Stochastic Characterization of Traction on Granular Terrain

J. Williams[1], B. Frank[2], W. Burgard[2], and J.C. Trinkle[1]

***Abstract*— Mobile robots traversing disaster sites, extraterrestrial landscapes, and other outdoor environments will encounter terrain covered with loose stones or rubble. When traversing such *granular terrain*, it will be important for the robot to have a model of available traction forces that can be used to plan trajectories and control the robot's gait as it crosses the terrain. Interaction with granular terrain is inherently difficult to model due to the enormous number of dynamic interactions with and between the many small bodies involved. In this paper, we explore two probabilistic models of traction with data from experiments performed with a robotic foot interacting with a bed of gravel. These models include Tustin friction and Gaussian processes. We present the results of these two independent models, as well as a third method incorporating both.**

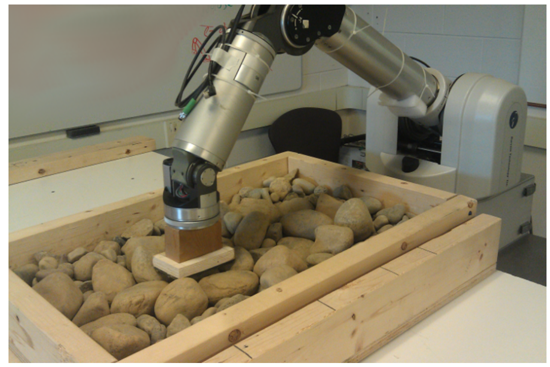

Fig. 1: Traction testbed with robotic foot.

I. Introduction

The motion of any mechanical device for which operation causes contacts between bodies is affected by friction forces. In some cases understanding the character of friction forces and how to predict them is critical for high-performance operation [8]. This fact has motivated research in actuators and transmission [1] and in feedback controllers that minimize the effects of friction on robot motion - especially stick-slip transitions, which are mathematically nonsmooth [6], [8].

The focus of this paper is on characterizing the traction available to mobile robots traversing granular terrain, where "*granular terrain*" is ground covered by a layer of loose stones, and "*traction*" is the force between the robot and the ground in the direction that propels the robot. One application that motivates our research is search-and-rescue scenarios. For example, a robot must provide aid to people as quickly as possible, but to do that, it must first traverse granular terrain such as can be found in the bed of a shallow river or a pile of rubble from a collapsed building. Another important application is the control of autonomous vehicles exploring extra-terrestrial frontiers, where the locomotion controller should try to avoid foot slippage, since sliding expends more energy than sticking/rolling contacts.

Future autonomous mobile robots will have non-contact terrain sensors, such as lidar, and real-time access to a terrain characteristics database containing a coarse description of the characteristics of the terrain near the robot, that will be useful for gait selection or driving speed. The work presented here forms the basis of a method that will ultimately provide a more detailed model of traction that can augment the information in a terrain database and provide useful input to a locomotion controller. The data needed to obtain the traction model are measurements of the contact forces and the relative contact velocities at the bottom of foot. This data can be obtained by body pose and joint displacement sensors and by force/torque sensors in the robot's feet.

The main contribution of this paper is the investigation of two methods for modeling friction and their applicability to granular terrain. First, we consider a parametric model, the Tustin model [10] for stick/slip friction. This model is mathematically nonsmooth, but any model that captures stick-slip phenomena must be nonsmooth. The second model is a non-parametric Gaussian process (GP) model obtained from the same data. We assess the ability of both these models to predict traction forces while sticking or slipping on various terrain. We also consider a combination of both methods by using the Tustin model as mean function of the GP model.

II. Background

A. Contact Friction Modeling

Friction models relate forces and relative velocities at contacts between bodies. Two classes of friction models are known as viscous and dry friction. The former are best suited for contacts with a viscous fluid, such as oil or mud, in the contact interface, while the latter is best suited to contact interfaces that are dry.

The main variables in friction models are the contact force F and relative velocity v vectors. It is easiest to express a friction model in terms of an effective tangent plane in the contact interface and its normal. As shown in Figure 3, corresponding components of force and velocity are: F_{n}, F_{t},

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v_{n}, and v_{t}, where the subscripts "n" and "t" connote normal and tangential components, respectively.

