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Soil Estimation Based on Dissipation Energy during Autonomous Excavation

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Abstract: This paper describes a new algorithm for the estimation of soils into different types employing an energy-based approach. Greatly simplifying the modeling of the tool-soil interaction process, energy components occurring during a dig are computed from simple force and bucket displacement measurements. In particular, the dissipation energy can be estimated allowing a prediction of the dynamic friction forces encountered during soil-tool interaction in the field of excavation. The proposed method measures force and displacement simultaneously during the extensively horizontal dragging phase while continuously recalculating the velocity, accumulated moved soil mass and total dissipation energy, creating a specific profile depending on the soil conditions. The creation of these profiles could be useful in providing information to a low level controller able to distinguish between different types soils. The method can thus be seen as an important component allowing robust and noise-free feedback in autonomous control in excavator vehicles.

1. INTRODUCTION

The worked soil deformation which occurs as a direct result of the interaction between excavator bucket and soil usually encountered during excavation is difficult to model using available mathematical models, from disciplines such as civil engineering and robotics. Mainly due uncertainties in the data and the complexity of the models, a real-time solution is normally not possible, making it difficult to develop excavator control schemes based on soil property estimation.

Hierarchical planning schemes have been proposed in the past to achieve excavator control, ignoring the properties of the underlying soil. Many such planning schemes are divided into a set of components abstracting the problem specificities and setting general goals at a high level, while low level control completes the execution of requested high level orders. These schemes exploit techniques based on radio navigation, tele-operation (S.Tafazoli., 2002a), (G.Vachkov., 2005), laser scanning equipment, in order to define an abstract representation of the geometry and localization of envisaged "dig regions".

This paper is concerned with the estimation and classification of soil types based on simple sensor measurements captured during the digging process, aiming at providing useful soil information for on-line low-level control.. The proposed process is making use of an energy-based description of the digging process to capture important properties of the dug soil. Typical trajectory planning in low level control can be decomposed into specific tasks such as "digging deeply", "digging horizontally", "moving rocks" (X.Shi,1995), "replacement" and "fragmentation" (S. P. DiMaio., 1998). Proposed robotic excavation strategies for low level control include PID (S.Tafazoli., 2002b), adaptive (F. Malaguti, 1994) , fuzzy-logic or neural network methods (G.Vachkov, 2005) and (X.Shi,1996), always requiring compatibility for communication with the embedded intelligence in the higher level (Quang Ha, 2002). On-line estimation of the worked soil is an important requirement for developing controller architecture for automated excavation (W.j, Hong, 2001) and extensive testing methods have been proposed based on civil engineering design including graphical methods (limit equilibrium) for estimating soil parameters to determine quasi static structural forces. Methods based on such conditions are useful but incomprehensive (e.g. for determining the starting force needed to move the bucket from rest). However, in the context of the autonomous excavation, dynamic friction force caused by the variation of the velocity of the tool needs to be taken into account during the continuous movement of the bucket.

The method and algorithms presented in this paper mainly focus on a novel energy identification method, The proposed approach uses a displacement versus time profile to compute a full velocity profile through iteration, at a certain sampling rate, by measuring the force and displacement simultaneously along any required trajectory. The proposed online algorithm is used to calculate a trace log of total energy involved, from which an estimation of the total dissipation energy is derived online during the movement of the bucket and potential energy and actual dissipation energy are derived offline;. Further, the algorithm is capable, still within real-time, to calculate the accumulated mass of moved soil pushed by the tool which allows for control of bucket (tool) extraction.

Therefore, the online energy mathematical base and measurement algorithm presented in this paper is an advanced and comprehensive, real-world practically applicable engineering tool.

