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A Near-to-Far Non-Parametric Learning Approach for Estimating Traversability in Deformable Terrain

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***Abstract*— It is well recognized that many scientifically interesting sites on Mars are located in rough terrains. Therefore, to enable safe autonomous operation of a planetary rover during exploration, the ability to accurately estimate terrain traversability is critical. In particular, this estimate needs to account for terrain deformation, which significantly affects the vehicle attitude and configuration. This paper presents an approach to estimate vehicle configuration, as a measure of traversability, in deformable terrain by learning the correlation between exteroceptive and proprioceptive information in experiments. We first perform traversability estimation with rigid terrain assumptions, then correlate the output with experienced vehicle configuration and terrain deformation using a multi-task Gaussian Process (GP) framework. Experimental validation of the proposed approach was performed on a prototype planetary rover and the vehicle attitude and configuration estimate was compared with state-of-the-art techniques. We demonstrate the ability of the approach to accurately estimate traversability with uncertainty in deformable terrain.**

I. Introduction

To enable safe autonomous navigation of a planetary rover, the ability to assess the terrain traversability is essential [1]. Traversability can be represented by aspects describing the terrain, including texture and geometry, and/or aspects related to the vehicle, such as the energy required to traverse the terrain or risk of instability for the platform [2]. This information is critical to the rover's path planning, whose objective is usually to minimize the situations that may compromise: a) the health and stability of the vehicle, or b) its ability to pursue its mission of exploration. However, it is well recognized that many scientifically interesting sites on Mars are located in very rough and heterogeneous terrains, for example with combinations of soils and rocks, and significant risks of terrain deformation. This presents numerous challenges in terms of terrain traversability estimation (TTE). To facilitate scientific exploration while maintaining rover safety, we are interested in developing TTE techniques that are appropriate for challenging terrains. In particular, our focus lies in the prediction of the vehicle attitude and configuration, which provides information on the difficulty of terrain traversal, and is crucial to anticipate risks to platform stability.

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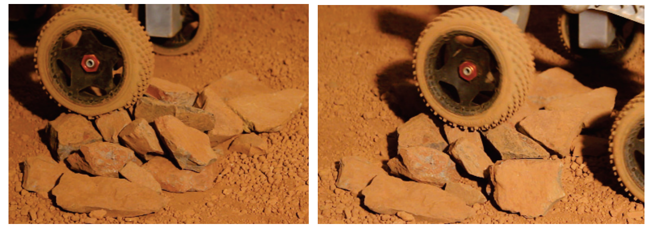


(a) (b)

Fig. 1. Rover traveling over deformable terrain: (a) before traversal (front wheel); (b) during traversal (back wheel). Note the differences of rock configurations between (a) and (b).

In challenging unstructured environments, such as on Mars, force from the rover can cause terrain deformation [3]. This affects the vehicle response and, therefore, its actual attitude and configuration. For example, such situations may be very common in sandy terrain, especially when strong wheel slip provokes wheel sinkage into the ground [4]. Another example is in the presence of unstable rocks that move as the rover travels over them (see Fig. 1). Accurate predictions of vehicle attitude and configuration in deformable terrain will enable safe and efficient operation during exploration, by anticipating situations where:

1) the stability of the rover may be compromised,
2) terrain traversal appears more challenging and dangerous than it will be in practice.

Previous work tackled the problem of TTE using terramechanics approaches, modeling the physical interaction between the wheel and the vehicle [3]. Wheel slip as well as other metrics for traversability were developed to quantify the difficulty of the rover traversing across the terrain [5], [6]. In order to better estimate terrain traversability, extensive work has been done to improve the estimation of the terrain/soil parameters necessary for terramechanics equations by empirical approaches [7]. However, a natural environment involves a large diversity of terrain, soil types, geometry, and appearances, and it is not practical to model each type of soil/rock as these elements exist in a heterogeneous nature. In addition, terrain deformation, and in particular its impact on vehicle configuration, is largely neglected in these state-of-the-art TTE techniques. Therefore, an accurate prediction of vehicle attitude and configuration is crucial for terramechanics approaches as well [5].

