

A method of online traction parameter identification and mapping

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Abstract: Fuel consumption of heavy-duty vehicles such as tractors, bulldozers etc. is comparably high due to their scope of operation. The operation settings are usually fixed and not tuned to the environmental factors, such as ground conditions. Yet exactly the ground-to-propelling-unit properties are decisive in energy efficiency. Optimizing the latter would require a means of identifying those properties. This is the central matter of the current study. More specifically, the goal is to estimate the ground conditions from the available measurements, such as drive train signals, and to establish a map of those. The ground condition parameters are estimated using an adaptive unscented Kalman filter. A case study is provided with the actual and estimated ground condition maps. Such a mapping can be seen as a crucial milestone in optimal operation control of heavy-duty vehicles.

Keywords: Traction control, Identification algorithms, Data storage, Kalman filters, Dynamic modelling, Vehicle Dynamics

1. INTRODUCTION

Increasing fuel costs due to progressing depletion of fossil resources put ever stronger requirements on the productivity, energy efficiency and related characteristics of heavy-duty vehicles. Optimization of the vehicle operation may be realized by various factors, such as implement positioning, tire pressure adjustment, traction and engine control. But one thing is common: determination of an optimal set point has to account for the properties of the ground-to-propelling-unit properties.

Primarily, the ground conditions influence the traction dynamics. These can be characterized by two factors – the energy efficiency and the adhesion coefficient, which equals the propulsion force normalized by the vehicle’s weight. Both can be considered as functions of the wheel slip ratio (see Fig. 1 for some adhesion-slip-curve examples on different soils). A detailed description of traction-slip characteristics may be found in Söhne (1964). High operation performance requires balancing the propulsion and the energy efficiency. This is complicated precisely due to the lack of online knowledge of the adhesion-slip curve.

So far, the methods of operation optimization, which account for the adhesion-slip relation, are mostly offline. The techniques of the so-called traction prediction (Schreiber et al., 2008; Battiato and Diserens, 2017) rely on certain empirical parameters of the propelling unit, chassis, type of soil etc. The user can thereby calculate an operation set point for a particular situation and adjust the settings accordingly, in a way similar to a look-up table. An immediate disadvantage of these methods is their offline nature, i. e., they do not account for changing ground conditions. On the other hand, the online methods do not use identification of the adhesion-slip characteristic. In particular,

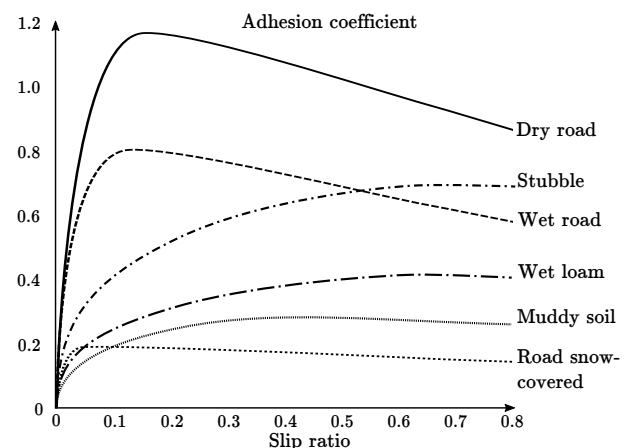


Fig. 1. Typical $\mu(s)$ -characteristics on different soils.

Reichensdörfer et al. (2018) proposed a nonlinear control design based on input-output linearization that takes oscillatory behavior of the powertrain into account. Ishikawa et al. (2012) suggested usage of GPS antennae to measure speed, calculate the slip ratio and adjust the implement position when the slip ratio exceeds a given threshold. It should be noted that the problems of traction control are also relevant in railway vehicles (Novak and Vařak, 2018). Neither of the above use identification of ground properties to adapt the control parameters.