2. ENERGY-BASED LEARNING ALGORITHM INVOLVING DETERMINATION OF THE DISSIPATION ENERGY

2.1 On-line Energy Measurement

The total dynamic friction force (*TDFF*) arising during excavation due to the interaction between the soil and the flat cutting surface penetrating the ground surface is difficult to model explicitly and in general consists of various components including Coulomb friction force (Sanjiv Singh,1995a), Viscous friction (related to damping), Stribeck friction, stiffness, shearing (T.V.Alekseeva,1972),(Leonard E. Bernold,1991),(F. Malaguti,1994) (overall soil resistance (SR)) and bucket load accumulation force (S. P. DiMaio,1998)). The *TDFF* depends critically both on the soil-type and the general excavation conditions. The main advantage of the proposed energy method is that no need arises for modeling this force complicatedly in terms of the number of variables and coefficients separately which must be adjusted to create a relative magnitude for all force components experimentally. Therefore, this unpredictable mathematical form of these four forces is not useful for online estimation. We rely instead on the Total energy or energy measurement (E_M) variable which is estimated directly from the measurements. EM consists of contributions from, the following, energy components defined as:

$$E_M = E_K + E_P + E_D \tag{1}$$

E_M = Total measurement energy E_K = Kinetic Energy, E_P = Potential Energy and E_D = Dissipation Energy.

2.2 Overall energy (E_M)

The overall energy, E_M , can be computed from measurements of the force acting on the bucket during the dragging phase. For any force-function *F(x)*, the equation energy may be calculated as the area under *F(x)* as shown in Fig. 1. Here X_m denotes the total displacement variable.

The shaded area in Fig. 1 represents the work done by the force along the specified path between points (a) and (b). Integrating *F(x)* with respect to displacement X allows us to compute the energy:

$$W_{ab} = \int_b^a F.dx \tag{2}$$

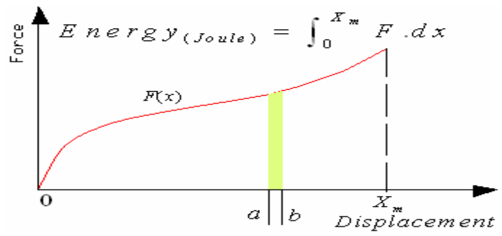

Fig. 1. Energy as the integral of force versus displacement.

By numerical integration (e.g. Employing the Trapezoidal Rule), the energy can be approximated: $W_{ab} = E_m = \frac{(x_{(n)} - x_{(n-1)}) \times (F_{(n)} + F_{(n-1)})}{2}$ where n is the sampling instance; we can obtain an estimate of the input energy and store the resulting data in an array of elements $E_{(n)}$.

2.3 Estimation of Kinetic Energy (E_K)

In this paper, the focus is on translational bucket movements which constitute the major part of the digging cycle in many cases – the soil is moved forward by the bucket i.e. it is mainly moving along a straight line (dragging phase). Under such conditions, rotational energy components can be neglected

$E_R = \frac{1}{2} I \omega^2 =$ Rotation kinetic Energy. On a flat cutting surface ER=0. Hence: $E_K = E_T + E_R$

Thus the kinetic energy is proportional to translation Energy ET, which the product of velocity (V) and mass (m):

$$EK = ET = \frac{1}{2} m \frac{dx}{dt}^2 = \frac{1}{2} m V^2 \tag{3}$$

By measuring the displacement at each sampling instance, $x_{(n)}$, and subtracting the displacement at the previous instance $x_{(n-1)}$ and then dividing by the sampling period Ts it is possible to estimate the velocity of the bucket with an accuracy of one sample i.e. the general formula is developed for defining the total velocity when inserting and also dragging the bucket as:

$$V_{ab} = V_{(n)} = \frac{(x_{(n)} - x_{(n-1)})}{(T_{(n)} - T_{(n-1)})} = \frac{(x_{(n)} - x_{(n-1)})}{T_S} \tag{4}$$

The resulting velocity data for all samples $V_{(N)}$ is finally stored in an array.

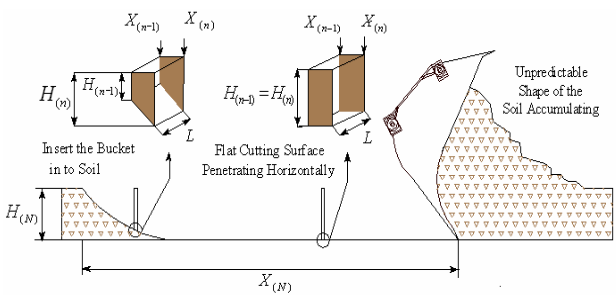

Fig. 2. Depicts Volume of displacement for one sample during bucket movement.