In this paper we propose a *near-to-far* learning approach to predict vehicle configuration on deformable terrain using a multi-task GP framework. The method first uses a state-of-the-art TTE method to compute an initial prediction of vehicle configuration under the assumption of rigid terrain from exteroceptive information. This estimation is then refined by accounting for the effects of possible terrain deformation on configuration. These effects are captured in the correlations between such rigid-terrain predictions and actual vehicle response learnt from experiments in a Mars analogue terrain. We use stochastic representations to implicitly consider uncertainties in sensing and localisation during learning and in operation, and provide an experimental validation of the prediction against ground truth.

The paper is organized as follows. Sec. II discusses recent related work on terrain traversability estimation. Sec. III details the proposed approach to predict terrain traversability in deformable terrain using the correlation between exteroceptive information with actual vehicle configuration. Sec. IV describes the implementation of our approach on our prototype rover. In Sec. V we propose an experimental validation of the approach and analyse the results obtained. Finally, Sec. VI proposes a conclusion and directions for future work.

II. Related Work

Previous approaches to terrain traversability estimation (TTE) from exteroceptive information include kinematic modeling methods to estimate the vehicle attitude and configuration based on a Digital Elevation Map (DEM) and the vehicle structure [8], [9]. However, without an extensive terramechanics model and complete knowledge of the terrain, these approaches cannot accurately estimate terrain traversability as the interaction between the wheel and terrain is very complex in deformable terrain. [1] proposed Terrain Adaptive Navigation (TANav) to classify the terrain into categories. This involved metric calculations such as inclination of the plane, roughness, and elevation of the visible terrain area. A full kinematic and dynamic forward simulation of the rover was then run using known terrain parameters from a database of Martian soil [10].

Recent literature showed that by learning the association between exteroceptive and proprioceptive sensor information, the response of the vehicle on the upcoming terrain could be anticipated [11]. This concept is known as *near-to-far* learning. [7] first learnt terrain parameters from proprioception training data and then associated these parameters with exteroceptive information. This allowed them to anticipate vehicle slip in operation. However, this approach assumes the terrain is rigid. [12] proposed a feature-based learning approach, in which the vehicle can learn terrain traversability from its interaction with different terrain types encountered during training. Data acquired from exteroceptive sensing were associated to the corresponding Rover-Terrain Interaction (RTI) features to build an inference model. These approaches are efficient at predicting aspects of RTI such as slip and vibration. However, they rely on accurate predictions of the attitude and configuration of the platform and do not consider the effects of terrain deformation on this prediction. Aspects such as low cohesion soil or unstable rocks need to be accounted for, since they can have a significant impact on the actual configuration of the rover. In this paper, we propose to use the concept of near-to-far learning to compute an estimate of the vehicle attitude and configuration that accounts for the effects of terrain deformation.

In previous work, the authors developed a GP-based framework that was able to estimate vehicle configuration more accurately than state-of-the-art results [13]. The approach, named Kin-GP-VE, exploited explicit correlation in vehicle configuration by learning a new kernel function to perform GP regression over vehicle experience. However, the work did not account for deformable terrain explicitly in the prediction process as it relied on training points obtained from a kinematic model with rigid terrain assumptions.

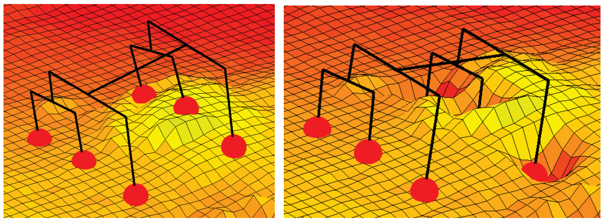
This paper addresses such shortcomings by predicting actual vehicle experience with terrain deformation from exteroceptive information. We refine the estimation results from Kin-GP-VE with correlations to local variations in vehicle configuration and actual vehicle experience during training. We show significant improvements in estimating vehicle configuration, in particular areas with terrain deformation, using geometry information only.

III. Approach

We introduce an approach to predict vehicle attitude and chassis configuration in deformable terrain using GP regression. For convenience, in the remainder of the paper we define *vehicle configuration (Φ)* to include vehicle attitude and chassis configuration, and *Rigid Terrain Traversability Estimation (R-TTE)* as the terrain traversability estimation over rigid terrain.

