On-Line Estimation of Soil Parameters Using the Kapvik Micro Rover

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Abstract

The Kapvik micro rover is used to estimate the soil parameters of terrain during traverse. The Kapvik rover is a 40 kg rover with a rocker boogie mobility system that has been instrumented to determine the forces acting on the wheel. A neural network is used to map the wheel states to the major soil parameters: cohesion, shear angle, and shear deformation modulus. In addition to the mobility control that can benefit from this information, there are scientific benefits as well.

1 Introduction

Greater autonomy in planetary rovers allows deployment in greater risk situations than previously allowed. Greater risk situations include driving through regions with large number of obstacles and difficult terrain. Terrain includes the type of soil and the geometry of the landscape. Recently, there has been wide interest in the estimation of soil properties and the classification of different soil by rovers during online procedures for greater autonomy. The benefits of characterizing the terrain being traversed can include scientific contributions. For example, water ice in the lunar regolith would effect the terrain characteristics.

The current Resource Prospector Mission is a mission to search the lunar south pole for water ice and to demonstrate in-situ resource utilization (ISRU) principles. A rover employs a drill to take core samples where ice is thought to be located in the lunar regolith. Due to the short duration of the mission lasting up to 7 days, it is critical that false positives of water ice not occur, else risk wasting time taking core samples where no ice exists. There is a need for simple and low-cost methods to determine locations of high probability of ice existing. A neutron spectrometer is employed to detect subsurface hydrogen which is a proxy for water but is unable to detect water ice directly. Another method for determining whether there is water ice in the regolith is by extracting soil parameters of regolith during the rover traverse. The soil parameters differ between dry regolith and both regolith containing ice and regolith which has a void due to past ice which has since evaporated. We propose the use of this method on the Resource Prospector Mission due to its cheap addition and its potential to improve reliability in taking samples which contain water ice.

In order to reduce the cost and complexity of employing these algorithms on board rovers, it is essential that the measurements used come from primary sensors that are standard on a planetary rover. Therefore, sensors used in navigation and path planning must be mainly used. Developing techniques to measured needed rovers states has been one of the challenging aspects of moving from in-lab demonstrations of soil parameter estimation to online rover technology. Iagnemma, Shibly, and Dubowsky [6] were able to estimate a reduced number of parameters by using assumed values for the shear deformation modulus and making assumptions about the symmetry of the stress distributions. This approach required the drawbar pull, motor torque, slippage, and wheel sinkage as inputs. Hutangkabodee et al. [5] made similar assumptions and were able to predict characteristics of low cohesion soils by assuming a value for the cohesion. Ding et al. [3] solved for all classical parameters without the symmetry assumptions by solving for decoupled analytical equations and using nonlinear optimization techniques. However, they did not explain what sensors they would use to get the measurements required for their algorithm to work. They required the drawbar pull, weight on wheel, motor torque, wheel slippage, and wheel sinkage.

Ray [7] analysed the uniqueness of the relationship between drawbar pull, weight on wheel, motor torque and slippage to the cohesion, shear angle, and shear deformation modulus. She discovered that without the sinkage the mapping was not unique, and therefore used a Bayesian multiple model estimation technique that did not include the sinkage as an input. This technique was able to pick the best set of terrain parameters from predetermined sets based on the literature. Cross, Ellery, and 'Qadi [2] used neural networks to map the same inputs as Iagnemma, Shibly, and Dubowsky [6] to the cohesion, shear angle and shear deformation modulus. They used a neural network which was trained from data sets generated from the terramechanics theory. The network was trained with the results for a range of sinkages in an attempt to eliminate the need for the value. The network was shown to converge to the correct set of soil parameters in simulation and limited hardware testing with the Kapvik micro rover.

Neural networks are able to replicate mappings of unknown nonlinear functions, a category which the wheel-soil interaction falls under. We expand on the work of Cross, Ellery, and ‘Qadi [2] by using the inputs of Ray [7]. Setterfield and Ellery [9] have solved the dynamics of the Kapvik micro rover to determine the forces and moments on each wheel from the rover’s sensors. This paper will outline the theory and the methods used in estimating the soil parameters using this neural network technique.