Since the dimensions of the bucket are fixed (e.g. constant bucket width L) and the volume of the accumulated soil at the front of the bucket, figure (2), for a given trajectory, is a function only of the horizontal and vertical displacements H

and X then by measuring these at every sampling instance. The total volume of the soil moved for any sample can be calculated as:

$$volume_{(n)} = \left(\frac{(X_n - X_{(n-1)}) \times (H_{(n-1)} + H_n)}{2}\right) \times l \tag{5}$$

The soil density (γ) to be worked is already known (C. Tan 2003), and so the mass of the soil accumulated in front of the bucket for any sample can be calculated as:

$$Mass_{(n)} = \left(\frac{(X_n - X_{(n-1)}) \times (H_{(n-1)} + H_n)}{2}\right) \times l \times \gamma \tag{6}$$

Fig. 2. depicts the factors involved in calculating the total volume of soil excavated as a series of integrals (total samples, N).

The kinetic energy at any sample can be estimated by computing mass and velocity at any sample:

$$EK_{(n)} = \frac{1}{2} \times \left(\left(\frac{(X_n - X_{(n-1)}) \times (H_{(n-1)} + H_n)}{2}\right) \times l \times \gamma\right) \times V^2 \tag{7}$$

By modelling and removing the kinetic energy component from the total measured energy the proposed total dissipation energy is obtained online. The online real-time algorithm to define the velocity, mass, total dissipation energy E_{DT} is shown in Fig. 3.

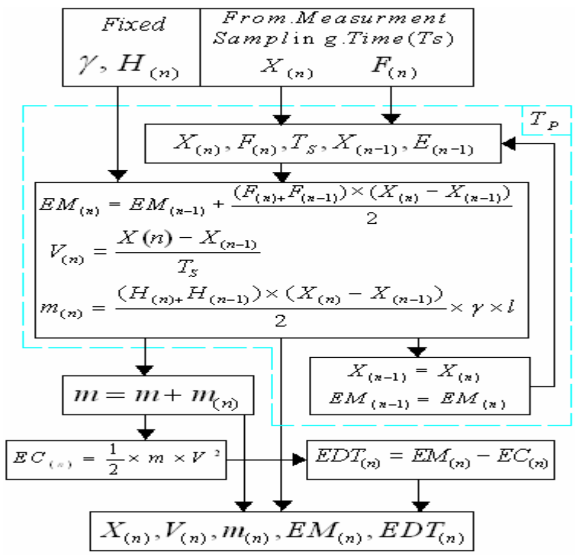

Fig. 3. Online algorithm defining actual dissipation energy.

2.4 Potential Energy (E_P)

The algorithm to compute potential energy is based on limit equilibrium analysis. By gathering data on the minimum energy required to move the selected bucket in the x-direction for different insertion depths ($H_{X\min}$) it is possible by using trend analysis to define energy as function of H for the minimum displacement, based on Limit equilibrium method (C. Tan 2003),(J. Atkinson,1993). ($E = f(H_{x(\min)})$). By rewriting equation as H, and substituting any current energy into these equations, the current depth ($H_{X(n)}$) can be defined for any sample along the dragging phase. By then subtracting the initial depth ($H_{X(\min)}$), the estimated actual height (h) of the accumulated soil for any current sample is determined.

At any sample, the estimated actual height (h) and the data of mass (m) of the accumulated soil is known during on-line estimation the potential energy of any sample can be defined as:

$$E_p = m.g.h \tag{8}$$

2.5 Dissipation Energy (E_D)

These assumptions are reasonable approximations where E_{DT} consists of addition of the potential and dissipation energy the total energy produce by the bucket during the displacement acts against (SR) soil resistance (after subtracting the E_K and remove the dynamic friction force dependent on velocity) and to create the unpredictable shape of accumulated soil mass above the ground surface which produced extra vertical force and so more SR.

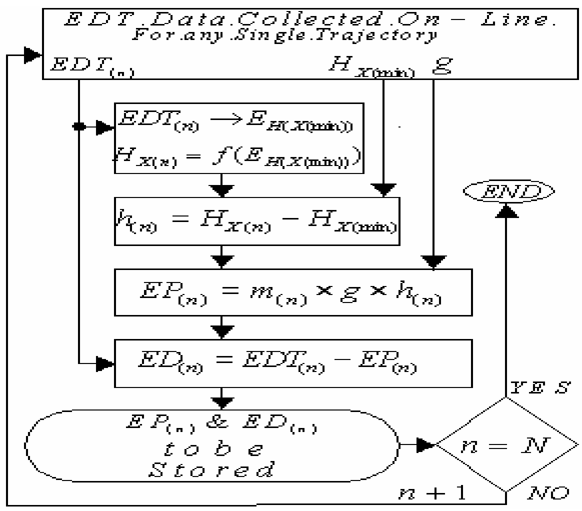

Fig. 4. Algorithm defining dissipation energy from online total dissipation data for any single dragging phase.