In the field of tribology, friction models are motivated by the fact that even if two hard contacting surfaces appear to be smooth, they are not. What may appear to be a large continuous contact patch between matched shapes is actually, at the microscopic level, a set of very small contact patches between tiny deformable peaks on the surfaces, called asperities. The net friction force of the contact is the sum of the friction forces generated over all the contact patches. At low sliding speeds, this force is dominated by yield strengths of the asperities, which at extremely low speeds can cold weld, and therefore stick. At high sliding speeds, the effects of fluid and particulate matter in the contact interface produces a viscous force which is approximately proportional to the sliding speed.

A commonly-used friction model is Tustin's model [10]. A typical plot of friction force versus slip speed is shown in Figure 2. The rapid change in friction force as sticking $v_{\mathrm{t}} = 0$ transitions to slipping $v_{\mathrm{t}} \neq 0$ is known as the Streibeck effect [2]. When the slip speed is zero, then the maximum friction force is F_{s}, which is proportional to the normal force, F_{n}. As the sliding speed increases, the maximum friction force approaches a linear asymptote that crosses the vertical axis at the value μF_{n}, where μ is the dry friction coefficient, and is also known as the coefficient of dynamic friction in the familiar Coulomb friction model.

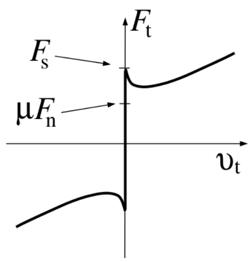

Fig. 2: Tustin Friction Model.

As shown in Figure 3, contact between a robot foot and granular terrain is analogous to the microscopic description of contact given above. The many contact points between the foot and the stones are like the asperities and the friction forces at those contacts are like their yield strengths. If the foot digs into the stone layer as it moves, the momentum transfer between the stones and the foot will generate a net traction force of viscous character. This is also expected to be the case if the stones are mixed with mud. Because of these similarities, we have adopted Tustin's friction model [10] for characterization of net traction forces.

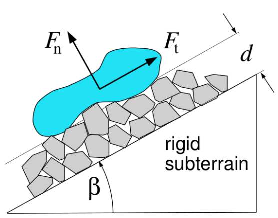

Fig. 3: Robot foot on granular terrain.

The Tustin model is a two-part, set-valued map that predicts or bounds the traction force, when given the normal force, the slip speed, and values of five parameters. The first part is an odd function that gives the traction force when the contact is slipping, i.e., $v_{\mathrm{t}} \neq 0$:

$$F_{\mathrm{t}}(F_{\mathrm{n}}, v_{\mathrm{t}}) = \mu F_{\mathrm{n}} + (F_{\mathrm{s}} - \mu F_{\mathrm{n}}) e^{-|v_{\mathrm{t}}/v_{\mathrm{s}}|^{\delta_{\mathrm{s}}}} + b v_{\mathrm{t}}, \qquad (1)$$

where b is the viscous friction coefficient and v_{s} and δ_{s} are the Streibeck velocity and exponent, respectively. The last parameter b is the slope of the linear asymptotes when $|v_{\mathrm{t}}|$ is large. The Streibeck parameters, v_{s} and δ_{s}, determine the shape of the curve connecting the extreme points on the vertical axis with the asymptote. During sticking contact, the Tustin model returns the set of possible friction values, not a single value:

$$||F_{\mathrm{t}}|| \leq \mu F_{\mathrm{n}}. \qquad (2)$$

B. Gaussian Process Models

Gaussian process models (GPs) are a powerful framework for non-parametric regression and are used to solve different machine learning tasks [9]. The idea is to model an unknown noisy function directly in terms of training data. More formally, a Gaussian process is defined as a collection of random variables, any subset of which is jointly Gaussian distributed. It is completely specified by a mean function $m(\mathbf{x})$ and a covariance function $k(\mathbf{x}_i, \mathbf{x}_j)$:

$$\mathbf{f} \sim \mathcal{N}(m(\mathbf{x}), k(\mathbf{x}_i, \mathbf{x}_j)). \qquad (3)$$