2 Kapvik Micro Rover

The Kapvik micro rover is a 40 kg rover that was built as part of the Exploration Surface Mobility (ESM) project by the Canadian Space Agency and was administered by MPB Communications. Kapvik was designed with a view to flight and consists of standard planetary rover sensors and payloads. In addition to the standard sensors for navigation purposes (wheel odometer, IMU, and sun sensor), Kapvik includes force sensors above each of the six wheel hubs (Figure 1) and a visual odometer for determining body velocity. Kapvik’s rocker-bogie mobility system, pan-tilt mechanisms, and body were designed, manufactured, and assembled at Carleton University. Setterfield and Ellery [9] have shown that the drawbar pull, weight on wheels, and motor torques can be estimated with the sensors available on Kapvik; this includes the navigation sensor suite, force sensors, and chassis measurements. The slippage is calculated from the rover body speed measured using a downward facing camera mounted on the body. The method developed by Ding et al. [3] determined the soil parameters from the wheel-terrain forces, slip, and wheel sinkage. The method was based on a least-squares optimization on several measurements of the same wheel through terrain. This method can be used at any single time instance by using the measurements at each of Kapvik’s six wheels. This gives a direct comparison of the results achieved with the neural network.

3 Terramechanicss

Terramechanicss involves the study of the wheel soil interaction while a vehicle drives on deformable terrain. When the soil is modelled as a deformable solid, Coulomb‘s failure criterion (Equation 1) is the principal model for soil-wheel stresses. The cohesion, shear angle, and shear deformation modulus (c, ϕ and K) are the most widely used parameters for characterizing soil.

Figure 1. : The Kapvik micro rover is shown in the Carleton University Mars Yard

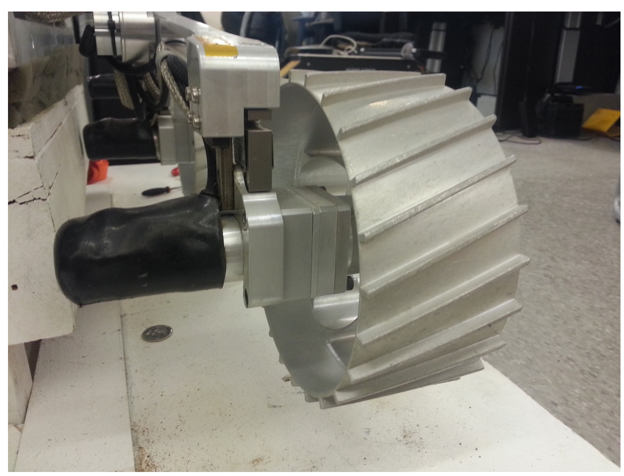

Figure 2. : The Kapvik micro rover has six wheels which are individually driven with a load sensor above each wheel to measure the force acting on the wheel

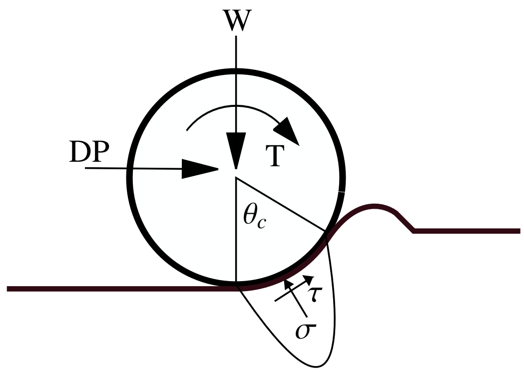

Figure 3. : **Forces Acting on a Wheel in Loose Soil**: The two forces and one moment action on the 2-dimensional wheel are shown. The shear and normal stress directions are also shown.

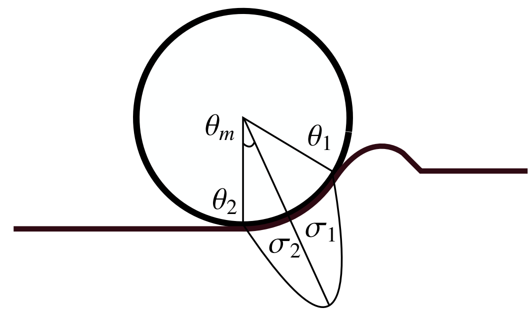

Figure 4. : **Defining Regions of Stress on a Wheel in Loose Soil**: The forward and backwards regions of the wheel-soil contact patch are shown. The location of maximum normal stress divides the two regions. To simplify the analysis, it is assumed that the located of maximum shear stress is the same as the location of maximum normal stress.