The dissipation energy (E_D) is calculated by subtracting the total dissipation energy (E_{DT}) (kinetic energy (E_K) and potential energy (E_P)) from the overall measurement energy (E_M) at every sampling instance. By carrying out this procedure iteratively (i.e. for every sample), the dissipation energy profile for the entire dragging phase can be determined:

$$E_{DT} = E_M - E_K$$

$$E_D = E_{DT} - E_P \tag{9}$$

Figure 4 shows a flow chart of the offline algorithm used to define the pure dissipation energy by removing the potential energy from total dissipation energy.

3. EXPEREMENTAL RESULTS

3.1 Test Rig

Fig. 5. (a) depicts the test rig with two degrees of freedom movement and a scaled model of the bucket attached. A test-bed with two different types of soil is used to simulated excavations. The low level control and data acquisition are implemented in Lab view and is combined with a 6-DOF force/torque sensor which is mounted on the test rig sledge. Any bucket movements in x and y direction can be measured using a position sensor and precision potentiometer respectively which are robust to noise and can be easily installed onto a robot arm or hydraulic actuator as shown in Fig. 5. (b).

The data related to the forces and displacement experienced by the bucket while it is forced through the soil along the x axis is recorded in order to estimate the dynamic soil properties for an accurate soil property estimation. The behavior of the actuators should be known and disturbances should be minimized. For this reason a pulley and weight assembly with known specifications is used. Utilizing different weights creating constant step forces applied to two types of soil (Garside 60 and Garside iron with densities of 1617 and 1475 kg/m3, respectively), a set of experiments are conducted.

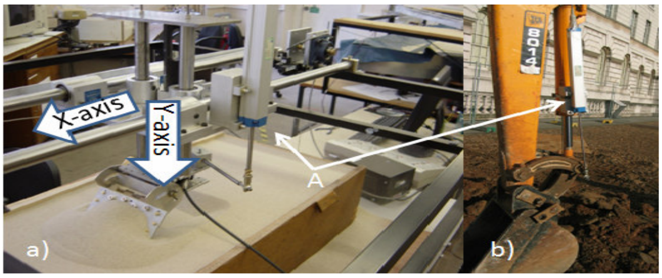

Fig. 5. (a) .The 2-DOF test rig. The carriage moves in x direction during excavation. The bucket movements can be measured in horizontal (x) and vertical (y) direction. (b) Position sensor (potentiometer) installed onto excavator arm.

The accuracy of the measurement of the energy components are increased by utilizing the trapezoidal rule and equation (5) and also the proposed modified on-line algorithm was applied to generate the corresponding total dissipation energy profiles EDT rather than the off-line estimation (S.M.Vahed, 2007), by removing the calculated kinetic energy component E_K .

3.2 Observations and Synopsis of Experimental Results

Several experiments were conducted involving different soil types. For each soil type unit step forces, F (7) to F (11) were applied for one single depth H and the displacement, velocity, mass and energy profile measurements were recorded in each case. In each case, the proposed algorithm was explained applied to generate the corresponding dissipation energy profiles E_D , by removing the kinetic energy E_K and potential energy E_P components. The obtained results are showninFig.6

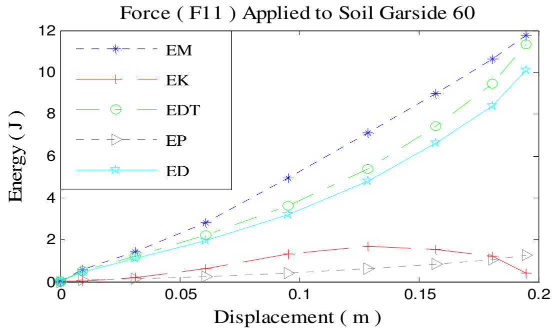

Fig. 6. Depicts E_D , estimated during dragging phase by subtracting E_K and E_P from E_M for any sample

The graphs in Figs. 6 and 7(a) demonstrate that there is a clear relationship between kinetic energy (E_K) and velocity for the corresponding trajectory. It can also be seen that the difference between measured energy E_M and dissipation energy E_{DT} , correlates well to the magnitude of velocity(for velocity variations from 0 to 0.1 m/s figure 7 (a)).