However, some empirical indices, such as the one based on the Brixius model (Brixius, 1987), started to find applications. For instance, Kim and Lee (2018) used it in a slip controller. Alexander et al. (2018) proposed using a data buffer coupled with a parameter optimization algorithm for traction parameter identification. Pentos and Pieczarka (2017) used an artificial neural network

to predict the influence of the soil texture, soil moisture and compaction etc. on the propulsion force and traction efficiency. Rajamani et al. (2012) developed observers to estimate friction coefficients of individual wheels during operation from various measurements, e. g., engine torque, brake torque and GPS measurements. Similarly Wang et al. (2004) developed a real-time tire-road friction coefficient measurement system which uses a differential GPS and a nonlinear longitudinal tire force model. Turnip and Fakhurroja (2013) used an identification approach based on the extended Kalman filter (EKF), whereas Hamann et al. (2014) suggested to use a superior variant of the EKF – the unscented Kalman filter (UKF). The UKF (Wan and Van Der Merwe, 2000; Van Der Merwe et al., 2004) will also be used in this work.

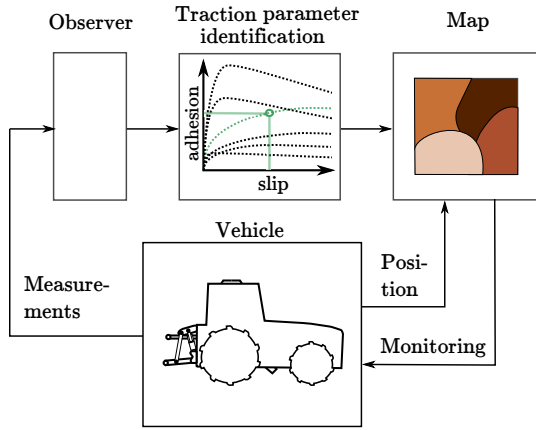


Fig. 2. General flowchart of the ground condition identification and mapping.

It can be observed from the literature, that the problem of ground condition identification is an actively researched topic and there are many open questions. The goal of this work is to develop means of online identification and mapping of those condition parameters. It continues the methodology developed in Osinenko et al. (2014, 2016); Osinenko and Streif (2017). An adaptive UKF is used for the identification of the ground-to-propelling-unit properties, namely, the adhesion and the rolling resistance coefficients. The slip-adhesion characteristic, or simply $\mu(s)$ -characteristic, is estimated from a single operating point. The way this is done is to use the model suggested in Osinenko and Streif (2017), and to reduce the number of its free parameters to a single one (see details in Sections 3 and 4). The traction parameters, as well as the said parameter characterizing the slip-adhesion relation, are mapped into a look-up table using GPS data recorded during operation. Data are extrapolated/interpolated using a distance-based weighing algorithm. Fig. 2 shows a general framework. To elaborate it, first the modeling matters are discussed in the next Section 2.

2. TRACTION DYNAMICS

Consider the wheel force diagram of Fig. 3. There, the vertical, or normal, force F_z is the sum of axle load $F_{z,axle}$ and wheel weight plus any vertical acceleration, see (3). The motor causes a driving torque M_d which exerts a horizontal force F_h at the wheel. The dynamical rolling radius r_d is defined to describe the deformed wheel's

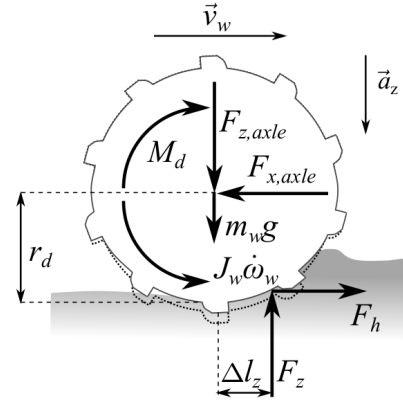


Fig. 3. Diagram depicts forces and torque at the wheel.

distance between its center and bottom. Due to the tire and soil deformation the point of application of the soil reaction forces is shifted by Δl_z . By convention the term $\Delta l_z F_z$ is assumed to be equal $r_d F_t$, where $F_t = \rho_t F_z$, i.e. the tire-deformation rolling resistance. The revolution speed of the wheel $\dot{\omega}_w$ can now be calculated using a torque balance approach, see (2). The reaction of the vehicle body $F_{x,axle}$ is exerted in the opposite direction of F_h . The rolling resistance is divided in the internal rolling resistance F_t with its coefficient ρ_t caused by the deformation of the tire and the external rolling resistance F_s with its coefficient ρ_s caused by the deformation of the soil. The force and torque balance yields:

$$m_w \dot{v}_w = F_h - F_{x,axle} - \rho_s F_z, \quad (1)$$

$$J_w \dot{\omega}_w = M_d - r_d F_h - r_d \rho_t F_z, \quad (2)$$

$$m_w a_z = F_z - m_w g - F_{z,axle}, \quad (3)$$

where m_w is the wheel mass, v_w is the ground speed, J_w is the wheels inertia, a_z is the vertical acceleration and g is the gravitation. The total rolling resistance is dominated by the soil-deformation resistance F_s and significantly influences the energy efficiency.

