
  - Using GP estimates in areas with little/no data

→ This work generates a complete representation of terrain traversability with uncertainty
Proposed Framework – Kin-GPVE

Learning Phase

Prediction Phase

Range Sensor → Pointcloud → Build Elevation Map → DEM → Vehicle-Terrain Kinematics

Proprioceptive Sensors → Obs. Rover Config → Learning Kernel Function

Localisation → Pose

Motivation for Learning Covariance Function

- Learning a covariance function suitable to problem at hand
  - Learn from real data
  - Better representation of vehicle configuration evolution
  - Propagation of uncertainty
- Benefit: Explicitly considering vehicle state evolution and propagation of uncertainty in learning framework

(Image source: Vasudevan et. al., JFR 2009)
Overview of Learning Process

1. Estimate the covariance matrix using Regularized Expectation Maximization
2. Combining covariance matrices using Maximum Entropy Covariance Selection (MECS)
3. Generalise the covariance matrix into a function for use in GP framework

Ken Ho | ICRA 2013
Experimental Setup

• Marsyard at Powerhouse Museum, Sydney
  – Mars Analogue Terrain
• Platform
  – Rocker-bogie chassis
  – Sensors:
    • Kinect RGB-D camera
    • IMU
    • Hall effect encoders
    • Intersense IS-1200 tracking system
• Experiments conducted at slow speed
Validation Strategy

Validation Part 1


Validation Part 2


Proprioceptive Sensor

Learning Kernel Function

Localisation

Obs. Rover Config → Pose → Kernel Fn.
Validation Part 1: Estimating Vehicle Configuration Using Proprioceptive Data

- Performance of learnt kernel function vs. state-of-the-art kernel functions

![Bar chart showing RMSE Error in Vehicle Config (deg) for different vehicle components: Roll, Pitch, Left Bogie, Right Bogie. The chart compares Learnt, Sq. Exp. Iso, and N.N. kernel functions.](chart.png)
Validation Part 2: Estimating Vehicle Configuration Using Exteroceptive Data

- Incomplete DEM from exteroceptive data
  - Areas with no data are white
  - Occlusions in elevation map ≠ Occlusions in vehicle config.
    - At least 1 wheel touches the ground with no data
Validation Part 2 (cont.)

- Prediction comparison of different methods
Kin-GP-VE Summary

- Consistent improvements in estimating vehicle configuration over state-of-the-art kernel functions
  - Learning kernel function most suitable for problem at hand
- Still restricted by simplifications and assumptions in kinematic model
Deformable Terrain…

• Need method for predicting vehicle configuration angles of the rover on deformable terrain
  – Refine estimate from Kin-GP-VE to account for terrain deformation
  – Include dynamic influences towards vehicle configuration
A Near-to-Far Non-Parametric Leaning Approach for Estimating Traversability in Deformable Terrain

Ken Ho, Thierry Peynot, Salah Sukkarieh

[Submitted to IROS 2013]
Different Approaches

- Rigid Terrain Traversability Estimation (R-TTE)

- Rigid to Deformable Terrain Traversability Estimation (R2D-TTE)
1. Predicting vehicle configuration on rigid terrain (R-TTE)
2. Learning correlations between prediction made in (1) and vehicle experience, which include vehicle configuration and terrain deformation from experience
Learning correlations between R-TTE and vehicle experience

- Multiple input GP regression by automatic relevance determination (ARD)
  - Sq-exp, separate length-scale for each input
    \[
    k(X, X') = \sigma_f^2 \exp \left( -\frac{1}{2} (X - X')^T M (X - X') \right) + \sigma_n^2 \delta_{pq} \quad M = \text{diag}(l)^{-2}
    \]

- Multi-task GP regression
  - Heteroscedastic noise
    \[
    k_q(X - z) = \frac{S_q |M_q|^{1/2}}{(2\pi)^{p/2}} \exp \left[ -\frac{1}{2} (X - z)^T M_q (X - z) \right]
    \]

  - Between 2 outputs
    \[
    \text{cov}[f_q(X), f_s(X')] = \sum_{r=1}^{R} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} k_{qr}(X - z) k_{sr}(X' - z') k_{ur,ur} (z, z') \, dz \, dz' \]
    \[
    \text{cov}[f_q(X), u_r(z)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} k_{qr}(X - z') k_{ur,ur} (z', z) \, dz' \]

Thierry Peynot | ICRA 2013 Planetary Rover Workshop
Validation Results

• Predicting vehicle roll over 500 validation points
Validation Results (cont.)

