TRAVERSABILITY PREDICTION FOR UNMANNED GROUND VEHICLES BASED ON IDENTIFIED SOIL PARAMETERS

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Abstract: A novel technique for identifying soil parameters on-line while traversing with a tracked vehicle on unknown terrain is presented. This technique, based on the Newton Raphson method is used to identify unknown soil parameters. Comparing with the Least Square method, it shows that the Newton Raphson method is better in terms of prediction accuracy, computational speed, and robustness to initial conditions and noise. For heavy tracked vehicle, cohesion has negligible effect on the vehicle performance. These identified soil parameters are then employed for traversability prediction for a tracked vehicle travelling on unknown terrain.

Keywords: Parameter Identification, Tracked Vehicles, Traversability, Interaction Dynamics.

1. INTRODUCTION

Unmanned Ground Vehicles (UGVs) have many potential applications, including space exploration, defense, agriculture, mining and construction. Most unmanned ground vehicles are currently controlled by tele-operation. Tele-operation requires continuous and repetitive human intervention, which hampers the speed of the vehicle and the range of potential applications (Zweiri et al., 2003). Further they have problems due to bandwidth limitations and communication time delays of the transmission link. Increased autonomy of ground vehicles will not only improve the safety of the operators, but also increase the range of potential applications.

Research on the autonomy aspect of UGV has been carried out in the past. Model-based autonomy is described by Kurien et al. (1998). This approach involves the use of automated reasoning algorithm and first principles models of physical system being controlled to achieve robust and autonomous operation, even in failures or anomalous situations. It is now being applied and developed for the NASA Mars Mission. Behavior-based autonomy is presented by Langer et al. (1994) and Rosenblatt (1997). In both papers, Distributed Architecture for Mobile Navigation (DAMN) is employed as a behavior-based architecture for autonomous mobile navigation system. It is a planning and control architecture in which a collection of independently operating behaviors collectively determines a robot's actions. Simultaneous Localisation And Mapping (SLAM) is presented by Nieto et al. (2003) and an algorithm named FastSLAM which addresses data association and real time implementation of the SLAM problem from a Bayesian point of view is employed. Dead reckoning estimation is applied by Schönberg et al. (1995). The dead reckoning position estimation and the absolute position measurement are fused by using Kalman filtering techniques to provide a corrected estimate. This approach is used to improve the heading error of an autonomous vehicle. The combination of fuzzy logic and neural network is employed by Freisleben and Kunkelmann (1993). The approach is used to tackle the problem of controlling a car to drive autonomously around an unknown race track. The basic idea of this proposal is to let a fuzzy controller supply the training data for a backpropagation neural network and used the trained network to drive the car on an unknown track race.

The autonomy of UGV can not only be improved by various methods mentioned above, but can also be improved by UGV acquiring information from the terrain which the UGV traverses on. This is where the soil parameter identification plays an important role. The real-time acquisition of accurate soil parameters based on a physical model and numerical techniques will enable a UGV to autonomously achieve an accurate traversability prediction and effective traction control. The key numerical technique employed and validated in this work is the Newton Raphson method, whereas the Least Square method is used for comparison purpose.

In recent years, there has been increasing interest in parameter identification in various engineering applications. An on-line identification of link parameters (mass, inertia and length) and friction coefficients of a full scale excavator arm is presented by Zweiri et al. (2004). An on-line soil parameter identification based on the Newton Raphson method is applied to autonomous excavation by Tan et al. (2003). The aim was to increase the excavation autonomy based on knowledge of soil parameters. The Linear Least Square estimator is employed as an on-line identification technique by Iagnemma et al. (2002) to identify two key soil parameters using on-board rover sensors. This estimator is applied to a simplified linearized model of the rover's wheel-terrain interaction. The Newton Raphson method and the Least Square method are employed by Song et al. (2004) and Hutangkabodee et al. (2004) for soil parameters identification for a tracked vehicle traversing on an unknown terrain.

In this paper, the work from Hutangkabodee (2004) is developed and added with the new features as follows.

- The effect of the soil cohesion on the performance of a heavy tracked UGV is investigated.
- The identified soil parameters are used for the traversability prediction for a tracked UGV traversing on an unknown terrain.

