International Journal of Automation and Computing 3 (2006) 244-251

Soil Parameter Identification for Wheel-terrain Interaction Dynamics and Traversability Prediction

Suksun Hutangkabodee*, Yahya Hashem Zweiri, Lakmal Dasarath Seneviratne, Kaspar Althoefer
Department of Mechanical Engineering, King's College London, Strand, London WC2R 2LS, UK

Abstract: This paper presents a novel technique for identifying soil parameters for a wheeled vehicle traversing unknown terrain. The identified soil parameters are required for predicting vehicle drawbar pull and wheel drive torque, which in turn can be used for traversability prediction, traction control, and performance optimization of a wheeled vehicle on unknown terrain. The proposed technique is based on the Newton Raphson method. An approximated form of a wheel-soil interaction model based on Composite Simpson's Rule is employed for this purpose. The key soil parameters to be identified are internal friction angle, shear deformation modulus, and lumped pressure-sinkage coefficient. The fourth parameter, cohesion, is not too relevant to vehicle drawbar pull, and is assigned an average value during the identification process. Identified parameters are compared with known values, and shown to be in agreement. The identification method is relatively fast and robust. The identified soil parameters can effectively be used to predict drawbar pull and wheel drive torque with good accuracy. The use of identified soil parameters to design a traversability criterion for wheeled vehicles traversing unknown terrain is presented.

Keywords: Soil parameter, traversability, Newton Raphson, Composite Simpson's Rule, wheeled vehicle.

1 Introduction

Wheeled vehicles traversing rough unknown terrain have many potential applications, including defence, mining, space exploration, and even private personal use. Most wheeled vehicles are still directly controlled by a driver to carry out tasks. However, without the knowledge of terrain characteristics a driver may find it difficult to control a vehicle effectively, and can unpredictably fail to complete a desired mission. An example of task failure is a wheeled vehicle stuck spinning in sandy terrain.

From wheel-terrain interaction dynamics, it can be seen that soil parameters play a vital role in determining vehicle drawbar pull and wheel drive torque, which in turn are utilized for developing traversability prediction criteria and traction control algorithms. The knowledge of soil parameters of unknown terrain is then advantageous for improving vehicle performance.

Research on wheel-terrain and track-terrain interactions, has developed since Bekker[1,2] started pioneering this area. The preliminary model for soil-wheel interaction was created and improved based on experimental data[1,2]. Wong, Reece, and Anafeko investigated and analysed the soil-wheel stress and deformation patterns of sand-like soils beneath a rigid wheel[3~5]. In [6], a slip-based traction model was developed theoretically, and used to establish an effective control law for a rover travelling on rough terrain. The rover's traversability could be improved by controlling wheel slip. Iagnemma and Dubowsky focused on the characteristics of a rigid wheel in deformable terrain for planetary rovers[7~9]. In [8], a vibration-based technique was employed as a terrain classification method. In [10], soil parameter identification for a tracked vehicle traversing unknown terrain was presented.

Soil parameter estimation for a wheeled vehicle traversing deformable terrain was carried out by Iagnemma and Dubowsky[7]. A Linear Least Square estimator was employed as an on-line identification method to identify two key soil parameters, cohesion (c) and internal friction angle (ϕ), using on-board rover sensors. The shear deformation modulus (K) was set to a representative value due to its insensitivity to the estimation algorithm.

This paper presents a method for identifying soil parameters required for predicting vehicle drawbar pull and wheel drive torque while traversing unknown terrain. The soil parameters to be identified are internal friction angle ϕ, shear deformation modulus K, and lumped pressure-sinkage coefficient $(k_c/b + k_\phi)$. The fourth parameter cohesion is not sensitive to drawbar pull, and is set to an average value. It is also shown that k_c and k_ϕ cannot be identified separately, but can

Manuscript received November 29, 2005; revised January 25, 2006.
This work was supported in part by the EPSRC (No. GR/S31402/01).
*Corresponding author. *E-mail address*:
suksun.hutangkabodee@kcl.ac.uk

be identified as a single lumped parameter $(k_c/b+k_\phi)$.

Composite Simpson's Rule is used to approximate the integrals of the original interaction model, as they cannot be integrated analytically. Through this process, the speed of identification is increased, as the identification algorithm does not have to execute numerical integration for each computational cycle. The Newton Raphson method is applied to a modified nonlinear wheel-terrain interaction model for soil parameter identification. This method has been shown to identify unknown parameters with high accuracy and rapid convergence[10,11].

Identification results show that the Newton Raphson method can accurately identify soil parameters with relatively fast speed. It is also shown to be robust to measurement noise and initial conditions. The drawbar pull and wheel drive torque predicted from the identified soil parameters, are shown to be relatively close to measured data, and can be used for vehicle performance optimization, traversability prediction, traction control, and trajectory planning. Extended from [12], this paper introduces a traversability criterion design based on the use of identified soil parameters. Wheel immobility occurs when the wheel drive torque required to traverse a terrain exceeds the torque generated by a wheel. This situation can be used to design a traversability criterion for traversability prediction. This is one of the steps towards the automation of a wheeled vehicle traversing unknown terrain.