Intuitively, the covariance function specifies the similarity of function values $f(\mathbf{x}_i)$ and $f(\mathbf{x}_j)$ depending on their inputs $\mathbf{x}_i$ and $\mathbf{x}_j$. A popular choice is the squared exponential covariance function, which is given by

$$k_{SE}(\mathbf{x}_i, \mathbf{x}_j) = \sigma_f^2 \exp\left(-\frac{1}{2}(\mathbf{x}_i - \mathbf{x}_j)^T \Sigma (\mathbf{x}_i - \mathbf{x}_j)\right). \qquad (4)$$

Here, $\Sigma = \mathrm{diag}(\ell_1, \ldots, \ell_d)^{-2}$ is the length-scale matrix and σ_f^2 the signal variance. These parameters together with the global noise level σ_n are known as the hyperparameters of the process.

We furthermore consider in our experiments the neural network covariance function [7], [12], [11], which is known to better adapt to non-smooth data and to account for variable frequency content of the underlying function. This covariance function is specified as

$$k_{NN}(\mathbf{x}_i, \mathbf{x}_j) = \sigma_f^2 \arcsin\left(\frac{\beta + 2\mathbf{x}_i^T \Sigma \mathbf{x}_j}{\sqrt{(\beta + 2\mathbf{x}_i^T \Sigma \mathbf{x}_i)(\beta + 2\mathbf{x}_j^T \Sigma \mathbf{x}_j)}}\right) \qquad (5)$$

with a bias factor β and Σ, σ_f as defined above.

Learning a GP model is equivalent to determining the hyperparameters of the covariance function that best explain the training data points. This is formulated as an optimization problem by maximizing the marginal log likelihood of the data given the model. We use a standard gradient optimization approach to find the best hyperparameters for a given dataset. More details on the problem formulation can be found in the work of Rasmussen and Williams [9].

In regression, we are interested in predicting the value y^* for a new observation $\mathbf{x}^*$ given a set of training points $\mathcal{D} =$

$\{(\mathbf{x}_i, y_i)\}_{i=1}^n$ with d-dimensional states $\mathbf{x}_i \in \mathbb{R}^d$ and target values $y_i \in \mathbb{R}$. We obtain the predictive distribution $p(y^* \mid \mathbf{x}^*, X, \mathbf{y})$ for a new observation $\mathbf{x}^*$ that is again Gaussian with mean

$$f_\mu^* = m(\mathbf{x}^*) + k(X, x^*)^T(K + \sigma_n^2 I)^{-1}(\mathbf{y} - m(X)) \quad (6)$$

and variance

$$f_{\sigma^2}^* = \quad k(\mathbf{x}^*, \mathbf{x}^*) - K(X, \mathbf{x}^*)^T(K + \sigma_n^2 I)^{-1}k(X, \mathbf{x}^*). \quad (7)$$

Here, I is the identity matrix, K refers to the covariance matrix built by evaluating the covariance function $k(\cdot, \cdot)$ for all pairs x_i, x_j of training points.

C. Related Work

Past research in compensation of friction effects in robotics includes efforts in parameter identification for various friction models similar to the Tustin model. Representative examples can be found in the works by Marton and Lantos [6] and Behmer [3]. The basic idea is to perform experiments on one joint at a time, and to design these experiments so that one can easily capture several of the model parameters. For example, starting with zero velocity, the joint torque is increased slowly until joint motion begins (stiction is broken) and then continues until a target relative velocity is achieved. The stiction breakage torques allow direct estimation of F_s and motions with large velocities are used to identify the viscous friction asymptote, thus identifying b and μF_n. Finally low velocity data can be used with a nonlinear least squares approach to identify the two Streibeck parameters, v_s and δ_s.

Much of the research in traction makes use of Bekker's work [4] and pertains to very heavy wheeled and tracked vehicles [13], [14], [15], [16], [17]. Though successful, these models do not apply directly to legged robots. Previous work also tends to focus on deformable soil, whereas rubble or rocky terrain may benefit from rigid body mechanics.

