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

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To safely navigate autonomously on unstructured terrain, a planetary rover requires the ability to: a) accurately and reliably estimate terrain traversability, and b) plan and execute safe paths to reach the desired goal. However, real-world considerations such as sensing limitations and uncertainties make these tasks particularly challenging in practice. This work proposes novel approaches to address some of these challenges, with experimental validation on a realistic platform and a Mars-analogue environment (Fig. 1).

I. Traversability Estimation via Kernel Learning in a Gaussian Process Framework

Traversability can be represented by aspects such as roughness of the terrain [1], expected energy required to traverse it, or risk for the platform to tip over or slip [2]. The aspect of traversability considered in this paper is represented by the attitude of the platform (pitch, roll) and the configuration of the rocker-bogie chassis, which are respectively associated with the vehicle stability and the difficulty to traverse over the terrain. State-of-the-art techniques to predict the rover's attitude and configuration angles on rough terrain using kinematic modeling on a digital elevation map (DEM) have been proposed (e.g. [3], [4]). However, they assume perfect and complete knowledge of the geometry of the underlying terrain, and use a deterministic model of the rover's kinematics. In practice, uncertainties in the terrain model and in the vehicle response can be significant and need to be considered.

Terrain representations built from onboard sensor data are often incomplete due to occlusions and sensor limitations. Therefore, the resulting traversability map is often incomplete. For safety, the commonly accepted recommendation has been to consider non-observed areas as non traversable [5]. However, relatively small gaps in the terrain data can be frequent. Therefore, in practice, existing rover navigation algorithms usually avoid large gaps (which may not always be necessary) but ignore those that are small [3] (which might be dangerous). Instead, the method we propose can provide an accurate estimate of traversability in these occluded areas with associated uncertainty.

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Fig. 1. Planetary rover "Mawson" used for experimental validations, shown in the Mars yard at the Powerhouse Museum in Sydney, Australia.

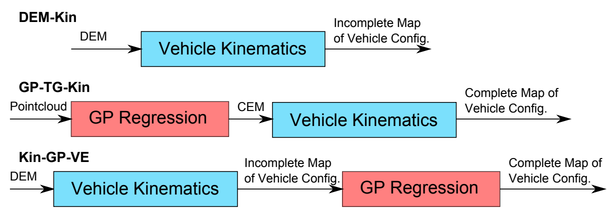

Fig. 2. Comparison of techniques to predict vehicle configuration.

In this work, we predict the rover's attitude and configuration angles by learning the vehicle response on unstructured terrain from experience [6]. The approach focuses on exploiting the explicit correlation in vehicle attitude and configuration during operation. We propose an architecture for estimating the kernel function based on vehicle experience in a manner that better represent the evolution of vehicle states and propagation of uncertainty. Gaussian Process (GP) regression, using exteroceptive data as training input, then provides a continuous representation of vehicle attitude and configuration over the terrain, with uncertainty in the output estimates, and accurate estimation of traversability in areas with little or no exteroceptive data. Fig. 3 shows the architecture of the approach, named (Kin-GP-VE).

We provide an extensive experimental validation of Kin-GP-VE on our planetary rover prototype (Fig. 1). We show the improvement in the estimation performance gained by kernel learning compared with results obtained using standard kernels We also show the improvement obtained compared to the prediction of the angles made using kinematic modeling on terrain models built via state-of-the-art GP techniques (Fig. 2).

As most of the state of the art, Kin-GP-VE estimates terrain traversability under the assumption that the terrain is rigid. However, terrain deformation during vehicle traversals is a relatively common phenomenon, which can have a significant impact on actual traversability. Therefore, in most recent work, we propose a new approach that can

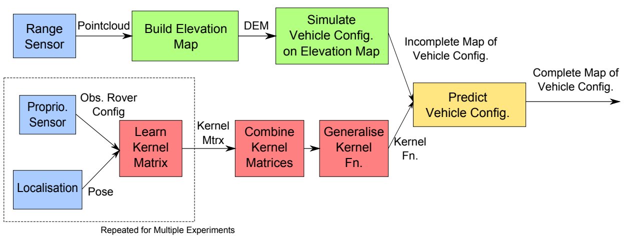

Fig. 3. System Architecture of Kin-GP-VE. In red: offline kernel learning. In green: online initial configuration estimation. In yellow: GP regression.

estimate traversability on unstructured terrain, including on potentially deformable terrain. Using the vehicle's attitude and conguration predicted from Kin-GP-VE as an input to learning, we propose to learn the corresponding response of the vehicle on terrain deformation. To this end, we correlate rigid terrain inputs from Kin-GP-VE, along with local variations of predicted vehicle states, with observations from experiments in a multi-task GP framework. We present the implementation of the approach and initial results of traversability estimation in non-rigid terrain.