2 Analytical model

Fig. 1 shows a free body diagram of a rigid wheel travelling on deformable terrain. An analytical model of a wheeled vehicle interacting with an unknown deformable terrain is described based on this figure.

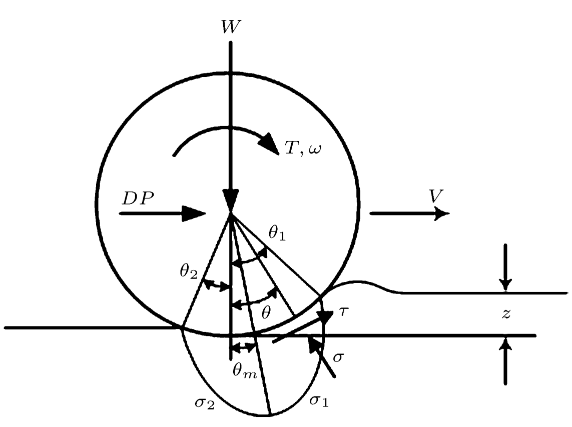

Fig. 1 Free body diagram of a rigid wheel on deformable terrain[7]

2.1 Force and moment balance

For simplicity, the wheel is assumed to be rigid. From Fig. 1, given a constant vehicle forward velocity, the interaction model for a rigid wheel traversing deformable terrain is obtained by considering the force and moment balance[7]:

$$W = rb\left[\int_{\theta_2}^{\theta_1}\sigma(\theta)\cos(\theta)d\theta + \int_{\theta_2}^{\theta_1}\tau(\theta)\sin(\theta)d\theta\right] \quad (1)$$

$$DP=rb\left[\int_{\theta_2}^{\theta_1}\tau(\theta)\cos(\theta)d\theta - \int_{\theta_2}^{\theta_1}\sigma(\theta)\sin(\theta)d\theta\right] \quad (2)$$

$$T = r^2 b\int_{\theta_2}^{\theta_1}\tau(\theta)d\theta \quad (3)$$

where W is vertical load applied to the wheel, DP is drawbar pull applied to the wheel from a suspension system, T is wheel drive torque produced by an actuator, θ is the arbitrary angular location of wheel-terrain contact measured from a vertical axis, θ_1 is the angle at which the wheel first makes contact with the terrain, and θ_2 is the angle at which the wheel loses contact with the terrain. σ is radial stress normal to the wheel-terrain contact, τ is shear stress tangent to the wheel-terrain contact, r is wheel radius, b wheel tread, ω angular velocity of the wheel, V forward velocity of the wheel, z sinkage of the wheel under the terrain surface, θ_m the angle at which maximum stress occurs, σ_1 the radial stress profile between θ_1 and θ_m, and σ_2 the radial stress profile between θ_m and θ_2.

2.2 Radial stress distribution

The radial stress at an arbitrary wheel-terrain contact point can be expressed as[7]

$$\sigma(z) = \left(\frac{k_c}{b}+k_\phi\right)(z)^n \quad (4)$$

where k_c, k_ϕ, and n, are pressure-sinkage coefficients.

In order to obtain an expression for radial stress as a function of angular location θ, sinkage expression as a function of θ is used[7]:

$$z(\theta) = r(\cos\theta - \cos\theta_1). \quad (5)$$

It is shown from experimental evidence[4] that actual radial stress can be characterised by two symmetric profiles (σ_1 and σ_2), as shown in Fig. 1. Therefore, radial stress under a rigid wheel traversing deformable terrain is given by:

$$\sigma(\theta) = \begin{cases}\sigma_1(\theta), & \theta_m < \theta < \theta_1\\ \sigma_2(\theta), & \theta_2 < \theta < \theta_m\end{cases} \quad (6)$$

where

$$\sigma_1(\theta) = \left(\frac{k_c}{b}+k_\phi\right)[r(\cos\theta - \cos\theta_1)]^n \quad (7)$$

and

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

The location of the point of maximum radial stress is at

$$\theta_m = \frac{\theta_1+\theta_2}{2}. \tag{9}$$

2.3 Tangential stress distribution

Shear stress at an arbitrary wheel-terrain contact point is given by[5]

$$\tau(\theta) = [c+\sigma(\theta)\tan\phi]\left(1-e^{-\frac{r}{K}[(\theta_1-\theta)-(1-i)(\sin\theta_1-\sin\theta)]}\right) \tag{10}$$

where c is cohesion, ϕ the internal friction angle, and K the shear deformation modulus.