$$\tau(\theta) = (c + \sigma(\theta)\tan\phi)\left(1 - e^{\frac{-j(\theta)}{K}}\right) \tag{1}$$

$$j(\theta) = r[(\theta_1 - \theta) - (1 - i)(\sin\theta_1 - \sin\theta) \tag{2}$$

The two-dimensional wheel has two net forces and one net moment acting on it due to the stress formed between the wheel and the soil. The net force in the direction of motion is called the drawbar pull. The net force perpendicular to the ground is the weight on wheels. The net moment is the resistant torque on the wheel. In order for there to be forward motion, the drawbar pull must be positive in the direction of travel. These forces can be expressed as the integral of the normal and shear stresses of the soil over the contact area of the wheel and soil, and are largely dependent on the stress distribution along the wheel. It is from these forces, particularly the weight on wheels and torque, and information on the rover motion that soil parameters are estimated.

$$DP = rb\left(\int_{\theta_2}^{\theta_1} \tau(\theta)\cos\theta d\theta - \int_{\theta_2}^{\theta_1} \sigma(\theta)\sin\theta d\theta\right) \tag{3}$$

$$W = rb\left(\int_{\theta_2}^{\theta_1} \sigma(\theta)\cos\theta d\theta + \int_{\theta_2}^{\theta_1} \tau(\theta)\sin\theta d\theta\right) \tag{4}$$

$$T = r^2 b \int_{\theta_2}^{\theta_1} \tau(\theta) d\theta \tag{5}$$

Bekker [1] developed an empirical model of the normal stress acting on the wheel that was expanded upon by Wong and Reece [10].

$$\sigma(\theta) = \left(\frac{k_c}{b} + k_\phi\right) z(\theta)^N \tag{6}$$

$$\sigma_1(\theta) = \left(\frac{k_c}{b} + k_\phi\right) r^N (\cos\theta - \cos\theta_1)^N \tag{7}$$

$$\sigma_2(\theta) = \left(\frac{k_c}{b} + k_\phi\right) r^N \left[\cos\left(\theta_1 - \frac{\theta - \theta_2}{\theta_m - \theta_2}(\theta_1 - \theta_m)\right) - \cos\theta_1\right]^N \tag{8}$$

The initial contact angle of the soil is directly proportional to the depth which the wheel is in the soil. The angle of maximum stress has been found to be dependent on slippage, introducing two additional empirical parameters. The rear contact angle is often assumed to be zero with a rigid circular wheel. If the wheel has lugs on it, the amount of soil kicked back is found to be proportional to the depth the wheel is in the soil.

$$\theta_1 = \arccos\left(\frac{r - z}{r}\right) \tag{9}$$

$$\theta_m = (c_1 + c_2 i)\theta_1 \tag{10}$$

$$\theta_2 = -\arccos\left(\frac{r - \eta z}{r}\right) \tag{11}$$

4 Neural Networks

Artificial neural networks (henceforth referred to simply as 'neural networks') are mathematical structures which use sequences of nonlinear computations to represent a nonlinear function. The most common structure for a feed-forward neural network is the multilayer perceptron (MLP) which involves an input layer, hidden layer(s), and an output layer. Each hidden layer consists of an arbitrary number of neurons. The input layer consists of the inputs to the system, and the output layer consists of a number of neurons consistent with the number of desired outputs.

Parameter	Variable	Magnitude	Units
Soil Deformation Exponent	N	1.1	-
Cohesion	c	250	Pa
Internal Friction Angle	ϕ	31.9	°
Shear Deformation Parameter	K	11.4	mm
Soil Modulus of cohesion	k_c	15.6	kPa/m^{N-1}
Soil Modulus of friction	k_ϕ	2407.4	kPa/m^N
Maximum Stress Angle Modulus	c_1	0.18	-
Maximum Stress Angle Modulus	c_2	0.32	-

Table 1. : **Soil Parameters for Sand**:

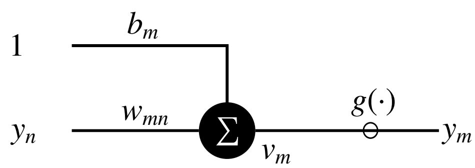

Figure 5. : **Neural Network**:

Figure 5 shows the model for an individual neuron. Each neurons is connected as shown to the previous layer of neurons. The output of the previous layer is propagated forward and the activation of the current neuron is the sum of all weighted activations from the layer previous plus a bias. The output of the current neuron is the activation level put through an activation function.