Several groups have investigated using on-board sensors for parameter estimation of deformable soil including Iagnemma *et al.*[16] and Hutangkabodee *et al.*[17]. Others have looked at more general terrain classification [18]. Larson *et al.* point out the importance of terrain classification with regard to gait efficiency. Knowing terrain properties provides for better control of gait parameters, increasing energy efficiency. We investigate a common friction model (Tustin) and GP models as representations for characterization and prediction of traction forces based on position and force data from on-board sensors.

Caurin and Tschichold-Gürman developed a control system for walking machines [5] that uses Bekker's equation to model sinkage, and a model satisfying the Mohr-Coulomb equation to represent slipping: $s/s_{max} = 1 - exp(-j/k_w)$. Although their system has the ability to adapt to different terrain, it is unclear if their system performs well on rocky or course granular terrain.

The Tustin model is a deterministic representation of friction that defines average behavior, but does not directly give information about the variance. For different data sets, one could estimate the five parameter values for the model to obtain joint probability distribution over them, and in this way obtain a stochastic model of traction. However, as pointed out by [14], parameter models such as this do not "explicitly consider uncertainty in terrain physical parameters."

Therefore, in this paper, we have chosen to learn Gaussian process models to characterize traction forces for different types of terrain. The advantage compared to a deterministic model, such as the Tustin model, is that GPs are able to model uncertainty in the data. In experiments, we investigate how useful these models are in predicting the traction forces for different terrain types.

Performing analogous experiments with a robot foot on a bed of stones is difficult in part because the constant sliding velocities cannot be held for long enough periods of time to extract asymptotic behavior from a single experiment. As a foot presses against the stones, the stones can suddenly give way and then lock up, causing fast transitions between the sticking and sliding regimes.

III. Experiment

A. Hardware & Setup

A foot constructed with a vinyl tred was attached to a Barret 7-DOF WAM arm with integrated 6-axis force/torque sensor in the wrist. In order to simulate a stepping motion, the arm was used in a augmented gravity compensation mode which applied an effective mass at the center of mass of the foot. The seventh joint was locked in place to avoid rotation of the foot below the sensor. The foot could then be placed anywhere in the workspace of the arm with a force applied above the sensor in any direction. A container with adjustable incline was constructed to hold the granular terrain that was positioned adjacent to the arm. The testbed is depicted in Figure 1.

B. Experimental Procedure

Experiments were completed for each combination of experimental parameters including two sizes of stones: small (#2 gravel) and big (#3 gravel); three angles of incline: $0°$, $10°$, and $15°$. Two additional experiments were completed on a flat surface for the foot with and without tred (relatively high and low friction, respectively). The terrain was oriented in the workspace of the arm such that the foot would be "stepping" uphill for inclines greater than $0°$. For each experiment, ten trials were performed where the foot was placed at the far end of the terrain and then a force was manually applied until the foot had displaced across the container. Joint positions and force data from these trials were recorded at 500 Hz.

IV. Data Analysis

Using forward kinematics on the joint position data, the velocity of the foot was calculated at every time-step. Knowing the orientation of the foot, we determine the velocity v_t in the negative traction direction, and from the force data in the reference frame of the foot, we transform to obtain the normal force F_{n} and traction force F_{t}.

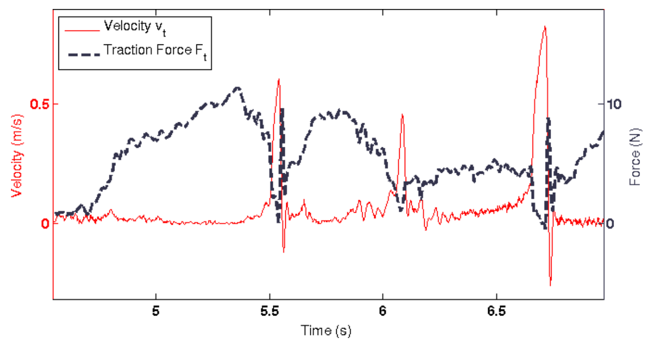

Fig. 4: Sample of traction force F_{t} and velocity v_{t} from an experiment.