This paper is organized as follows. Section 2 describes the analytical straight-line motion model of a tracked UGV traversing on an unknown terrain. In Section 3, the implementation of the identification techniques is presented. Section 4 shows identification results and discussion. In Section 5, the effect of soil cohesion on the performance of a large-scale tracked UGV is illustrated. The traversability prediction based on the use of identified soil parameters is described in Section 6. Section 7 concludes the paper with a brief discussion and future work.

2. ANALYTICAL MODEL

The model employed in this paper is a straight-line motion model for a tracked UGV. The reason for using the straight-line motion model is that soil parameters of a particular terrain on which a tracked vehicle is traversing are usually constant over a wide range and do not change no matter how the tracked vehicle moves (either in straight line or in curvature). Also, it provides a relatively simple set of equations, sufficient for the purpose of identifying soil parameters. However, soil parameter identification based on a steering model will be carried out and compared to straight-line motion in the future work.

To identify soil parameters, the system model equations for a tracked UGV traversing on an unknown terrain are required. The overall system model is composed of a dynamic model, a kinematic model, and a track-terrain interaction model. The detailed derivation of the overall system model is illustrated in Song et al. (2004) and Hutangkabodee et al. (2004) works. The overall system model equations are presented as follows:

$$\ddot{x}_e = \frac{F}{m} - g\mu_r \,, \qquad (1)$$

where $\ddot{x}_e$ is the linear acceleration of the vehicle along X_e direction, F is the tractive force on both vehicle tracks in X_e direction, μ_r is the coefficient of the longitudinal resistance, g is the earth's gravitational acceleration, and m is the mass of the tracked vehicle.

$$F = (Ac + W\tan\varphi)[1 - \frac{K}{il}(1 - e^{-il/K})] \,, \qquad (2)$$

where $A = 2bl$ is the contact area of the tracks, $W = pA$ is the normal load due to the weight of the tracked vehicle, p is the vertical pressure over the terrain, and i is the track slip.

$$M_s - (F - W\mu_r)r = I\ddot{\theta} \,, \qquad (3)$$

where M_s is the sprocket torque for both vehicle tracks, r is the sprocket radius, I is the mass moment of inertia of a sprocket wheel about the sprocket wheel central diameter, and $\ddot{\theta}$ is the angular acceleration of both sprocket wheels.

$$\dot{x}_e = r[\dot{\theta}(1-i)] \,, \qquad (4)$$

where $\dot{x}_e$ is the linear velocity of the vehicle along X_e direction, and $\dot{\theta}$ is the angular velocity of both sprocket wheels.

Equation (2) is the track-terrain interaction dynamic equation (Wong, 2001) for sand-like terrain. Equation (1), (3), and (4) are the simplified models derived from the general steering system model for a tracked UGV (Wong, 2001).

Equation (2) is the main focus for the identification process since it contains the relevant soil parameter terms, cohesion (c), internal friction angle (φ) and shear deformation modulus (K). In this paper, the identification for these three soil parameters is carried out.

3. IMPLEMENTATION OF IDENTIFICATION TECHNIQUES

The detailed descriptions of the Newton Raphson method and the Least Square method are presented in Song et al. (2004).

The Newton Raphson method and the Least Square method are implemented to identify soil parameters for UGV track-terrain interaction dynamics. The

Newton Raphson method implementation is shown in Fig. 1. Vector $\boldsymbol{p}$ has three soil parameters which are cohesion (c), internal friction angle (φ), and shear deformation modulus (K). Measurement vector $\boldsymbol{x}$ contains three sets of measured data (tractive force, F and slip, i) from Wong (2001). The track-terrain interaction model described by Equation (2) in section 2 and measurement vector $\boldsymbol{x}$ are used to identify unknown soil parameters. Applying the Newton Raphson method, Equation (2) can be expressed as:

$$\begin{bmatrix} f_1(c,\varphi,K,F_1,i_1) \\ f_2(c,\varphi,K,F_2,i_2) \\ f_3(c,\varphi,K,F_3,i_3) \end{bmatrix} = 0\,, \qquad (5)$$

where $\boldsymbol{p} = [c,\varphi,K]^T$, and $\boldsymbol{x} = [F,i]^T$.