$$v_m = g\left(\sum\nolimits_n w_{mn} y_n\right) \quad (12)$$

Where v is the activation of a neuron, w_{mn} is the weight from neuron n in the previous layer to neuron m, and g is the activation function. The output of the neuron is y. The activation function is usually sigmoid in nature and can be binary (ranging from 0 to 1) or bipolar (ranging from -1 to 1). We use the bipolar sigmoid function.

$$g(x) = \frac{2}{1 + e^{-Ax}} - 1 \quad (13)$$

The constant coefficient A can be adjusted to change the gradient of the activation function. It can be set by the user or it can be optimized as part of the training algorithm. Neurons can be placed in several different configurations. For our purpose, we use the multi-layer perceptron (MLP) which is of the feedforward network type. The MLP is shown in Figure 6.

In order for the neural network to successfully represent the desired nonlinear function, the weights in the network are adjusted through a training scheme. The most popular method for training MLP is the backpropagation method which is a gradient decent method. A training set of input-output pairs is used to train the network. The inputs are fed into the network and the activations are fed forward to the output layer. The difference between the given output and the desired output (sometimes called the innovation) is computed and is propagated backwards through the network to adjust the weights between each layer [4]. It has been shown that the backpropagation method is simply a degenerate form of the extended Kalman filter which requires much less computations to achieve the same level of accuracy in training [8]. However, the training of the neural network is done off-line prior to implementation. Therefore the high-computation part of the neural network is done off-line and the on-line functionality of the neural network is low in computational costs.

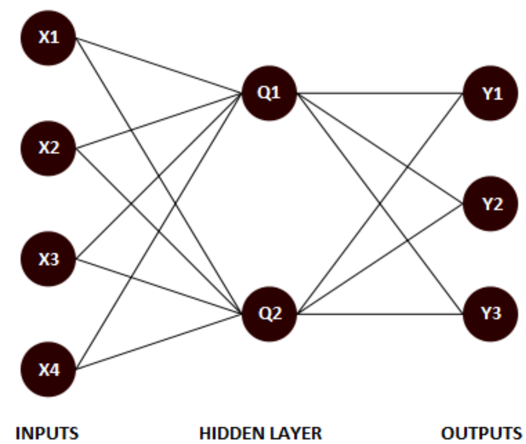

Figure 6. : MLP

Neural networks are well suited to mapping highly nonlinear functions such as the mapping between forces and soil properties. Given a suitably large training set of pairs of inputs and their measured outputs, the neural network is trained to replicate the function as a "black box." Although the neural network does not help with discovering an empirical formula for the wheel-soil interaction, we can use it to predict the soil characteristics based on the rover measurements. The proposed inputs to the system are the forces and moments of the rover, drawbar-pull, weight-on-wheels and wheel torque, in addition to the slippage of the rover and an additional parameter. The additional parameter is wheel sinkage in the literature for many methods. However, individual wheel sinkage can be difficult to estimate or measure. Therefore, we initially use wheel sinkage as the fifth input, but look to replace it with a more easily measured state.

5 Rover Dynamics

The two unscented Kalman-Bucy filters presented in [9] provide the forces and torque on each individual wheel. The first estimator includes the resistive torque on each wheel and the wheel slippage. The second estimator includes the wheel terrain contact angle, the weight on wheel, and the drawbar pull. The sensors used in the two filers are wheel encoders, boogie angle measurements, force sensors, an inertial measurement unit (IMU), and visual velocimeter. The control vector is the input wheel torques.

The ability to separate the drawbar pull to the individual effort by each wheel is dependant upon having a two-dimensional load cell above each wheel. Since Kapvik has only a one-dimensional load cell, only the front wheel connected to the rocker can have its individual drawbar pull developed. The drawbar pull of the two wheels on the boogie can be estimated by assigning values proportional to the relative weight on wheel of the two wheels.

6 Conclusion

A method for predicting the soil parameters is described. A neural network is trained to map the drawbar pull, weight on wheel, motor torque, slippage, and an additional parameter to the cohesion, shear angle, and shear deformation modulus of the soil. The input values are obtained through two Kalman-Bucy filters. This method can be compared using the algorithm presented in [3] as they have the same rover inputs. The training of the neural network takes place in the Carleton University Mars Yard. Once the training is complete, the algorithm has a very low computational load, which is a primary requirement for algorithms being placed on the Resource Prospector Mission.

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