The adhesion coefficient μ characterizes the relation between the horizontal and vertical force as follows:

$$F_h = \mu F_z. \quad (4)$$

The part of the horizontal force that actually drives the wheel forward is called net traction ratio κ

$$\kappa = \mu - \rho_s. \quad (5)$$

The following definition of slip is used:

$$s = 1 - \frac{|v|}{r_d |\omega_w|}, \quad \text{if } |v| \leq r_d |\omega_w|, \\ s = -1 + \frac{r_d |\omega_w|}{|v|}, \quad \text{if } |v| > r_d |\omega_w|. \quad (6)$$

It ranges from -1 (locked wheel) to 1 (spinning on the spot). The energy efficiency η is defined by the formula:

$$\eta = \frac{\kappa}{\kappa + \rho} (1 - s). \quad (7)$$

Note that κ , μ and η are functions of slip s .

The soil deformation rolling resistance is summarized into $F_s = \sum_{i=1}^4 F_{si} = \rho_s m g$. The vehicle dynamics in driving direction now are

$$m \dot{v} = \sum_{i=1}^4 F_{hi} - F_{dx} - \rho_s m g, \quad (8)$$

where m is the vehicle mass, F_{dx} is the horizontal part of the drawbar pull, i.e. the implement resistance and i is the wheel index.

The tire deformation resistance ρ_t mainly depends on tire type and inflation pressure and can therefore be estimated prior to operation. A value of $\rho_t = 0.015$, as suggested by Schreiber and Kutzbach (2007), is used for simulation studies in this work. The soil deformation resistance ρ_s and μ will be estimated using a state observer, i.e. Kalman filter, see Section 3. The dynamical rolling radius

$$r_d = r_0 - \Delta r, \quad (9)$$

where r_0 is the unloaded wheel radius and Δr is the tire deformation, can be approximated from vertical forces using the empirical formula suggested by (Guskov et al., 1988, p.40):

$$\Delta r = \frac{F_z}{2\pi \cdot 10^5 \cdot p_t \sqrt{\frac{b_t}{2} r_0}}, \quad (10)$$

with p_t the tire air pressure and b_t the tire section width.

The parameters J_w , m_w , m and r_0 are assumed known. For details on estimation of F_z and M_d , please refer to Osinenko et al. (2015b). The state model is required by the state observer/parameter estimator introduced in the following Section 3.

3. GROUND CONDITION IDENTIFICATION

This section describes first the method of identifying the adhesion and rolling resistance coefficients, and then proceeds to the $\mu(s)$ -characteristic.

3.1 Online traction parameter identification

The identification algorithm used in this work bases on the adaptive UKF suggested in Zhe Jiang et al. (2007). The details thereof are given for the sake of completeness whereas the core of the method lies with the identification of the $\mu(s)$ -characteristic and mapping of the ground condition parameters. As mentioned above, the two parameters that impact the performance of the vehicle the most are adhesion coefficient μ and soil-deformation rolling resistance ρ_s . For their identification, an adaptive UKF with a fuzzy-logic supervisor (AUKF-FS) is used. Its purpose is to estimate the state \mathbf{x}_k from the measured output \mathbf{y}_k . The generic model description behind the UKF reads:

$$\begin{aligned} \mathbf{x}_k &= f(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{q}_{k-1}, \\ \mathbf{y}_k &= h(\mathbf{x}_k) + \mathbf{r}_k. \end{aligned} \quad (11)$$