II. Motion Planning with Learnt Control Uncertainty

Motion planning for mobile robots must consider various forms of uncertainty, including *control uncertainty*, particularly in environments that expose the robot to the risk of serious mechanical damage. Robots such as planetary rovers are designed for mobility in unstructured environments, but in such challenging and variable terrains, control uncertainty can highly affect the execution of any planned path and jeopardise the safety of the platform. Accurately predicting executed behaviour in response to a given control input is difficult for planetary rovers due to complex terramechanics [2]. For previously unobserved terrain, prior models of terrain properties may not be available. It is thus important to model control uncertainty with a method that can be feasibly executed online during operation of the robot, and to validate such a model experimentally.

Our approach is to build a statistical mobility model from experience, represented as a Gaussian process (GP) [7]. We learn GP models for terrain traversal that map environment features to a distribution of resulting rover configurations (in state space) for a set of control actions. We consider uncertainty in the heading of the platform and in distance travelled. The GP models are used to build a stochastic transition function for use in motion planning. The planning goal is to compute a policy that allows the robot to reach a given goal location while maintaining the safety of the platform. Platform safety is represented by a cost function over a DEM, which is constructed *a priori* using an on-board 3D sensor. We compute the policy using dynamic programming (DP), where the resolution of discretised geometric states is equal to that provided in the elevation map. Fig. 4 shows an overview of the system.

We consider two alternative approaches to learn the mobility prediction model. In the first method, the distributions

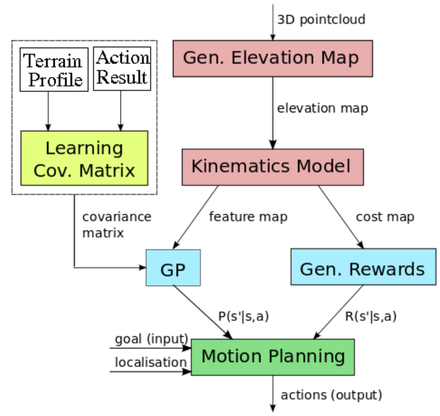

Fig. 4. System Outline. Colours indicate perception (red), offline learning (yellow), estimation (blue) and planning (green).

of expected outcomes of each action are learnt from *proprioceptive* data: the *measured* variations of configuration angles of the platform during the course of action execution. In the second method, they are learnt from *exteroceptive* data: the variations of configuration angles during the action, as *predicted* using the kinematics model of the rover and the DEM built from exteroceptive data.

The two variants of our proposed approach for motion planning with stochastic control are implemented on the planetary rover, and validated experimentally on Mars-analogue terrain (Fig. 1). We report results from over 1000 simulated and 300 experimental runs. We compare rover performance in executing policies constructed with and without control uncertainty. Our results show empirically that planning with control uncertainty improves the rover's ability to navigate safely on unstructured terrain. We also compare the performances obtained using the two alternative ways to learn the mobility prediction model. The results show that the method learning from exteroceptive data provide the rover with the ability to navigate safely even on deformable terrain. This work demonstrates the value of planning under uncertainty for planetary rovers, using a real platform in a realistic environment.

References

[1] S. B. Goldberg, M. W. Maimone, and L. Matthies, "Stereo vision and rover navigation software for planetary exploration," in *Proc. IEEE Aerospace Conf.*, 2002.
[2] G. Ishigami, G. Kewlani, and K. Iagnemma, "Statistical Mobility Prediction for Planetary Surface Exploration Rovers in Uncertain Terrain," in *IEEE ICRA*, 2010.
[3] S. Lacroix, A. Mallet, D. Bonnafous, G. Bauzil, S. Fleury, M. Herrb, and R. Chatila, "Autonomous rover navigation on unknown terrains: Functions and integration," *Int. J. Robotics Research*, vol. 21, no. 10-11, pp. 917–942, 2002.
[4] M. Tarokh and G. McDermott, "Kinematics modeling and analyses of articulated rovers," *IEEE Trans. Robotics*, vol. 21, no. 4, pp. 539–553, 2005.
[5] A. Kelly and A. Stentz, "Analysis of requirements for high speed rough terrain autonomous mobility part 1: Throughput and response," in *Proc. IEEE ICRA*, 1997.
[6] K. Ho, T. Peynot, and S. Sukkarieh, "Motion planning and stochastic control with experimental validation on a planetary rover," in *to appear in IEEE ICRA*, 2013.
[7] R. McAllister, T. Peynot, R. Fitch, and S. Sukkarieh, "Motion planning and stochastic control with experimental validation on a planetary rover," in *IEEE/RSJ IROS*, 2012.