- Predicting deformation over 500 validation points
Validation Results (cont.)

• Predicting vehicle roll and left bogie angle over areas with higher deformation than that experienced during training
Validation Results (cont.)

- Overall RMSE from experiments
Conclusions and Future Work

• Novel method for predicting vehicle configuration angles of a planetary rover over deformable terrain.

• Will consider terrain descriptors other than geometry that would contribute towards discerning deformable terrain, such as color and texture.

• Require more accurate measurements of the changes in terrain geometry as the rover traverses over it.
  – Can be obtained from an external observation setup, such as a geo-referenced LIDAR or a multi-camera system.
Motion Planning and Stochastic Control with Experimental Validation on a Planetary Rover

Angela Lui, Rowan McAllister, Thierry Peynot, Robert Fitch and Salah Sukkarieh

[IROS 2012]
[JFR ?]
Motion Planning in Unstructured Terrain

Objective:
to traverse unstructured terrain towards a goal reliably and safely

Motion planning needs to take into account uncertainty
  • localisation
  • mapping
  • control

Our approach considers uncertainty in control and is practical for real platform on realistic unstructured terrain
Most approaches use a deterministic motion planner (A*, RRT, PRM) to compute candidate paths, assess control uncertainty along each one, execute the “best” candidate.

Using this method, control uncertainly modelled by either:
- expected feedback controller's deviations,

- terramechanics,

  [Ishigami 2010]

Limitations:
- Planning and control are decoupled.
- LQG: assumes homogeneity of control uncertainty.
- Terramechanics: difficult to model non-homogeneous terrain locally
Stochastic Mobility Prediction Model

- Uncertain outcomes of control action executions: deviations in yaw, heading and distance
- Unstructured terrain: given one action, outcomes depend on profile of terrain traversed
- Learn a model of control uncertainty by experience (learn stochastic mobility prediction)

Implementation:
- Learning: Train Gaussian Processes (GP) with multiple action executions and observed terrain profiles during traversals.
- Use GP regression to obtain a stochastic transition function in motion planning (ability to query a predictive distribution of outcomes for any action and terrain profile)
  \[ p(\Delta s | \lambda(s, a), a) \]
- Prediction: use DEM and kinematics model to predict pitch and roll evolution that will be mapped to action outcomes distribution.
• Stochastic model of mobility prediction (stochastic transition model learnt from experience)

• Compute policies using Dynamic Programming (DP)

Bellman Eq. for optimal policy:

\[
\pi^*(s) = \arg \max_a \left\{ \sum_{s'} P(s'|s, a) \left( R(s', s, a) + \gamma V(s') \right) \right\}
\]
Implementation

- **Action set:**
  - CRAB actions (8 directions)
  - ROTATE actions (Clockwise, Anti-Clockwise)

- Digital Elevation Map (DEM)
- Method to predict traversability (rover configuration angles, e.g. Kinematic Modelling)
- Cost map: penaliser per action + terrain cost (difficulty)
Framework
Learning Mobility Prediction from Proprioception (LfP)
Learning Mobility Prediction from Proprioception (LfP)
Training

- Multiple executions of each action (total 500+) on large variety of terrain profiles
  - Logging localisation, vehicle attitude & configuration, DEM
- Features $\lambda$ better representing the terrain profiles (evolution of vehicle attitude and chassis configuration during action execution), determined using PCA on the training data

$$p(\Delta s | \lambda(s, a), a)$$
LfP - Training Data

Training data: heading outcomes (radians) marginalised by action

(a) $\Delta s_{\text{head}}$ for crab($0\pi$)
(b) $\Delta s_{\text{head}}$ for crab($\pm \frac{\pi}{4}$)
(c) $\Delta s_{\text{head}}$ for crab($\pm \frac{\pi}{2}$)