Taylor Series expansion is used to approximate the non-linear equation of the functions and the expansion for the first function is as

$$\begin{aligned}[f_1(c,\phi,K)]_{(k+1)} &= [f_1(c,\phi,K)]_k \\ &+ \left[\left.\frac{\partial f_1}{\partial c}\right|_{c,\phi,K} \Delta c + \left.\frac{\partial f_1}{\partial \phi}\right|_{c,\phi,K} \Delta\phi + \ldots \right. \\ &\left. + \left.\frac{\partial f_1}{\partial K}\right|_{c,\phi,K} \Delta K \right] + [\text{Higher - order terms}]. \end{aligned} \qquad (6)$$

For function f_2, and f_3, similar expansions can be derived. Higher order terms of the series are neglected because the series will be calculated in an iterative manner to approximate the function. Note that the partial derivatives are evaluated at the estimated values of the parameters and therefore computable to a simple numerical value.

Let $[c,\varphi,K]_0^T$ be an initial guess. Applying Newton Raphson Method to Equation (5), the matrix representation for Newton Raphson method for our case is presented as

$$\begin{bmatrix} c \\ \varphi \\ K \end{bmatrix} = \begin{bmatrix} c \\ \varphi \\ K \end{bmatrix}_0 - J^{-1} \begin{bmatrix} f_1(c,\varphi,K,F_1,i_1) \\ f_2(c,\varphi,K,F_2,i_2) \\ f_3(c,\varphi,K,F_3,i_3) \end{bmatrix}, \quad (7)$$

where J (Jacobean matrix) = $\left.\begin{bmatrix} \frac{\partial f_1}{\partial c} & \frac{\partial f_1}{\partial \varphi} & \frac{\partial f_1}{\partial K} \\ \frac{\partial f_2}{\partial c} & \frac{\partial f_2}{\partial \varphi} & \frac{\partial f_2}{\partial K} \\ \frac{\partial f_3}{\partial c} & \frac{\partial f_3}{\partial \varphi} & \frac{\partial f_3}{\partial K} \end{bmatrix}\right|_0$.

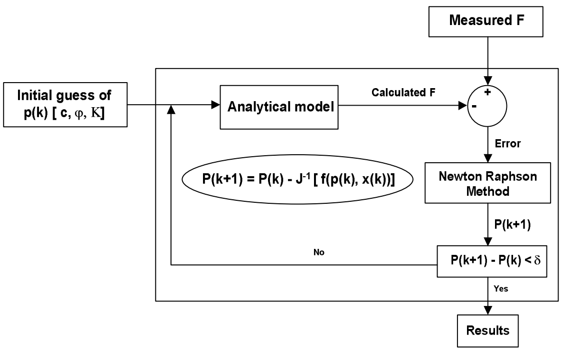

Fig. 1. Diagram showing implementation of Newton Raphson method for soil parameter identification

Table 1 Identified soil parameters

	Newton Raphson Method		Least Square Method	
	Predicted Values	Error (%)	Predicted values	Error (%)
c (kPa)	0.65	18.18	16.48 (diverged)	2896
φ (degree)	40.08	0.05	34.78	13.27
K (m)	0.0182	1.11	0.0185	2.78
Elapsed time (s)	0.016		0.156	

4. IDENTIFICATION RESULTS AND DISCUSSION

4.1 Identification Results

For three parameter identification, three sets of measured data from Wong (2001) pp.176 are used in the identification scheme (i_1 = 0.0248, F_1 = 207.32 kN; i_2 = 0.0344, F_2 = 223.81 kN; i_3 = 0.07, F_3 = 259.81 kN). The identification results for a set of initial conditions are shown in Table 1. The actual values are: cohesion, c = 0.55 kPa, internal friction angle, φ = 40.1 degree, and shear deformation modulus, K = 0.018 m. The identification errors are calculated with respect to these actual values and presented in Table 1.

For comparison purposes, the same set of initial conditions is used for soil parameter identification using the Least Square method and the simulation results are shown in Table 1 with their errors from the actual values.

It can be seen from Table 1 that the speed of convergence of the Newton Raphson method is about 10 times faster than that of the Least Square method. The accuracy of the identification for Newton Raphson method is better than Least Square method. This is clear by observing a huge difference between the identification error of φ from the Newton Raphson method (0.05%) and that from the Least Square method (13.27%). Also, the identified K value using the Newton Raphson method is about 2.5 times more accurate than the result using the Least Square method. For the identified cohesion value, the Least Square method gives the diverged value while the Newton Raphson method provides a result with an 18.18% error.