2.4 Model for soil parameter identification

If θ_2 is assumed to be zero, since for practical applications θ_2 is very small while a wheeled vehicle is traversing deformable terrain, then soil parameter identification is given by

$$DP = rb\left[\int_0^{\theta_m}\tau_2(\theta)\cos\theta d\theta + \int_{\theta_m}^{\theta_1}\tau_1(\theta)\cos\theta d\theta - \int_0^{\theta_1}\sigma(\theta)\sin\theta d\theta\right] \tag{11}$$

where $\tau_1(\theta)$ and $\tau_2(\theta)$ are the shear stress regions between $\theta_m < \theta < \theta_1$ and $0 < \theta < \theta_m$, respectively.

The third integral term in (11) can be integrated analytically to yield

$$DP = rb\left[\int_0^{\theta_m}\tau_2(\theta)\cos\theta d\theta + \int_{\theta_m}^{\theta_1}\tau_1(\theta)\cos\theta d\theta - \frac{1}{r(n+1)}\left(\frac{k_c}{b}+k_\phi\right)z_0^{n+1}\right] \tag{12}$$

where z_0 is sinkage at the $\theta = 0$ position, and can be calculated from

$$z_0 = r(1-\cos\theta_1). \tag{13}$$

The first two integral terms of the drawbar pull model in (12) cannot be integrated analytically. The Composite Simpson's Rule is applied to (12) to find an approximation of the integrals, in order to facilitate the implementation of the identification method on the model, and also to increase the speed of soil parameter identification.

For the integral $\int_a^b f(x)dx$, suppose that interval $[a,b]$ is subdivided into $2m$ subintervals of equal width, $h = \frac{b-a}{2m}$, by using the equally spaced sample points $x_k = x_0 + kh$ for $k = 0,1,2,\cdots,2m$. The Composite Simpson's Rule for $2m$ subintervals is given by

$$E(f,h) = \frac{h}{3}[f(a)+f(b)] + \frac{2h}{3}\sum_{k=1}^{m-1} f(x_{2k}) + \frac{4h}{3}\sum_{k=1}^{m} f(x_{2k-1}). \tag{14}$$

This is a numerical approximation to the integral of $\int_a^b f(x)dx$ and can be written as

$$\int_a^b f(x) \approx E(f,h). \tag{15}$$

Drawbar pull (DP), based on Composite Simpson's Rule approximation, and DP based on numerical integration, are shown in Fig. 2. It can be observed that the DPs derived from both methods are relatively close throughout the entire slip range. Hence, Composite Simpson's Rule gives good estimates of integral terms in the original wheel-terrain interaction model, and can accurately be employed for soil parameter identification purposes.

Equation (12), with the first 2 integral terms approximated by Composite Simpson's Rule, is the main focus for the identification process since it contains relevant soil parameter terms. Soil parameter identification is carried out in Section 5.

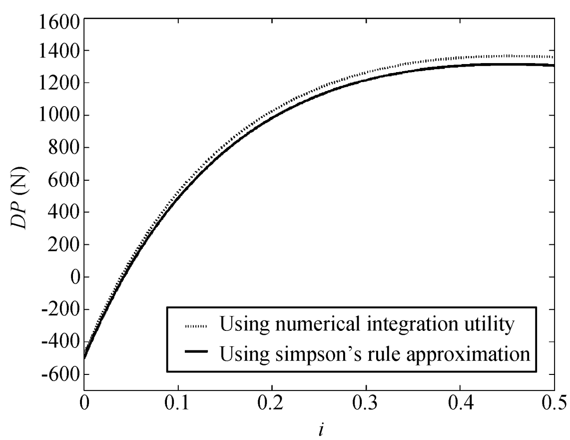

Fig. 2 Comparison of DP characteristics based on Composite Simpson's Rule and numerical integration

3 Example of soil parameter characteristics

In this section, some soil parameter terms in the wheel-terrain interaction model (DP model) are examined, and their effect on the overall soil parameter identification process evaluated.

3.1 Cohesion c

Cohesion c is not very sensitive in the interaction dynamic model, as illustrated by the plot of c against drawbar pull DP, as shown in Fig. 3.

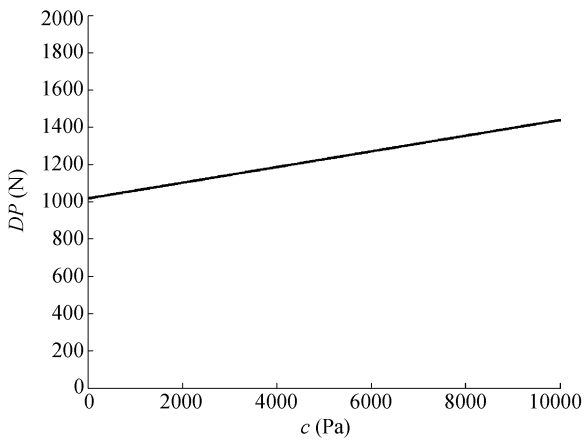

Fig. 3 Plot of cohesion against predicted DP from (12) at 22.11% slip and 37 degree entry angle, using a wheel with 0.627 4 m radius, and 0.152 4 m tread[3]

Note: The range of cohesion used in Fig. 3 is the real range of cohesion of 80% of the world's soil.