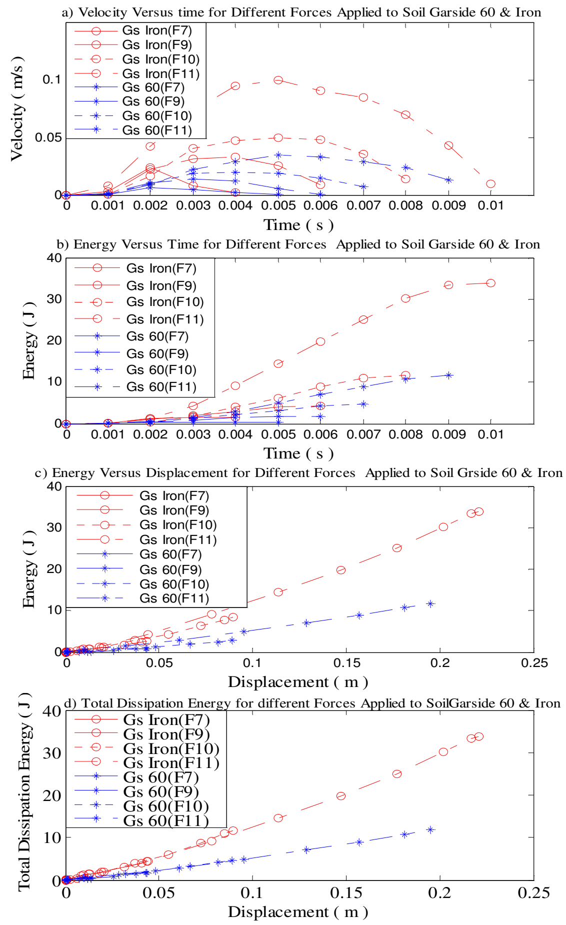

Fig. 7. (a) velocity and (b) energy E_M for four different forces versus time applied to two soils Garside 60 & Garside Iron ; Graph (c) depicts energy E_M and (d) E_{DT} for four different forces versus displacement applied to two soils Garside 60 & Garside Iron .

This means that the part of the total force used to move the bucket through the soil counteracts accumulating soil above the ground surface that creates potential energy (E_P) and that extra mass causes an increase in downwards force in turn creating more friction force or more (E_D).The velocity and energy versus time were measured and computed online and then stored for each soil-type as shown in Figs. 7. (a) and (b), displaying velocity and energy versus time for different external applied forces respectively. The depicted graphs are not easily analyzable (even if considering a single soil type), in order to determine mechanical soil properties in the terms of the displayed physical variables. From Fig.7.(c). (E_M as a function of displacement) and (d) (E_{DT} versus displacement) , it can be seen that the energy variable is now much more highly correlated to the soil-type and insensitive to the applied force. This was consistently observed in all experiments and, hence, shows that E_{DT} as function of displacement has a remarkable unique signature for given soil type. The relationship between E_{DT} and displacement is an appropriate measure for soil classification, which was a major challenge to achieve.

After each experiment the accumulated mass in front of the bucket is collected and the weight measured on a set of accurate scales. When compared to online calculations performed by the proposed algorithm. There is an acceptable performance error from 3% to 8% for short and long displacements respectively.

By repeating the experiment for different blade insertion depths (*H*), and subtracting the calculated kinetic energy component E_K , results for E_{DT} are obtained Fig. 8. By observing these results it seems that there is clear similarity response for applied forces in any chosen depth *H*.