4.2 Robustness Test

A robustness test is carried out in order to examine whether the Newton Raphson method will converge

Table 2 Newton Raphson method in the presence of noisy input data

	c	φ	K
Original data	18.18 %	0.05 %	1.11%
Data with noise	18.18%	2.22 %	4.44%

to the correct solution when different initial conditions ($\boldsymbol{p_0}$) are used. 100 different vectors of $\boldsymbol{p_0}$, containing random positive values in the range [0, 89], were used, and in each case the identified values converged to the true values. This gives an indication that Newton Raphson method is very robust giving the true converged soil parameter values over a wide range of initial conditions, $\boldsymbol{p_0}$. Changing the cohesion value does not have noticeable effect on the tractive force result. In other words, tractive force is not sensitive to this parameter value. Hence, the accuracy of its identified value is not our main concern. The results indicate that the Newton Raphson method has promising potential for on-line soil parameters identification.

Note : In practice, the range of soil parameters is as follows:
- [0 – 69 kPa] for cohesion (c),
- [6 – 40 degree] for internal friction angle (φ),
- [0.006 – 0.05 m] for shear deformation modulus (K).

It can be seen that the range of initial conditions used for this robustness test, [0, 89] covers the real range of the soil parameters above. This indicates that, in the Newton Raphson technique, the selection of any initial conditions within the real range of the soil parameters will lead to the successful soil parameter identification.

For the Least Square method, after sampling several initial conditions ($\boldsymbol{p_0}$), it can be concluded that this method is not at all robust as it hardly gives the correct solution for three soil parameters simultaneously. Also, it is never able to converge to a reasonable cohesion value irrespective of the initial condition.

To evaluate the sensitivity of the Newton Raphson method to noise, a white noise signal of amplitude [-3, 3] % was superimposed on the measured data (both F and i). The results are summarized for each soil parameter in comparison with the original data without white noise. From Table 2, it can be seen that the Newton Raphson method is relatively robust to noise.

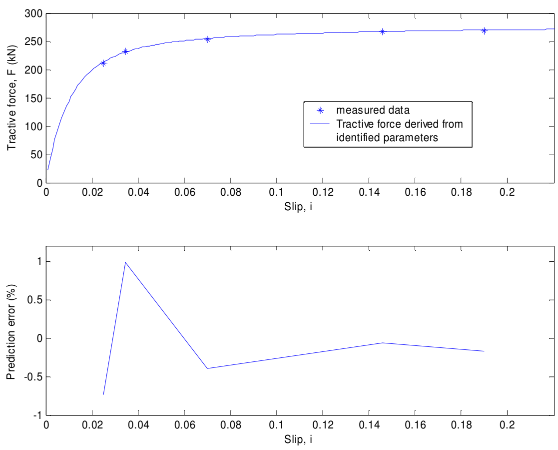

Fig. 2. Comparison between measured and predicted tractive force using the Newton Raphson method and the prediction error

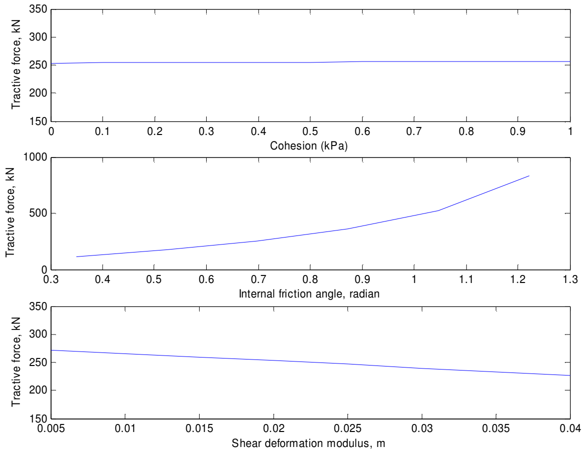

Fig. 3: Comparison between the effect of cohesion, internal friction angle and shear deformation modulus on the tractive force (for heavy vehicle, W = 329,000 N)

4.3 Validation of the Identified Soil Parameters

The identified soil parameters using the Newton Raphson method from Table 1 are used to predict back tractive force and compare the results with the measured data (Wong, 2001) for validation purposes. Fig. 2 shows the comparison between measured and predicted tractive force using the Newton Raphson method identified soil parameters, with a prediction error range from -0.7 to 1%. This reflects a very good prediction accuracy of the tractive force. Thus the identified soil parameters can be used for UGV traversability prediction and trajectory planning in real time based on accurate predicted tractive force. This is beneficial for autonomy purposes of UGVs.