The actual value of cohesion of the soil being used for this experiment is c = 689.48 Pa. It can be seen in Fig. 3, that the corresponding predicted DP should be 104 7.22 N. However, measured DP from the experiment may not be very close to that predicted. For instance, if measured DP under the same conditions as in Fig. 3 is 1 150 Pa (about 10% above its predicted value), then identified cohesion will be 4 322.74 Pa, which is inaccurate compared to its actual value (about 527% error). A worst case scenario occurs when measured DP is below 1 000 N. This could cause identified cohesion to become negative. This is because cohesion is relatively insensitive to DP, as changing cohesion by a large margin will hardly change DP. On the other hand, varying DP slightly will hugely affect the value of c.

Plots of internal friction angle ϕ, and shear deformation modulus K, against DP, are shown in Fig. 4. It can be seen that unlike cohesion, changes in ϕ and K cause significant changes in DP. When measured DP is used to predict ϕ and K, it will give results close to its actual value. Table 1 proves this point, where ϕ and K are identified from measured DP 5% away from its predicted value, and have only 1.05% and 3.41% error from their actual values respectively.

In Table 1, two designated values of measured DP (one below its predicted DP, and another above) are employed to identify each soil parameter effectively.

It can be observed from Table 1, that shifting DP from its predicted value by only 5%, results in approximately 180% error of identified c value. When attempting to identify c with other soil parameters, this will cause other soil parameters not to converge to their real values. Therefore, to avoid this characteristic of c affecting other soil parameters in multi-soil-parameter identification, it is fixed at a value of 3 000 Pa. This is the cohesion value averaged over a wide range of soil types giving 9.5% average variation of drawbar pull over a wide range of slip. However, it does not include soils with an extremely high cohesion value, e.g. c = 68 950 Pa for heavy clay (Waterways Experiment Stn., WES)[6].

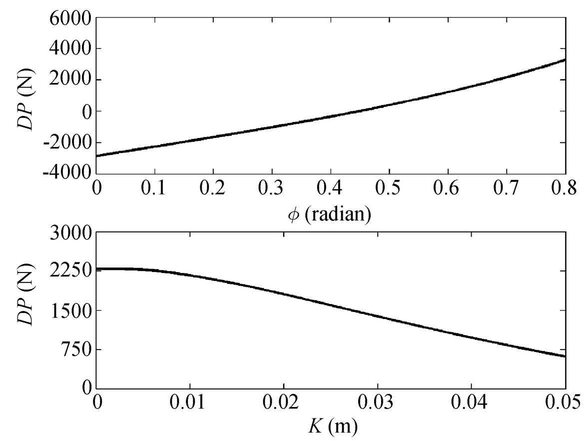

Fig. 4 Plot of internal friction angle and shear deformation modulus, against predicted DP from (12) at 22.11% slip, and 37 degrees entry angle, using a wheel with 0.627 4 m radius and 0.152 4 m tread[3]

Table 1 Identification of each soil parameter using measured DP 5% below, and 5% above its predicted value

	Measured DP = 5% below its predicted value	Error (%)	Measured DP = 5% above its predicted value	Error (%)
Identified c (Pa)	-555.73	-180.60	1 934.69	180.60
Identified ϕ (degree)	32.95	-1.05	33.65	1.05
Identified K (m)	0.039 4	3.41	0.036 8	-3.41
Identified k_c (N/m^{n+1})	46 352	-9.00	55 520	9.00
Identified k_ϕ (N/m^{n+2})	220 591	-12.00	280 746	12.00
Identified n	0.487 6	3.61	0.454 5	-3.42

Note: The actual values of these soil parameters are shown in Table 2.

3.2 Shear deformation modulus K

A simplified version of (1) and (3) combined were used in [7], to estimate c and ϕ. It was noted that in their model, T is relatively insensitive to K; hence K is not estimated and assigned a representative value.

In this study, the full dynamics model (12) is used as given by [7], and with this model DP is not insensitive to K as shown in Fig. 4, and can effectively be identified.

3.3 Pressure-sinkage coefficients k_c and k_ϕ

The pressure-sinkage coefficient $k_c/b + k_\phi$, will be a constant for constant b values. Since the wheel tread b is constant in the current application, a lumped pressure-sinkage coefficient $S = k_c/b+k_\phi$ is used in (12) for DP prediction.

4 Identification method and implementation

The identification method for soil parameter estimation for wheel-terrain interaction is crucial, for fast, accurate, and robust identification. This will enable the effective approximation of wheel drive torque and drawbar pull, in real-time, and enable optimal traversing of unstructured terrain. The Newton Raphson method is particularly suitable for this application, because it has been shown to identify unknown parameters with high accuracy and rapid convergence[10,11]. In addition, the Newton Raphson method doubles its accuracy at each iteration[13]. In comparison, other methods can be computationally expensive, and therefore limited in their real-time applicability, plagued by saddle point solutions and non-optimal local minima, and sensitive to measurement noise.