Here, $\mathbf{x}_k \in \mathbb{R}^n$ is the state vector, $\mathbf{u}_k \in \mathbb{R}^p$ is the input vector, $\mathbf{y}_k \in \mathbb{R}^m$ is the output vector, $f(\mathbf{x}_{k-1}, \mathbf{u}_{k-1})$ is the non-linear state model, $h(\mathbf{x}_k)$ is the measurement model, $q_k \sim \mathcal{N}(0, \mathbf{Q})$, $r_k \sim \mathcal{N}(0, \mathbf{R})$ are the state and measurement random noises with zero mean and covariance \mathbf{Q} and \mathbf{R} respectively, \mathcal{N} denotes the normal probability distribution, k is the time step index, $n, m, p \in \mathbb{N}$ are dimensions. The algorithm can be parted into two major steps, prediction and update. For the prediction part, first so-called sigma-points have to be calculated. These points are able to accurately capture the posterior mean and covariance after propagation through the system (11) up to the 3rd order (Taylor series expansion, please refer to

Wan and Van Der Merwe (2000) for details). In the second part of the prediction the UKF computes the estimate probability distribution (PD) using the sigma-points as follows:

$$\begin{aligned} \text{PD}(\hat{\mathbf{x}}_{k|k-1} | \mathbf{y}_1 \dots \mathbf{y}_{k-1}) &:= \\ \mathcal{N}\left(\hat{\mathbf{x}}_{k|k-1} \middle| \sum_{i=0}^{2n} \mathcal{W}_m^{(i)} \chi_{k|k-1}^{(i)}, \mathbf{P}_{k|k-1}\right). \end{aligned} \quad (12)$$

In (12), $\mathbf{P}_{k|k-1}$ is the *a priori* estimate covariance, and $\chi_{k|k-1}^{(i)} = f\left(\chi_{k-1|k-1}^{(i)}, \mathbf{u}_{k-1}\right)$ are the sigma-points with the weights $\mathcal{W}_c^{(i)}$, $\mathcal{W}_m^{(i)}$, $i = 0, \dots, 2n$. The predicted mean is computed from the sigma-points by the formula:

$$\hat{\mathbf{x}}_{k|k-1} = \sum_{i=0}^{2n} \mathcal{W}_m^{(i)} \chi_{k|k-1}^{(i)}.$$

The *a priori* estimate covariance is calculated as follows:

$$\begin{aligned} \mathbf{P}_{k|k-1} &= \sum_{i=0}^{2n} \mathcal{W}_c^{(i)} \left(\chi_{k|k-1}^{(i)} - \hat{\mathbf{x}}_{k|k-1} \right) \cdot \\ &\quad \left(\chi_{k|k-1}^{(i)} - \hat{\mathbf{x}}_{k|k-1} \right)^\top + \mathbf{Q}, \end{aligned} \quad (13)$$

where $\mathcal{W}_c^{(i)}$, $i = 0, \dots, 2n$ are weight factors.

The update step involves recalculating the sigma-points from $\mathcal{N}(\hat{\mathbf{x}}_{k|k-1} | \mathbf{P}_{k|k-1})$. The mean of the predicted output

$$\hat{\mathbf{y}}_k = \sum_{i=0}^{2n} \mathcal{W}_m^{(i)} h\left(\chi_{k|k-1}^{(i)}\right)$$

and covariance

$$\begin{aligned} \mathbf{S}_k &= \sum_{i=0}^{2n} \mathcal{W}_c^{(i)} \left(h\left(\chi_{k|k-1}^{(i)}\right) - \hat{\mathbf{y}}_k \right) \cdot \\ &\quad \left(h\left(\chi_{k|k-1}^{(i)}\right) - \hat{\mathbf{y}}_k \right)^\top + \mathbf{R}, \end{aligned}$$

as well as the state and output covariance,

$$\mathbf{C}_k = \sum_{i=0}^{2n} \mathcal{W}_c^{(i)} \left(\chi_{k|k-1}^{(i)} - \hat{\mathbf{x}}_{k|k-1} \right) \cdot \left(h\left(\chi_{k|k-1}^{(i)}\right) - \hat{\mathbf{y}}_k \right)^\top$$

are then used to calculate the Kalman gain $\mathbf{K}_k = \mathbf{C}_k \mathbf{S}_k^{-1}$. The last step is to update estimate mean with

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k (\mathbf{y}_k - \hat{\mathbf{y}}_k) \quad (14)$$

and the a posteriori covariance now becomes

$$\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1} - \mathbf{K}_k \mathbf{S}_k \mathbf{K}_k^\top. \quad (15)$$