(d) $\Delta s_{\text{head}}$ for crab($\pm \frac{3\pi}{4}$)
(e) $\Delta s_{\text{head}}$ for crab($\pi$)
(f) $\Delta s_{\text{yaw}}$ for rotate($\pm \frac{\pi}{4}$)
Training data: distance travelled (m) marginalised by action
Example of Policies

Policy \( \text{yaw} = 0 \)

No uncertainty considered (LfP)

Distance uncertainty considered (LfP)
Results: Rigid Terrain Traversal

No uncertainty considered (LfP)
Results: Rigid Terrain Traversal
Results: Rigid Terrain Traversal

Distance uncertainty considered (LfP)

Start

Goal
# Results: LfP - Rigid Terrain

<table>
<thead>
<tr>
<th>Uncertainty considered</th>
<th>Total runs</th>
<th>Successful runs (temporarily stuck)</th>
<th>Stuck (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>24</td>
<td>17 (12)</td>
<td>7 (29%)</td>
</tr>
<tr>
<td>Distance &amp; Yaw</td>
<td>24</td>
<td>17 (8)</td>
<td>7 (29%)</td>
</tr>
<tr>
<td>Heading &amp; Yaw</td>
<td>21</td>
<td>17 (8)</td>
<td>4 (19%)</td>
</tr>
</tbody>
</table>

**Graphs:**
- **Terrain Cost**
  - None
  - Distance
  - Heading
- **No. of actions**
  - None
  - Distance
  - Heading
Results: LfP - Deformable Terrain

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>19</td>
<td>17 (7)</td>
<td>2 (10%)</td>
</tr>
<tr>
<td>Distance &amp; Yaw</td>
<td>20</td>
<td>17 (5)</td>
<td>3 (15%)</td>
</tr>
<tr>
<td>Heading &amp; Yaw</td>
<td>19</td>
<td>17 (6)</td>
<td>2 (10%)</td>
</tr>
</tbody>
</table>

![Graphs showing terrain cost and number of actions]
LfP: Conditions/Limitations

• DEM (sufficiently) accurate
  – (accuracy vs. resolution of DEM/state space)
• Correct kinematic model
  – Low speeds
• Terrain *before* rover traversal (as seen by exteroceptive sensors, i.e. DEM) corresponds to terrain *during* rover traversal (when observed via proprioception)
  – i.e. no terrain deformation (rigid terrain)
Learning Mobility Prediction from Exteroception (LfE)
Results: LfE – Rigid Terrain

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<th>Stuck (%)</th>
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</thead>
<tbody>
<tr>
<td>None</td>
<td>22</td>
<td>17 (8)</td>
<td>5 (23%)</td>
</tr>
<tr>
<td>Distance &amp; Yaw</td>
<td>19</td>
<td>17 (5)</td>
<td>2 (10%)</td>
</tr>
<tr>
<td>Heading &amp; Yaw</td>
<td>19</td>
<td>17 (2)</td>
<td>2 (10%)</td>
</tr>
</tbody>
</table>
## Results: LfE – Deformable Terrain

<table>
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<th>Successful runs (temporarily stuck)</th>
<th>Stuck (%)</th>
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<tbody>
<tr>
<td>None</td>
<td>20</td>
<td>17 (6)</td>
<td>3 (15%)</td>
</tr>
<tr>
<td>Distance &amp; Yaw</td>
<td>22</td>
<td>17 (5)</td>
<td>0 (0%)</td>
</tr>
<tr>
<td>Heading &amp; Yaw</td>
<td>21</td>
<td>17 (4)</td>
<td>0 (0%)</td>
</tr>
</tbody>
</table>

![Bar chart showing the Terrain Cost for different types of uncertainty considered.](chart1.png)

![Bar chart showing the No. of actions for different types of uncertainty considered.](chart2.png)
Motion Planning with Stochastic Control

Summary:
• The proposed approach learns a model of control uncertainty directly from experience, which is used explicitly in the computation of a motion policy.
• Experimental validation shows increased reliability (reduced failures) and safety (reduced cost)

Future Work:
• Explicitly account for terrain deformation
• Integrate other types of uncertainty (perception, localisation...)
• Online GP learning & real-time DP (policy updates)
Acknowledgments

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