State-of-the-art techniques to predict rover configuration (R-TTE) operate in two steps. First, they build a geometric representation of the terrain. Second, they predict the configuration of the platform at a query state s, which includes location and heading, $s = \{x, y, \psi\}$, by placing the rover chassis on the terrain model. This prediction of the configuration on rigid terrain $(\Phi_{rigid}(s))$ is consistent with the geometry as it was observed *a priori*. However, when the rover traverses over unstable terrain, the rover-terrain interaction may cause a deformation of the terrain, which changes its geometry at the location considered. Consequently, the *actual* configuration of the rover, $\Phi_{deform}(s)$, will be different from $\Phi_{rigid}(s)$. This can only be measured on location, by proprioceptive sensors. To illustrate the impact of terrain deformation in terms of changes in elevation, we performed a simple numerical comparison of vehicle attitude with simulated terrain deformation (see Fig. 2).

Arguably, to some extent terrain deformation can be anticipated by observing terrain geometry. Relying on experience, humans are capable of evaluating the potential for deformation by observing the terrain geometry only. For example, a random pile of rock may appear stable and solid, or on the contrary unstable and loose (see Fig. 3). Therefore, we propose to predict the actual vehicle configuration $\Phi_{deform}(s)$ in the case of terrain deformation, based on an initial rigid-terrain prediction $\Phi_{rigid}(s)$ from R-TTE and



(a) (b)

Fig. 2. Vehicle attitude in a simulation environment: (a) without terrain deformation, (b) with $10cm$ of terrain deformation. With terrain deformation, the vehicle experienced a change of 18°in roll and 10°in left bogie angle.

Fig. 3. Stable rocks (left) and unstable rocks (right)

terrain geometry. We call this approach *Rigid-to-Deformable TTE (R2D-TTE)*.

In the example above, it is not possible to evaluate the stability of the structure with only on the elevation observation at one particular query state s. The estimation relies on an observation of the variations of local geometry in the surrounding area. Similarly, when predicting the configuration at s, the local variations in vehicle configuration will provide information about the changes of configuration due to terrain deformation, i.e. $\Phi_{deform}(s) - \Phi_{rigid}(s)$.

The proposed approach will demonstrate that inference on terrain deformation and the resulting vehicle configuration can be made by the rover from experience and without knowledge of terrain properties such as soil cohesion. This inference is made in a stochastic manner to account for uncertainties in the observations during training and operation.

The system architecture of R2D-TTE is illustrated in Fig. 4. The inputs of the system are exteroceptive data obtained in the form of a 3D point-cloud. Offline, we learn the correlations between the predictions made on rigid terrain ($\Phi_{rigid}(s)$) and vehicle experience, which includes $\Phi_{deform}(s)$ (from proprioception) and terrain deformation. We can then predict vehicle configurations and terrain deformation online from $\Phi_{rigid}(s)$.

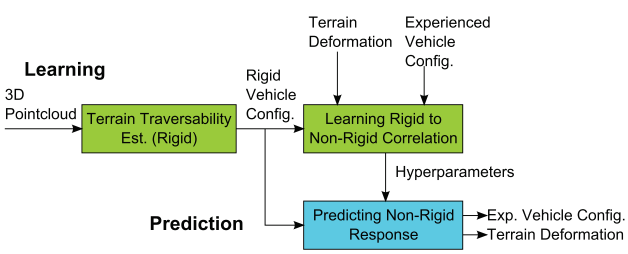


Fig. 4. System architecture for Rigid to Deformable Terrain Traversability Estimation (R2D-TTE)

The following section outlines the process used to compute Φ_{rigid}. We then describe how we capture the local variations in vehicle configuration. Finally, we present the process of establishing the correlations between Φ_{rigid} and Φ_{deform} using multi-task GP regression.

A. Kin-GP-VE

To provide the initial prediction of vehicle configuration under the assumption of rigid terrain, i.e. Φ_{rigid}, we use an implementation of R-TTE named Kin-GP-VE [13]. In this method, a training phase to learn the kernel function first gathers vehicle configuration data with corresponding localization during terrain traversals on rigid terrain. The kernel matrix of the vehicle configuration is learnt from proprioceptive data and then generalized into a function form for GP regression. Using training data, terrain traversability can be estimated in a GP framework over an entire DEM using an incomplete map of vehicle configurations estimated from a kinematic model as inputs. Therefore, once this process is completed, we can query the corresponding configuration $\Phi_{rigid}(s)$ for any query state s on the map.