The small sample in Figure 4 depicts the complexity of the stick-slip behavior on granular terrain and a relationship between F_{t} and v_{t}. There are three regions of obvious slipping where v_{t} spikes before the foot quickly returns to sticking. At these moments when slipping occurs, the traction force drops to near zero. In two of these cases, we see v_{t} become negative immediately upon reestablishing sticking, corresponding to opposing spikes in the traction force. Dynamic effects such as this are possible in a large number of scenarios due to the complexity of the terrain, but effectively the foot is colliding with an object or dynamically linked set of objects and experiencing some bounce-back.

Another interesting aspect observable in Figure 4 is the variation in the value of F_{t} before slipping. In two examples, it appears to decrease before slip occurs. This could be due to a decrease in F_{N}, but it is also distinctly possible that this was cause by the slipping or rolling of terrain beneath the foot. The values of v_{t} in themselves are interesting, especially in the second case where the foot seems to slip and stick rapidly before and after the peak. These oscillations could be due to stick-slip behavior between two or more stones not in direct contact with the foot.

The data was smoothed by a simple moving average and downsampled by a factor of five. Models were fit only to data with velocities in the range $0.005 \leq v_{\mathrm{t}} \leq 0.2$ (majority of data). Data with negative velocities or too near zero are filtered. We evaluate friction model learning in a 10-fold cross-validation and compare the results of the Tustin model and the GP models.

A. Tustin Model

Given the inputs F_{n} and v_{t}, and the output F_{t}, a nonlinear least squares curve fitting was done to estimate the five parameters of the Tustin model.

For each type of terrain, the results of the ten cross-validation fittings were used to determine a set of Tustin parameters. The estimated parameters are summarized in Table I.

TABLE I: Median Tustin parameters from sample of four terrain datasets, all at $0°$ incline.

	Small stones	Large stones	Flat	Flat, low friction
μ	0.71	4.54	0.843	0.952
$F_s\ (N)$	13.52	7.70	0.534	0.6430
$v_s\ (m/s)$	-0.841	0.128	0.079	0.225
δ_t	-0.017	0.011	420	2.60
$b\ (kg/s)$	-23.4	-37.4	7.49	0.023

B. Gaussian Process Friction Models

In addition to the parametric Tustin model, we investigate modeling the dependency of the friction forces F_{t} on the sliding velocities v_{t} and normal forces F_{n} using GPs. We learned GP friction models for different terrain and compared these models to the corresponding Tustin models. In our experiments, we considered different covariance functions, the squared exponential (Eq. 4) and the neural network (Eq. 5) covariance function. Furthermore, we considered using the Tustin model as mean function of the GP model. Since the runtime for learning GP models is cubic in the number of training points, we subsampled the considered datasets and used 300 training points for learning a GP model. Considering larger numbers of input points did not increase the prediction accuracy in our experiments.

C. Model Comparison

To assess the ability of the considered friction models to predict the traction forces, we performed a 10-fold cross-validation using 10 independent datasets for each type of terrain, learning the model on a combination of 9 datasets, and evaluating the prediction error for the tenth dataset. This was done for 8 different types of terrain that are described in detail in Section III-B: small stones with an angle of 0 (S0), 10 (S10), and 15° (S15); big stones with an angle of 0 (B0), 10 (B10), and 15° (B15); a flat surface with high (TF) and low friction (Tf).

Examples of learned models for the Tustin parameter fittings are shown in Figure 5. The correspondence to the Gaussian process models (shown in Figure 6 for the squared exponential covariance function) is clearly visible. Additionally, we show a 2d plot of the GP mean and variance in Figure 7 and Figure 8, respectively. In our experiments, we consider the mean absolute prediction error. A comparison of the different models in terms of the prediction error is shown in Figure 9. These experiments illustrate that the different models we considered perform similarly for different types of terrain. The non-parametric GP model is able to model the friction behavior of the robot similar to the parametric model. The prediction error is in general much higher for the datasets recorded on the stones than for the flat surfaces. This is due to the non-deterministic behavior of the foot on the stones, which results in very “noisy” data. The GP models this “noise” in the variance for the predicted datapoints. In Figure 8, the variance of the GP models is illustrated for different terrains, we observe that t for the. The variance is much higher for the rocky terrains than for the flat surfaces.