The Newton Raphson method is an iterative method used to solve nonlinear algebraic equations. To obtain a solution, an initial guess, which is based on prior knowledge of the problem, is used to start the identification process. The solution is reached by incrementally improving the initial guess until a predefined performance measure (here the difference between the measured drawbar pull and predicted drawbar pull) falls below a pre-defined threshold δ.

Using the Composite Simpson's Rule modified wheel-terrain interaction model of (12), soil parameters ϕ, K, and S are identified using the Newton Raphson method. The implementation of the Newton Raphson method is illustrated in Fig. 5. Three sets of measured data are required for this purpose. Drawbar pull (DP), wheel slip (i), and sinkage measured at $\theta = 0(z_0)$. Since the entry angle (θ_1) is a function of z_0 as shown in (13), knowing z_0 θ_1 can be predicted. In this identification process, cohesion c is set to an average value for the reason described in Section 3.

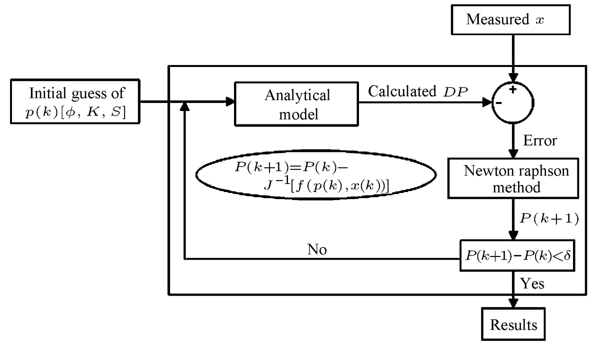

Fig. 5 Diagram showing implementation of the Newton Raphson method for soil parameter identification

Let $p = [\phi, K, S]^{\mathrm{T}}$ be a vector of soil parameters to be identified, and $x = [DP, i, z_0]^{\mathrm{T}}$ be a vector of measured data.

$$\begin{bmatrix} f_1(\phi, K, S, DP_1, i_1, z_{01}) \\ f_2(\phi, K, S, DP_2, i_2, z_{02}) \\ f_3(\phi, K, S, DP_3, i_3, z_{03}) \end{bmatrix} = 0. \tag{16}$$

Let $p{=}[\phi, K, S]_0^{\mathrm{T}}$ be an initial guess. Then applying the Newton Raphson Method gives

$$\begin{bmatrix} \phi \\ K \\ S \end{bmatrix} = \begin{bmatrix} \phi \\ K \\ S \end{bmatrix}_0 - J^{-1} \begin{bmatrix} f_1(\phi, K, DP_1, i_1, z_{01}) \\ f_2(\phi, K, DP_2, i_2, z_{02}) \\ f_3(\phi, K, DP_3, i_3, z_{03}) \end{bmatrix} \tag{17}$$

where

$$J = \left.\begin{bmatrix} \dfrac{\partial f_1}{\partial \phi} & \dfrac{\partial f_1}{\partial K} & \dfrac{\partial f_1}{\partial S} \\ \dfrac{\partial f_2}{\partial \phi} & \dfrac{\partial f_2}{\partial K} & \dfrac{\partial f_2}{\partial S} \\ \dfrac{\partial f_3}{\partial \phi} & \dfrac{\partial f_3}{\partial K} & \dfrac{\partial f_3}{\partial S} \end{bmatrix}\right|_0 .$$

5 Test results and discussion

Table 2 shows the soil parameter values for compact sand taken from [4].

Table 2 Soil parameters for compact sand[4]

Soil parameters	ϕ (degree)	33.3
	c (Pa)	689.48
	K (m)	0.038 1
Pressure-sinkage coefficients	k_c (N/m^{n+1})	50 936
	k_ϕ (N/m^{n+2})	250 668
	n	0.470 6

To identify three soil parameters, three sets of measured data from [4] were used with the Newton Raphson method ($i_1 = 0.040\,8$, $z_{01} = 0.146\,6$ m, $DP_1 =$ 171.27 N; $i_2 = 0.134\,8$, $z_{02} = 0.154\,9$ m, $DP_2 = 799.25$ N; $i_3 = 0.228\,8$, $z_{03} = 0.172\,2$ m, $DP_3 = 1\,120.38$ N). The identification algorithm was programmed using Matlab 6.5, and run on an Intel Pentium (R) 4 processor at 2.80 GHz CPU, with 1.00 GByte of RAM. The identification results of soil parameters using the Newton Raphson method are tabulated in Table 3. The identification errors calculated with respect to actual parameter values are also presented in Table 3, together with identification time (Elapsed time).

It can be seen from Table 3 that the Newton Raphson method gives relatively accurate results, with percentage errors ranging from 2.91% for ϕ, to 22.77% for S. Identification speed is relatively fast, with 0.15 second elapsed time. It should be noted that the speed of identification could be further increased if the code and processor were optimized.