5. VEHICLE WEIGHT EFFECT ON SENSITIVITY OF THE MODEL TO COHESION

Another finding from the conducted experiments using the Newton Raphson method is that the identification procedure for cohesion seems to have a very slow convergence rate here since during the iterative process the cohesion values do not change much from its initial condition value (0.65 kPa). This shows one of the strengths of the Newton Raphson method – the ability to handle parameters of interest individually. This is the important aspect as the cohesion parameter is found to have various effects on tractive force depending on the weight of a tracked vehicle. The weight of the tracked vehicle used in our experiment is considered a heavy or large-scale system (W = 329,000 N). Further investigation is carried out as shown in Figs. 3 and 4. Fig. 3 shows the variation of tractive force with respect to cohesion, internal friction angle, and shear deformation modulus for heavy tracked vehicle and Fig. 4 compares the variation of tractive force with respect to cohesion for heavy and light tracked vehicles (W = 300 N).

It can be seen from Fig. 3 that the tractive force is insensitive to the cohesion in heavy tracked vehicle case (large-scale) as a big change in cohesion has a very little effect on the tractive force. On the other hands, changes of internal friction angle and shear deformation modulus have a clear effect on the tractive force. However, for light or small-scale tracked vehicles, the cohesion has a noticeable effect on the tractive force, Fig. 4.

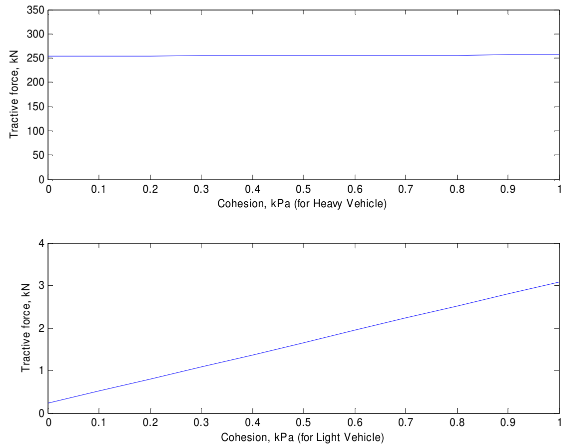

Fig. 4. Comparison between the effect of cohesion for heavy vehicle (W = 329,000 N) and that for light vehicle (W = 300 N)

It can be concluded here that in a large-scale tracked vehicle system, the cohesion term in the track-terrain interaction dynamic model (Equation (2)) is negligible and Equation (2) can be rewritten as follows:

$$F = W \tan\varphi[1 - \frac{K}{il}(1 - e^{-il/K})]\,. \qquad (8)$$

To validate this finding, the simplified track-terrain interaction dynamic model for a heavy tracked vehicle (Equation (8)) is compared with the original track-terrain interaction dynamic model (Equation (2)) and measured data from Wong (2001) as in Fig. 5.

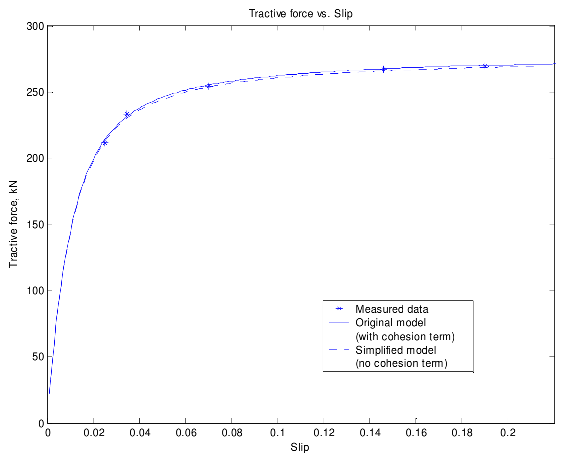

Fig. 5. The comparison of tracitve force - slip plots from the simplified model, Equation (8), original model, Equation (2) and measured data (Wong, 2001) for a heavy vehicle

From Fig. 5, it is clear that the simplified track-terrain interaction dynamic model presents a very close match to the original model and the measured data. Moreover, from Fig. 6, the error percentage of the simplified model ranges from -0.4 to 1.4% while that of the original model ranges from -1 to 0.8%. Therefore, the simplified model is valid for the heavy vehicle and can replace the original model in order to increase the computational speed and reduce computational cost associated with the system since the identification technique needs to identify only two parameters.