B. Local Variations of Vehicle Configuration

As mentioned above, we argue that the observation of local variations of vehicle configuration around the query state s contributes to the prediction of the difference between the actual configuration after terrain deformation, Φ_{deform}, and the initial prediction Φ_{rigid}. To capture these local variations, we use the profile and planform curvatures (illustrated in Fig. 5a and 5b respectively) of each component of the vehicle configuration, computed over a 3×3 neighbourhood in the DEM grid [14]. Consider the DEM neighbourhood shown in Fig. 5c, where (i, j) represent the corresponding indices of the discretised position (x, y) on the DEM, from which we want to predict the vehicle configuration. For each angle in Φ we compute the corresponding curvature. For example, for the roll, ϕ, this can be expressed as:

$$\begin{aligned} \phi_{curv_{profile}} &= \frac{2(DG^2 + EH^2 + FGH)}{G^2 + H^2}, \\ \phi_{curv_{planform}} &= \frac{-2(DH^2 + EG^2 - FGH)}{G^2 + H^2}, \end{aligned} \quad (1)$$

where:

$$\begin{aligned} D &= \frac{\phi_{i,j-1} + \phi_{i,j+1}}{2} - \phi_{i,j}, \; E = \frac{\phi_{i-1,j} + \phi_{i+1,j}}{2} - \phi_{i,j}, \\ F &= \frac{-\phi_{i-1,j-1} + \phi_{i-1,j+1} + \phi_{i+1,j-1} - \phi_{i+1,j+1}}{4}, \\ G &= \frac{-\phi_{i,j-1} + \phi_{i,j+1}}{2}, \; H = \frac{\phi_{i-1,j} - \phi_{i+1,j}}{2}, \end{aligned} \quad (2)$$

and $\phi_{i,j}$ denotes the configuration angle predicted at position index (i, j) and heading ψ, i.e. taken from $\Phi_{rigid}(s)$. We then combine these two components with:

$$\phi_{curv} = \phi_{curv_{profile}} - \phi_{curv_{planform}}. \quad (3)$$

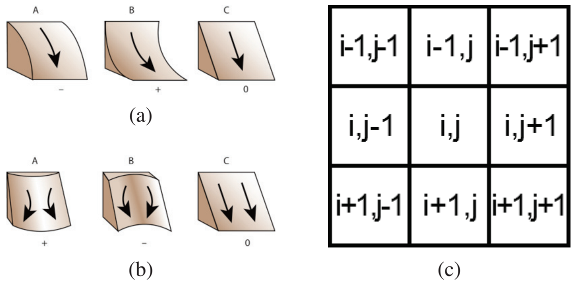


Fig. 5. (a) Profile Curvature. (b) Planform Curvature. (c) Cell reference of the vehicle position index (i, j) for determining $\phi(i, j)$ on the DEM.

Each vehicle configuration angle and corresponding combined curvature, such as the combined curvature for vehicle roll (ϕ_{curv}), are included in the training input X, which is used for learning.

C. Learning Configuration in Deformable Terrain with GPs

1) Multiple Input GP Regression by Automatic Relevance Determination (ARD): To estimate vehicle response from deterministic inputs we use GPs to learn the underlying model of spatially correlated data with uncertainty [15]. Gaussian approaches are multivariate Gaussian distributions that are defined by a mean function $m(X)$ and a covariance function $k(X, X')$

$$\begin{aligned} &m(X) = E[f(X)], \\ &k(X, X') = E[(f(X) - m(X))(f(X') - m(X'))], \end{aligned} \tag{4}$$

where X is our training input that includes $\Phi_{rigid}(s)$ estimated using Kin-GP-VE, and the corresponding curvatures. The details of our implementation are given in Sec. IV-B.

To enrich the learning process, we introduce a multi-dimension representation of vehicle states in our training input vector to incorporate the different training inputs. We use inputs from $\Phi_{rigid}(s)$, which is deterministic, and thus we expect consistent "perceived" vehicle configuration extrapolated purely from terrain geometry information.

We use GP regression with the Squared-Exponential (Sq-Exp) covariance function with added noise [16]. This was selected based on its ability to model all orders of additive interactions, and automatically determine which orders of interaction are important based on ARD, which results in high modeling efficacy and model interpretability. Using a separate length scale for each training input dimension, we can determine the correlation between each training input [15]. Consider the Sq-Exp kernel function in its parametric form:

$$\begin{aligned} &k(X, X') = \\ &\sigma_f^2 \exp\left(-\frac{1}{2}(X - X')^T M (X - X')\right) + \sigma_n^2 \delta_{pq}, \end{aligned} \tag{5}$$