Table 3 Soil parameter identification results

Soil parameters	Actual values	Identified values	Error (%)
ϕ (degree)	33.3	34.27	2.91
K (m)	0.038 1	0.040 3	5.77
$S = k_c/b + k_\phi$	584 894	451 723	22.77
Elapsed time (s)		0.15	

A robustness test was carried out to examine whether the Newton Raphson method would converge to the correct solution when different initial guesses (p_0) were used. It was found that the Newton Raphson method is very robust, as all initial conditions within parameter ranges as shown in Table 4, give true converged soil parameter values.

Table 4 The range of initial conditions of soil parameters that produce a converged solution

Lower boundary	Soil parameter	Upper boundary
5	ϕ (degree)	89
0.015	K (m)	0.089
70 000	$(k_c/b + k_\phi)$ (N/m^{n+2})	31×10^{11}

To check the sensitivity of the Newton Raphson method to sensor noise, 5% white noise was superimposed on the measured data (DP, z_0, and i). The percentage error of the identified soil parameters with white noise, are shown in Table 5.

Table 5 The influence of white noise applied to measured data

	With actual measured data	With measured data and white noise
Error of identified ϕ(%)	2.91	6.10
Error of identified K(%)	5.77	15.75
Error of identified S(%)	22.77	24.66

In Table 5, the biggest error was 24.66% (increased from 22.77%), while the biggest increase in error was for K (from 5.77% to 15.75%). As expected, increasing sensor noise levels, lead to increased parameter identification error. However, it can be seen that the Newton Raphson method is relatively robust to sensor noise.

The identified ϕ, K, and S, using the Newton Raphson method from Table 3 (with 3 sets of measured data as identification inputs) were used to predict drawbar pull, using Composite Simpson's Rule with the modified form (12), and the results compared with the measured data from [4]. Fig. 6 shows a comparison between measured drawbar pull, and drawbar pull predicted from 2 sets of identified soil parameters — one identified using 3 sets of measured data, and another identified using 6 sets of measured data. When using 6 sets of measured data to identify ϕ, K, and S, the Generalized Newton Raphson method[11] was used. This method was employed when the number of data points M was greater than the number of equations N (in this case, $M = 6$ and $N = 3$). It can be seen that both predicted drawbar pull values are relatively close to their measured values (rms prediction errors are 156.80 N, and 111.50 N, respectively). It should be noted that the more measured data was used to identify soil parameters, the more accurate was the predicted drawbar pull.

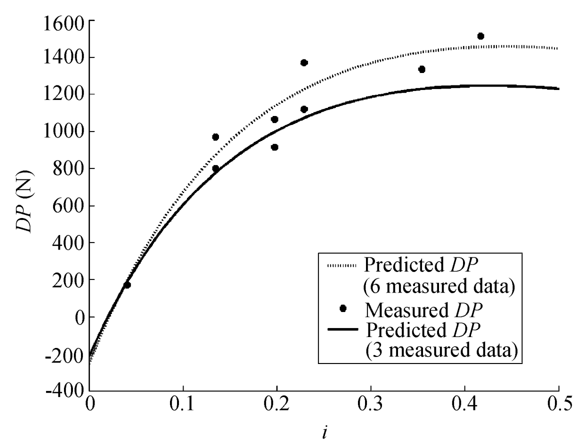

Fig. 6 Comparison between drawbar pull predicted from identified soil parameters, using 3 and 6 measured data, and measured drawbar pull

Similarly, identified ϕ, K, and S from Table 3, were used to predict wheel drive torque using Composite Simpson's Rule in the form of (18), and the results compared with measured data from [4]. Equation (18) was derived from (3) assuming $\theta_2 = 0$. Fig. 7 shows a comparison between measured wheel drive torque, and wheel drive torques predicted from 2 sets of identified soil parameters — one identified using 3 sets of measured data, and another identified using 6 sets of measured data. Again, the Generalized Newton Raphson method was used to identify ϕ, K, and S with the 6 sets of measured data. It can be seen that both predicted wheel drive torques are relatively close to their measured values (the rms prediction errors are 187.34 N·m, and 96.97 N·m, respectively. It should also be noted that the more measured data was used to identify soil parameters, the more accurate was the predicted wheel drive torque.

$$T = r^2 b\left(\int_0^{\theta_m} \tau_2(\theta).d\theta + \int_{\theta_m}^{\theta_1}(\theta).d\theta\right) \qquad (18)$$

where $\tau_2(\theta)$ and $\tau_1(\theta)$ are derived from (10) using $\sigma_2(\theta)$ and $\sigma_1(\theta)$, respectively.

Hence, from the above results it can be concluded that identified soil parameters can be employed for traversability prediction, traction control, and trajectory planning in real-time, based on the accurate prediction of drawbar pull and wheel drive torque. Although more measured data inputs would improve drawbar pull and wheel drive torque prediction, processing time would be increased, and the real-time aspect of the application affected.