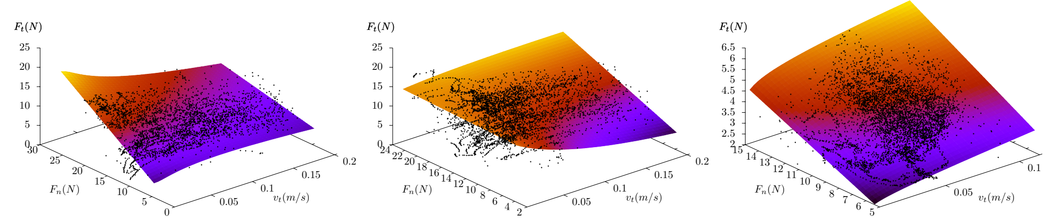

Fig. 5: Tustin models for different terrains: Small stones (left), Big stones (middle), flat surface (right).

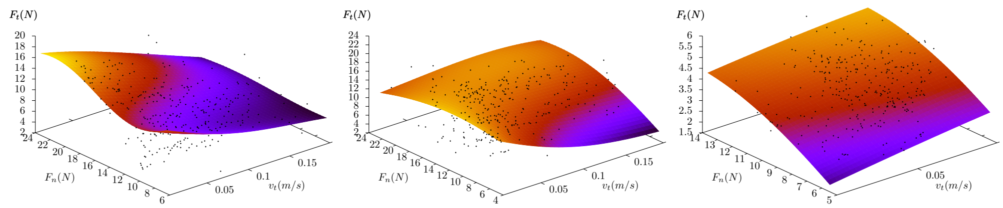

Fig. 6: GP models for different terrains: Small stones (left), Big stones (middle), flat surface (right).

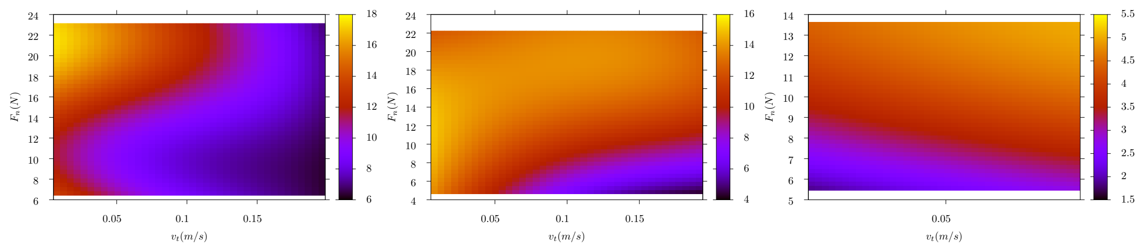

Fig. 7: GP predictive mean (2d) for different terrains: Small stones (left), Big stones (middle), flat surface (right).

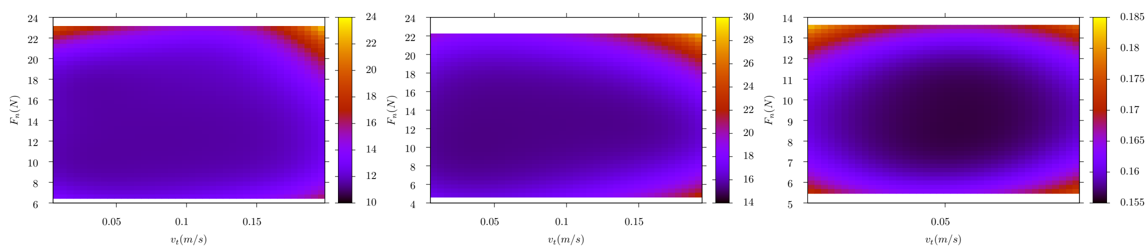

Fig. 8: GP predictive variance (2d) for different terrains: Small stones (left), Big stones (middle), flat surface (right).