where $\theta = \left(\{M\}, \sigma_f^2, \sigma_n^2\right)^T$ is a vector containing the hyperparameters for the kernel function, and δ_{pq} is noise. Matrix M is:

$$M = diag(\mathbf{l})^{-2}, \tag{6}$$

where $\mathbf{l}$ is a vector of positive values for each length scale, which we can optimize via marginal likelihood marginalization. The log marginal likelihood can be expressed as:

$$\log p(z|X, \theta) = -\frac{1}{2} z^T K^{-1} z - \frac{1}{2} logK - \frac{n}{2} log 2\pi, \tag{7}$$

where n is the number of data points, and K is the kernel matrix for the training targets z, which include $\Phi_{deform}(s)$. The details of our implementation are given in Sec. IV-B.

2) Multi-task GP Regression: Most GP implementations model only a single output variable. As the outputs (vehicle states) in this prediction process are highly correlated, we cannot use an independent model for each output, such as multi-kriging. Joint-predictions are possible, although it is non-trivial to define the covariance functions for predicting outputs. In addition, it is difficult to define cross-covariance functions that result in positive definite covariance matrices required for GP regression.

One approach to account for correlations between outputs employs Convolution Processes (CP) [17]. In this approach, each output can be expressed as the convolution between a smoothing kernel and a latent function. Consider a set of Q functions, where each function is a convolution between a smoothing kernel k_q and a latent function $u(z)$:

$$f_q(X) = \int_{-\infty}^{\infty} k_q(X - z)\, u(z) dz, \tag{8}$$

We use the Sq-Exp kernel function with isotropic distance measure for the smoothing kernel, and assume heteroscedastic noise:

$$k_q(X - z) = \frac{S_q |M_q|^{1/2}}{(2\pi)^{p/2}} \exp\left[-\frac{1}{2}(X - z)^T M_q (X - z)\right]. \tag{9}$$

More generally, we can consider the influence of multiple latent functions on the function y_q, and also an independent process such as noise $w_q(x)$:

$$\begin{aligned} y_q(X) &= f_q(X) + w_q(X) \\ &= \sum_{r=1}^{R} \int_{-\infty}^{\infty} k_{qr}(X - z)\, u_r(z) dz + w_q(X). \end{aligned} \tag{10}$$

If we assume the latent functions to be independent GP functions, we can express the covariance between two different functions $y_q(X)$ and $y_s(X')$ using a multiplication of Gaussian distributions to obtain Gaussian kernels:

$$\begin{aligned} &cov\left[f_q(X), f_s(X')\right] = \\ &\sum_{r=1}^{R} \int_{-\infty}^{\infty} k_{qr}(X - z) \int_{-\infty}^{\infty} k_{sr}(X' - z')\, k_{u_r u_r}(z, z')\, dz' dz. \end{aligned} \tag{11}$$

Similarly, the correlation between the latent function and any given input can be computed as:

$$cov\left[f_q(X), u_r(z)\right] = \int_{-\infty}^{\infty} k_{qr}\left(X - z'\right) k_{u_r u_r}\left(z', z\right) dz'. \tag{12}$$

Using the covariance matrices in Eqs. (11) and (12), we can perform joint-prediction of $\Phi_{deform}(s)$ and terrain deformation by iteratively calculating the matrices for each latent function and input.

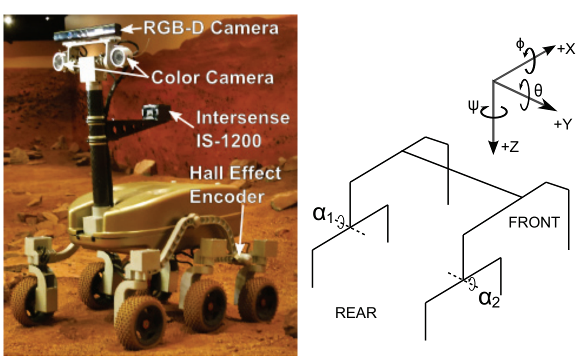
IV. Implementation

We demonstrated the implementation of the framework in an experimental setting with a rover platform on a Mars-analogue terrain. During learning, we performed experiments to engage the rover in the range of motions that it was likely to encounter during operation. We first predicted the $\Phi_{rigid}(s)$ on the visible terrain using Kin-GP-VE. We then learnt the hyperparameters that described the correlations between the predictions from Kin-GP-VE, vehicle experience, and terrain deformation in a multi-task approach. During operation, we estimated $\Phi_{rigid}(s)$ using Kin-GP-VE, then performed a GP regression using the learnt hyperparameters to determine a continuous representation of $\Phi_{deform}(s)$ and deformations.