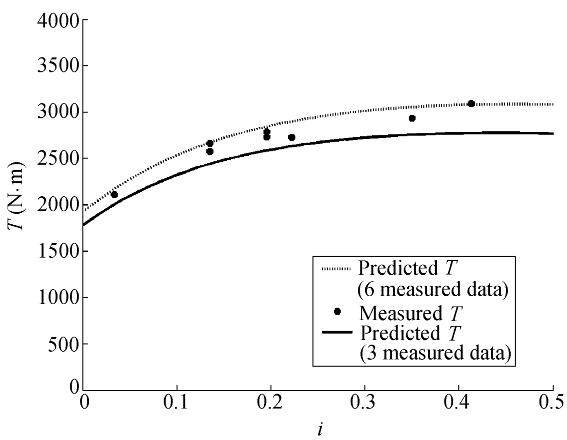

Fig. 7 Comparison between wheel drive torque predicted from identified soil parameters, using 3 and 6 measured data, and measured wheel drive torque

6 The use of identified soil parameters for traversability prediction

The soil parameters identified from the method proposed in this paper, can be used to improve the performance and automation of a wheeled vehicle travelling on unknown terrain. This section shows a traversability criterion design based on the use of the identified soil parameters.

When wheel drive torque required to traverse a terrain exceeds the torque generated by a wheel, a wheeled vehicle will be immobile. In other words, it will get stuck spinning in the terrain. A traversability criterion for a wheeled vehicle on unknown terrain can then be designed based on this situation, as shown in Fig. 8. The soil parameters identified in Section 5 can be used to predict the wheel drive torque required for a wheeled vehicle to traverse the terrain.

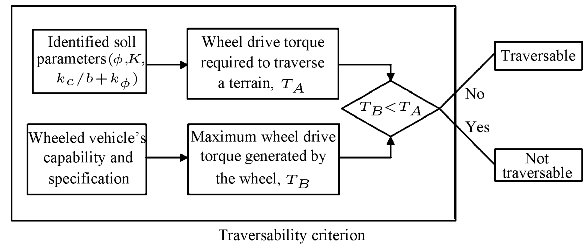

Fig. 8 A simple traversability criterion design diagram

A simple numeric example for traversability criterion design, for the traversability prediction of a wheeled vehicle travelling on unknown terrain, is described in Fig. 9. Fig. 9 shows wheel drive torque, predicted using the soil parameters of four different terrain types. Given a capability to generate 3 kN·m wheel drive torque, a wheeled vehicle will be able to traverse three terrains (sandy loam, dry sand, and snow, all of which require less than 2 kN·m of wheel drive torque) but not clayey soil (for which about 4.5 kN·m of wheel drive torque is required for vehicle traversal).

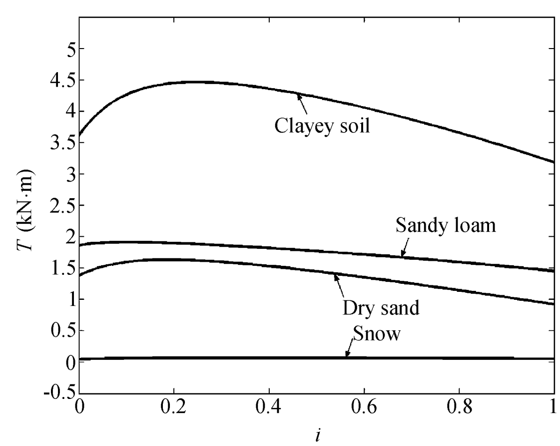

Fig. 9 The threshold wheel drive torque upon which a wheeled vehicle can traverse four different terrains (soil parameters for all terrain types are taken from [7])

7 Conclusions and future work

This paper presents a method to identify the set of soil parameters required to predict drawbar pull and wheel drive torque from measurements of slip, sinkage, and drawbar pull $[i, z_o, DP]$, for a wheeled vehicle traversing unknown terrain. The soil parameters identified are internal friction angle (ϕ), shear deformation modulus (K), and lumped pressure-sinkage coefficient ($S - k_c/b + k_\phi$). The Newton Raphson method was used for identification, using an approximated form of wheel-terrain interaction model using a Composite Simpson's Rule. Results show that the method can identify soil parameters accurately and robustly with relatively fast speed. The drawbar pull and wheel drive torque predicted from the identified soil parameters, are shown to be in good agreement with their measured values. Hence, drawbar pull and wheel drive torque can be effectively predicted and used for vehicle performance optimization. The concept of wheeled vehicle immobility in a terrain was presented. Wheeled vehicle immobility can in turn be used to design simple traversability criterion for a wheeled vehicle traversing an unknown terrain.

Future work will focus on an investigation of wheel-terrain interaction characteristics under various vehicle conditions, e.g. different vehicle weights using a purpose-built test rig. Also, an extension for the identification of another pressure-sinkage coefficient "n" will be attempted, and a wheeled vehicle travelling over terrain with extremely high cohesion will be investigated.