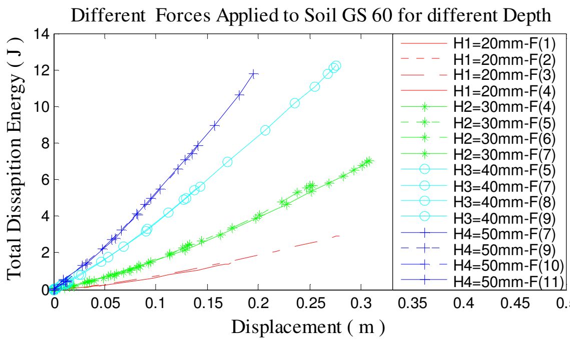

Fig. 8 Depicting E_{DT} versus Displacement for different depth

By utilizing the proposed energy-based method, any soil type can be described as a single equation that soils property can characteris as mathematical model of soils property for any applied forces with different velocity. The polynomial mathematical model of two soils Garside 60 and Iron shows in equation (10) and table. (1). Depicts the valuation of coefficients.

$$EDT = A \times X^2 + B \times X + C \qquad (10)$$

$$A = f_A(H) = \alpha_A \times H^3 + \beta_A \times H^2 + \upsilon_A \times H + \sigma_A$$

$$B = f_B(H) = \alpha_B \times H^3 + \beta_B \times H^2 + \upsilon_B \times H + \sigma_B$$

The initial amount of measured energy versus displacement in this experiment when compared to the rest is negligible at any different depth (*H*). $\sigma_{a,b\&c} \cong 0$. Hence:

$$C = f_C(H) = \alpha_C \times H^3 + \beta_C \times H^2 + \upsilon_C \times H + \sigma_C = 0$$

Table 1: coefficient of Soils Garside 60 & Iron

	α_A	β_A	υ_A	σ_A	α_B	β_B	σ_B
Gs 60	**4.9**	**-25**	**246**	**-33**	**-1.4**	**9.6**	**-6**
Gs Iron	**-1.3**	**7.46**	**4**	**-0.6**	**3.8**	**-22**	**456**

Along the entire required range of horizontal displacement *X* it is possible to choose any arbitrary point as an equilibrium point at which we can determine the quasi-static force (minimum force from rest to movement, where velocity is tending towards 0; the kinetic energy is already removed from the result) by taking the derivative of the dynamic soil equation of E_{DT} at different depths *H* (equation (10)).

The quasi-static force can be determined by choosing an equilibrium point where *x*=0 as below.

$$F = \frac{\partial ED}{\partial X}\Big|_{x=0} = \alpha_B \times H^3 + \beta_B \times H^2 + \upsilon_B \times H$$

By rewriting the solution for pressure (*Pa*=quasi-static force/(Area=HL)) we get:

$$P_a = \alpha_B \times H^2 + \beta_B \times H \qquad (11)$$

The result of the chosen equilibrium point from the main equation E_{DT} at the start is demonstrated in equation (11). It shows the similarity of its dependency on pressure and varying *H* to the commonly accepted methods of Coulomb active Wedge Theory ($P_a = \frac{1}{2} \times \gamma \times H^2 - 2 \times S_u \times H$) and Rankin "state of stress" Analysis. The novel method and algorithm presented in this paper shows the successful achievement of estimating the dynamic behaviour of a worked soil as a mathematical model. The approach is fast enough to capture experimental data for estimating any soil type in real time with unpredictable soil conditions in real environments.

The data that is continuously garnered online within dynamic mathematical models can be used in control design and can also be used for pattern recognition concerning classification of soil types online.

4. CONCLUSIONS

A novel and practical method has been presented in this paper for the estimation of soil types utilizing derivations of energy theorem approaches that has great potential to be used on-line within a low level controller. The algorithm developed, based on energy methodology, can continuously measure and compute displacement, velocity, accumulated soil mass and total dissipated energy profiles for each soil type. By subtracting the kinetic energy component, the dependence on the dynamic-friction force is made more prominent.

The total dissipation energy-displacement curves which were gathered during the experimental study show remarkably similar characteristics, despite large variations in the magnitude of the applied forces.

The proposed approach leads to a new and robust on-line soil-type identification using a newly developed mathematical model for soil, and is a practical and technically powerful approach for use in control design.

The inclusion of the soil mass estimation allows for future control options regarding extraction of the excavator bucket.

Equilibrium analysis theories were used to define the pure dissipation energy by extracting the kinetic energy component from the total measured energy. The energy components calculated are potential, kinetic and pure dissipation energy, all of which can be used for optimization of the trajectory with respect to time.

Further work will aim at extending the method to the case where a rotational kinetic energy component is included when extracting the bucket out of the soil.

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