A. Platform - Mawson Rover

Mawson, our rover platform, is a 6-wheeled rover with a rocker-bogie chassis and individual steering motors on each wheel (Fig. 6). Onboard sensors include:

- two color cameras and an RGB-D camera (Microsoft Kinect^{TM}) mounted on a pan-tilt unit, tilted down $\approx 25°$, which is used primarily for terrain modeling.
- two Hall-effect encoders (α_1, α_2) on the rear bogie mechanisms, and a potentiometer on the rocker differential, to measure the configuration of the chassis.



(a) (b)

Fig. 6. (a) Mawson Rover. (b) Chassis Configuration.

During our experiments, localization data was obtained using the Intersense IS-1200 motion capture system, which combines camera and IMU sensor data to determine the 6-DOF sensor pose $(x, y, z, \phi, \theta, \psi)$ (where ϕ is the roll, θ the pitch and ψ the yaw) with an accuracy of 2 cm and 1° respectively. Pose is given with respect to a constellation of fiducials in the environment, which were geo-referenced using surveying equipment. This pose was used for ground truth in our validation process.

3D point-clouds provided by the RGB-D camera are used to obtain exteroceptive data. For outdoor operations, where the RGB-D camera may be unable to provide a point-cloud, 3D point-clouds obtained from dense stereovision can be used instead without affecting the conclusion of this study.

In order to associate the point-clouds acquired by the RGB-D camera with the localization, we performed exteroceptive calibration between the two sensors off-line to estimate the transformation between them [18].

B. GP Learning Inputs and Outputs for Vehicle Response Prediction

In our experiments, we collected data that included terrain geometry, vehicle attitude, and configuration. The training input X included $\Phi_{rigid}(s)$ estimated from Kin-GP-VE, as defined in Fig. 6(b):

$$X = [\phi, \phi_{curv}, \theta, \theta_{curv}, \alpha_1, \alpha_{1_{curv}}, \alpha_2, \alpha_{2_{curv}}]. \tag{13}$$

This was discretized over 32 equally spaced yaw angles to facilitate learning with fewer data points.

The training target z included the $\Phi_{deform}(s)$ experienced when the vehicle traversed the terrain, and the actual terrain deformation ($\mathcal{T}_{deform}$):

$$z = \left[\phi_{exp}, \theta_{exp}, \alpha_{1_{exp}} \alpha_{2_{exp}}, \mathcal{T}_{deform}\right]. \tag{14}$$

Terrain deformation is included in the training target as it is strongly correlated with $\Phi_{rigid}(s)$ and $\Phi_{deform}(s)$. Since these correlations are accounted for in the GP regression, the estimation accuracy of $\Phi_{deform}(s)$ is improved with the inclusion of terrain deformation in the training target.

We use a binary variable to indicate terrain deformation that provokes a change in vehicle configuration, i.e. 1 if deformation has occurred, 0 if it has not. We define deformation to have occurred if the difference between $\Phi_{rigid}(s)$ and $\Phi_{deform}(s)$ gathered from localization is higher than 0.1 radians. This was determined by combining the uncertainty in proprioceptive data and $\Phi_{rigid}(s)$ estimated from Kin-GP-VE. This discrete approach was favored over a continuous representation of the change in terrain geometry because of the adverse effects of sensor and localization error on accurately determining terrain deformation. Instead, we predicted the occurrence of any terrain deformation that may affect vehicle configuration and quantified it with respect to the regression noise in the training input.

V. Experiments and Results

To facilitate learning in an environment similar to Martian terrain, we conducted experiments at the Marsyard, an indoor Mars analogue terrain hosted at the Powerhouse Museum in Sydney, Australia. Three areas, with different terrain characteristics, were selected for experiments. To validate the proposed approach, we performed experiments to evaluate the accuracy of the predictions achieved by the proposed approach and compared the results with other state-of-the-art methods described in Sec. II. We compare our results against Kin-GP-VE, which demonstrated marked improvement over state-of-the-art R-TTE methods [13]. As a baseline, we also provide comparisons against DEM-Kin, which predicts vehicle configuration based on vehicle kinematics directly on a DEM [9]. Predictions of $\Phi_{rigid}(s)$ were made with a Root Mean Squared Error (RMSE) of $3°$ to $8°$. Learning was performed with approximately 30000 points of exteroceptive data with corresponding measurements of $\Phi_{deform}(s)$ collected from the localization system during traversals, which we consider to be ground truth. A further 5000 points of data were collected for cross-validation. We used a grid resolution of *5cm*, which is approximately equivalent to the radius of the wheel of the rover.