References

[1] G. Bekker. *Introduction of Terrain-Vehicle Systems*. University of Michigan Press, MI, USA, 1969.

[2] G. Bekker. *Theory of Land Locomotion*. University of Michigan Press, MI, USA, 1956.

[3] O. Onafeko, A. R. Reece. Soil Stresses and Deformations Beneath Rigid Wheels. *Journal of Terramechanics*, vol. 4, no. 1, pp. 59−80, 1967.

[4] J. Y. Wong, A. R. Reece. Prediction of Rigid Wheel Performance Based on the Analysis of Soil-Wheel Stresses - Part I. *Journal of Terramechanics*, vol. 4, no. 1, pp. 81−98, 1967.

[5] J. Y. Wong. *Theory of Ground Vehicles*, 3rd ed., John Wiley & Sons Inc., New York, 2001.

[6] K. Yoshida, H. Hamano. Motion Dynamics of a Rover with Slip-Based Traction Model. In *Proceedings of IEEE International Conference on Robotics & Automation*, vol. 3, pp. 3155−3160, 2002.

[7] K. Iagnemma, S. Kang, H. Shibly, S. Dubowsky. Online Terrain Parameter Estimation for Wheeled Mobile Robots with Application to Planetary Rovers. *IEEE Transactions on Robotics*, vol. 20, no. 5, pp. 921−927, 2004.

[8] C. Brooks, K. Iagnemma. Vibration-Based Terrain Classification for Planetary Rovers. *IEEE Transactions on Robotics*, vol. 21, no. 6, pp. 1185−1191, 2005.

[9] K. Iagnemma, S. Dubowsky. *Mobile Robots in Rough Terrain: Estimation, Motion Planning, and Control with Application to Planetary Rovers*. Springer-Verlag, Berlin, 2004.

[10] S. Hutangkabodee, Y. H. Zweiri, L. D. Seneviratne, K. Althoefer. Multi-Solution Problem for Track-Terrain Interaction Dynamics and Lumped Soil Parameter Identification, In *Proceedings of 5th International Conference on Field & Service Robotics (FSR 05)*, North Queensland, Australia, pp. 520−531, 2005.

[11] Y. H. Zweiri, L. D. Seneviratne, K. Althoefer. Parameters Estimation for Excavator Arm Using Generalized Newton Method. *IEEE Transactions on Robotics*, vol. 20, no. 4, pp. 762−767, 2004.

[12] S. Hutangkabodee, Y. H. Zweiri, L. D. Seneviratne, K. Althoefer. Performance Prediction for Wheeled Vehicle Traversing Unknown Terrain Based on Identified Soil Parameters, accepted for Proceedings of IEEE International Conference on Robotics & Automation, Florida, USA, May 2006.

[13] W. H. Press, S. A. Teukolsky, W. T. Vetterling, B. P. Flannery. *Numerical Recipes in C: The Art of Scientific Computing*. Cambridge University Press, February 1993.

Suksun Hutangkabodee was born in Thailand in 1976. He received his B.Eng. in mechanical engineering from Chulalongkorn University, Bangkok, Thailand in 1999. He received his M.Sc degree in computer-aided mechanical engineering from King's College London, England in 2002, and is currently working towards a Ph.D. at the same institution.

His research interests include vehicle-terrain interaction dynamics and soil parameter identification.

Yahya Hashem Zweiri obtained his B.Sc. degree in Mechanical Engineering from the University of Jordan, Jordan and his Ph.D. degree in Diesel Engines Modelling and Estimation from King's College London, England, 2003. He is currently a Research Fellow in the Department of Mechanical Engineering at King's College London, working on the vehicle-terrain interaction dynamics of unmanned ground vehicles. He is also an Assistant Professor in the Department of Mechanical Engineering, Mu'tah University, Jordan, and is currently on leave from Mu'tah University.

He has over 16 years research experience in the modelling, estimation, and control of mechanical systems, and has published over 40 refereed research papers in international journals and conference proceedings. His research interests include non-linear modelling, estimation, and control.

Lakmal Dasarath Seneviratne obtained his B.Sc (Eng.) and Ph.D. degree in Mechanical Engineering from King's College London. He is currently a professor in Mechatronics at King's College London. He is also the Director of the Centre for Mechatronics and Manufacturing Systems Engineering at King's College London.

His main research interests include Robotics and Intelligent Autonomous Systems.

Prof. Seneviratne is a Member of the IEEE.

Kaspar Althoefer holds a degree in Electronic Engineering from the University of Technology Aachen, Germany. He carried out his doctoral research in the Department of Electrical and Electronic Engineering at King's College London (KCL), where he completed his Ph.D. in 1997. He is now a Lecturer in the Department of Mechanical Engineering at KCL.

Being engaged in research on mechatronics since 1992, he has extensive expertise in the areas of robot-based applications, sensing and embedded intelligence.

Dr. Althoefer is a Member of the IEEE and the IEE.