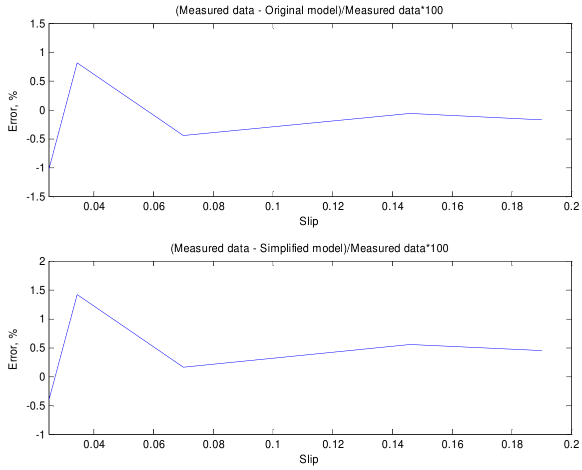

Fig. 6. The comparison between the percentage error (with respect to measured data) of the tractive force from the original model, Equation (2) and that from the simplified model, Equation (8)

6. TRAVERSABILITY PREDICTION

The identified soil parameters derived from section 4 can potentially be used for traversability prediction. These identified soil parameters are used to set the traversability criteria of a UGV travelling on an unknown terrain. The idea for this is basically based on the comparison between the tractive force required for UGV to traverse on that particular terrain and the maximum tractive force a UGV can produce (through the driving torque from UGV sprocket wheels). If the tractive force required for the UGV to traverse is more than the maximum tractive force that UGV can produce, the UGV will not be able to traverse on that terrain.

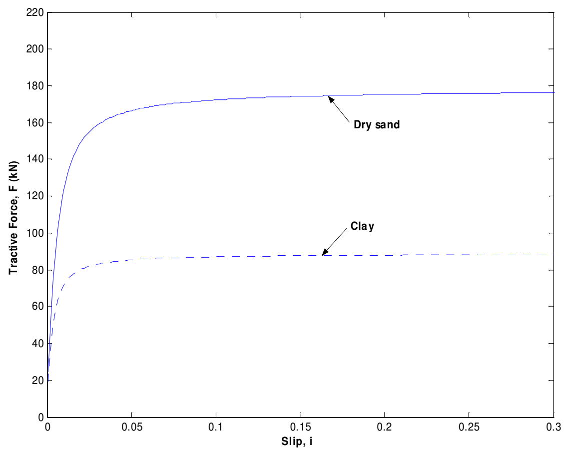

Fig. 7. The threshold tractive force upon which a UGV can traverse for different terrains (soil parameters for dry sand and clay taken from Tuan, 1999)

Fig. 7 illustrates the idea of traversability prediction mentioned above. Given a tracked UGV with a capability of producing 120 kN tractive force, it can be seen from Fig. 7 that for the whole range of slip this UGV is able to traverse only on clay (about 90 kN tractive force required) but not on dry sand (about 180 kN tractive force required).

Another aspect of traversability criteria needed to be look at is the circumstances where the track of a UGV gets stuck in the terrain while it is spinning. Certain criteria need to be built to allow a UGV or an operator to know when this situation will occur. The future research will also incorporate this aspect.

7. CONCLUSION AND DISCUSSION

The Newton Raphson method and the Least Square method are applied as soil parameter identification techniques for an analytical straight line model of a tracked vehicle traversing on an unknown planar terrain. The Newton Raphson method is compared to the Least Square method and results show that the Newton Raphson method is far better in terms of parameter identification accuracy, robustness to a wide range of initial conditions, robustness to noise, ability to handle parameters of interest individually, and computational speed.

By applying the Newton Raphson method for soil parameter identification, it is found that in large-scale UGVs, the cohesion term in the track-terrain interaction dynamic model is negligible since it has a very small effect on the UGVs' performance. Consequently, by using the simplified track-terrain interaction dynamics model without the cohesion term, the computational speed of the algorithm can be increased and the real-time application of the UGV can be improved.

The tractive force-based traversabiltiy criteria of a UGV on a particular unknown terrain are established based on the acquisition of soil parameters identified from the Newton Raphson method. With those traversability criteria and the UGV maximum tractive capacity knowledge, the traversability prediction can be achieved.

The future work will focus on investigation of the situation where a tracked UGV getting caught in the terrain while the tracks are spinning and subsequently set up traversability criteria based on that. Also, research on trajectory tracking and traction control based on the use of the identified soil parameters will be carried out.

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