A. *Predicting* Φ_{deform} *from* Φ_{rigid}

We evaluated the ability of our approach to predict vehicle configuration in deformable terrain using exteroceptive sensing. We first predicted $\Phi_{rigid}(s)$ using Kin-GP-VE. These data were then used to calculate the local variations of vehicle configuration and to train the hyperparameters of the GP, which were used to predict the vehicle configuration over each of the training areas. The result from the GP regression was cross-validated with proprioceptive data obtained during traversals. In each of the results, N denotes the number of latent functions used in the GP regression.

The GP regression results for pitch and deformation probability over 500 validation points can be seen in Fig. 7 and Fig. 8 respectively. The estimate made using R2D-TTE is more resistent to deviations in the input data and yields a more accurate estimate based on correlations between exteroceptive and actual vehicle experience compared with the estimate made using R-TTE methods.

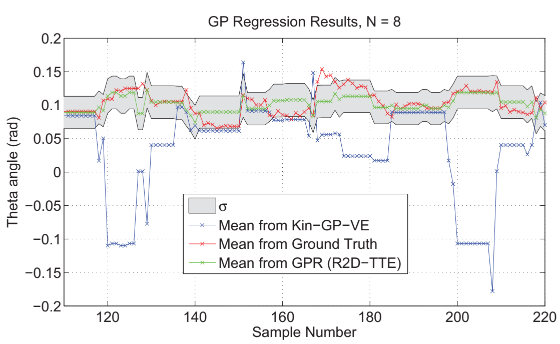


Fig. 7. GP regression results for predicting θ over 500 validation points, zoomed over sample number 110 to 220. Grey area indicates a 1σ confidence interval.

Fig. 9 shows the RMSE in vehicle roll, over areas defined as rigid or deformable terrain. It shows improvements in estimates using R2D-TTE over Kin-GP-VE and DEM-Kin, with reduced estimation error of up to 55% and 73% of the vehicle roll estimate over rigid and deformable terrain, respectively, compared with Kin-GP-VE, and up to 61% and 78% compared to DEM-Kin. Although the RMSE using R2D-TTE over rigid terrain is still lower than the RMSE of the estimate over deformable terrain, it is a significant

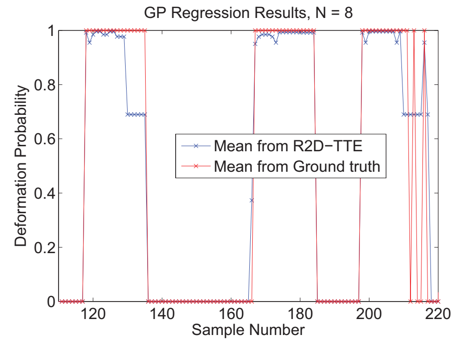


Fig. 8. GP regression results for predicting $\mathcal{T}_{deform}$ over 500 validation points, zoomed over sample number 110 to 220.

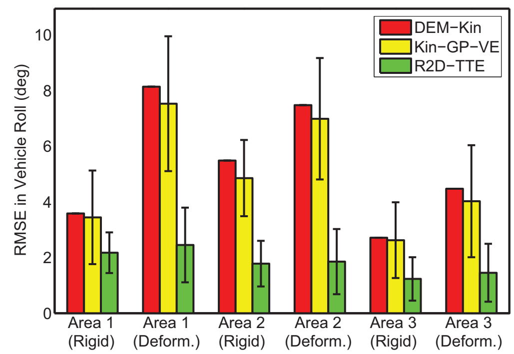


Fig. 9. RMSE in vehicle Roll from GP regression results for Kin-GP-VE and R2D-TTE

improvement over the state-of-the-art R-TTE techniques, which are not designed to consider deformation.