D. Terrain Identification

One application of the learned friction models could be to provide an estimate of the type of terrain that the robot is dealing with for a given observation of v_t, F_n, and F_t, e.g. by determining the model that minimizes the distance between predicted and measured F_t. In a second experiment, we therefore evaluate, how well the models are able to predict the friction forces for different terrains and whether they allow to make this distinction. We evaluated, in another 10-fold cross-validation experiment, for each terrain dataset the prediction error when applying the different available terrain friction models. The results of this experiment are summarized in Figure 10. This figure illustrates that the models learned for different stone environments are not very specific as the prediction errors are similar across different stone datasets. However, we notice that the models representing flat surfaces perform in general significantly worse as predictors for traction on rocky surfaces and vice versa. The distinction between flat and rocky surfaces is therefore possible. Furthermore, the models representing the flat surfaces are very accurate as mean error values on these datasets were approximately equal to the mean error of the force sensor ($\sim$ 0.4 N).

This indicates, that the considered data allows to model stick-slip behavior and characterize traction for smooth surfaces but does not fully capture the friction characteristics of rocky surfaces. Other factors not modeled here might influence slipping (e.g. relative position of stones to each other).

V. Conclusions

An understanding of traction on various types of terrain is essential for improving the performance of mobile robot controllers. There has been significant research pertaining to wheeled robots that use models of wheel-soil mechanics. In this paper, we considered probabilistic models that might be useful for improving traction control for a robotic foot

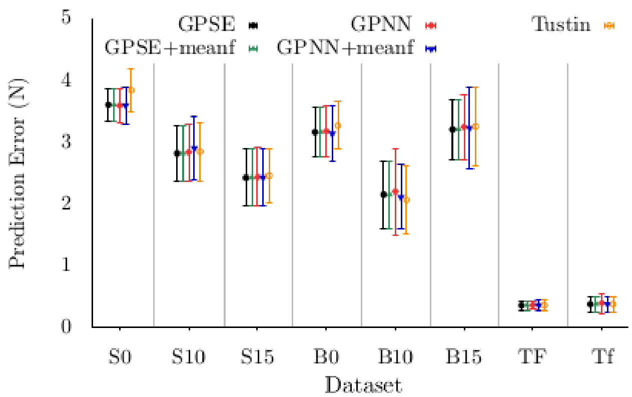

Fig. 9: Comparison of the prediction error for the Tustin model, the GP models with squared exponential (SE) and neural network (NN) covariance function, and the GP models using the Tustin model as mean function. We evaluated the mean absolute prediction errors for datasets recorded on different terrain (horizontal axis).

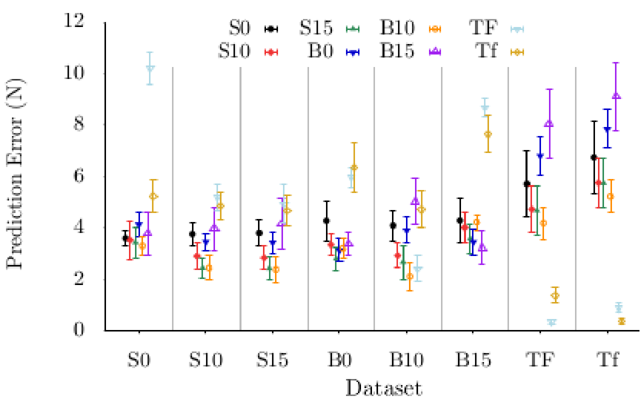

Fig. 10: Cross-evaluation of traction models learned and evaluated on different types of terrain: the horizontal axis represents the terrain types tested on. Plotted is the mean absolute prediction error for evaluating each of the learned models on every terrain type.

on granular terrain. In particular, we discussed two models for predicting traction force using an onboard force sensor: the parametric Tustin model and the non-parametric Gaussian process. In experiments, we showed that both models perform similarly on different types of terrain. The benefit of using Gaussian process models is that they are able to take into account noise in the training data and additionally provide a predictive variance. Considering the stochastic nature of the stick-slip behavior on granular terrain, it might be interesting to consider advanced GP models that are able to deal with input-dependent noise. Depending on the application, ideas for future work include considering the dependency of control inputs on the movement of the robot for different types of terrain and e.g. learn control policies to avoid slipping.

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