We also evaluated the ability of the approach to estimate vehicle configuration in an area with more deformation than that experienced during training, using hyperparameters learnt from other training areas. This was done by introducing a terrain feature that changed its geometry significantly when the rover traversed over it. The GP regression results can be seen in Fig. 10, which shows the prediction for pitch and left bogie angles over 65 validation points. We see that the mean estimate from R2D-TTE occasionally underestimated the vehicle configuration in areas with high terrain deformation (i.e. sample number 20 to 42 in Fig. 10). This may be a result of inaccurate inputs from R-TTE, which hinders the ability of R2D-TTE to anticipate the impact of terrain geometry on vehicle configuration in deformable terrain. However, the associated uncertainties account for such cases and the resulting error (w.r.t ground truth) still lies within the 1σ confidence interval.

Fig. 11 shows the estimate of terrain deformation, which is predicted as a probability. A higher error can be seen in estimating this quantity. This may be attributed to a compounding of errors from the sensor and localization during experiments, which can lead to additional errors in the estimate from Kin-GP-VE and the association between exteroceptive and proprioceptive data. As the ground truth in deformation is a qualitative measure, actual deformation may have been mis-represented in the training data due to different error sources.

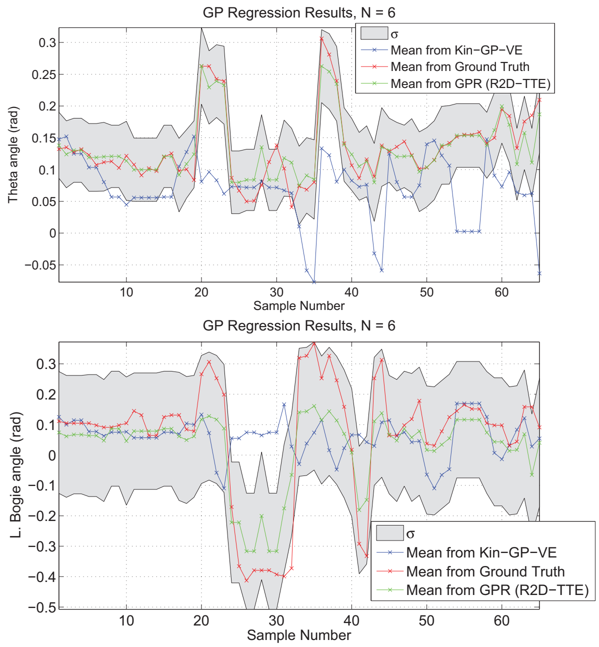


Fig. 10. GP regression results for predicting θ and α_1, respectively, over an area with higher deformation than that experienced during training. Grey area indicates a 1σ confidence interval.

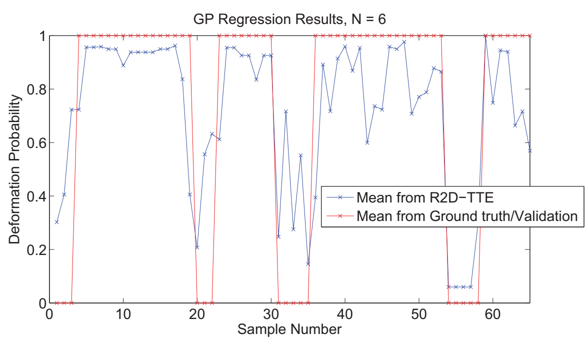


Fig. 11. Deformation probability predictions over an area with higher deformation than that experienced during training

VI. Conclusion

This paper introduced a novel method for predicting vehicle configuration angles of a planetary rover over deformable terrain. The proposed method first uses a state-of-the-art R-TTE method to predict vehicle attitude and configuration, and then refines this prediction by accounting for effects of terrain deformation using learnt correlations between Φ_{rigid} and Φ_{deform}. Experimental validation of the method showed significant improvement in estimating vehicle configuration over state-of-the-art techniques, particularly in deformable terrain. In addition, the validation process demonstrated the ability to provide predictions of vehicle configuration in an area with more terrain deformation than that experienced during training. In future work, we will consider terrain descriptors other than geometry that would contribute towards discerning deformable terrain, such as color and texture, to improve estimation accuracy.

Although the proposed approach was able to estimate the probability of terrain deformation, the training data contained errors from the experiments such as sensor and localization errors, which may lead to misrepresentation of the actual deformation. Therefore, further improvement in the estimation accuracy of vehicle configuration and terrain deformation would require more accurate measurements of the changes in terrain geometry as the rover traverses over it. In future work, we plan to obtain this information from an external observation setup, such as a geo-referenced LIDAR or a multi-camera system.

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