The choice of the state noise covariance \mathbf{Q} is crucial. An inappropriate choice may result in divergence issues (Fitzgerald, 1971). It was suggested to introduce an adaptation matrix \mathbf{A}_k so that the state noise covariance becomes effectively $\mathbf{A}_k \mathbf{Q}$ (for an extensive description, please refer to Osinenko et al. (2014)). The adaptation matrix is computed by matching the covariance of the true \mathbf{y}_k and the estimated output $\hat{\mathbf{y}}_k$ in the sense of

$$\arg \min_{\mathbf{A}_k} (\mathbf{P}_{k|k-1} - \mathbf{K}_k \bar{\mathbf{S}}_k \mathbf{K}_k^\top), \quad (16)$$

where the covariance of \mathbf{y}_k is computed from a sample of some size M :

$$\bar{\mathbf{S}}_k = \frac{1}{M-1} \sum_{i=k-M+1}^k (y_i - \hat{y}_i)(y_i - \hat{y}_i)^\top. \quad (17)$$

The adaptation of the state noise covariance \mathbf{Q} helps avoid estimate divergence, but it may result in a too noisy estimate. This is due to the fact that the noise covariance of the KF defines the tracking strength: the higher \mathbf{Q} is, the more noisy the estimate becomes, but large \mathbf{Q} is needed to avoid divergence. The smaller \mathbf{Q} is, the more smooth the estimate is, but there is a risk of divergence. To balance these effects, it was suggested to introduce a fuzzy-logic system (FLS) to additionally supervise the UKF (Abdelnour et al., 1993). If the vehicle undergoes a phase of intense dynamics, the FLS adaptation factor is set high. If the dynamics are steady, the FLS adaptation factor is small. The adaption of \mathbf{Q} aids the user by taking care of UKF tuning in an automatic manner. The resulting filter is called AUKF-FS. Such a fuzzy classification of dynamics was used in electrified mobile machinery in Osinenko et al. (2015a) and Osinenko and Streif (2017).

According to the vehicle dynamics model of Section 2, the state vector for the AUKF-FS consists of the wheel speeds, vehicle ground speed v , adhesion coefficients for each wheel and the soil deformation rolling resistance coefficient:

$$\mathbf{x} = (\omega_{w1}, \dots, \omega_{w4}, v, \mu_1, \dots, \mu_4, \rho_s)^\top.$$

The wheel speeds and vehicle ground speed form the output vector:

$$\mathbf{y} = (\omega_{w1}, \dots, \omega_{w4}, v)^\top.$$

For the mapping of the identified traction parameters it is assumed that the vehicle has access to GPS, this also allows, in particular, for speed measurement. Different means are possible for that sake, e. g., revolution counter on non-drive wheels, a radar etc.

The input vector includes the drive torques, front vertical force F_{zf} and longitudinal component of the drawbar pull:

$$\mathbf{u} = (M_{d1}, \dots, M_{d4}, F_{zf}, F_{dx})^\top.$$

Drive torque can be determined in hydraulic and electrical drive trains, while for mechanical drive trains the measurement/estimation is more elaborate. Front wheel vertical force can be measured in the suspension and the rear wheel vertical force can then be calculated using vehicle parameters. Draft force measurement F_{dx} can be obtained through magnetoelastic sensors or strain gauges installed in load pins.

The tire deformation rolling resistance coefficients ρ_t are assumed as fixed parameters. The dynamical rolling radii r_{d1}, \dots, r_{d4} are computed using (9) and (10). Propagation of the sigma points through the model formed by (2) and (8) is performed using the fourth-order Runge-Kutta method. The dynamics of unknown parameters and rear vertical force $\mu_1, \dots, \mu_4, \rho_s, F_{zr}$ are unknown. It is assumed that they do not change during one integration step so that their dynamics are neglected. More details are given

in Osinenko et al. (2015b). It can be easily checked that the overall system is observable. Two variables, ω_w and v , are directly measured. The other two states can be uniquely calculated at each time step using equations (2) and (8). The next section focuses specifically on the identification of the $\mu(s)$ -characteristic.

3.2 Adhesion characteristic identification

With the state observer from the previous section the parameters μ and ρ_s are estimated, which provides relevant information of ground conditions. As was stated above, the adhesion coefficient is a function of slip (Fig. 1). The shape of the respective curves changes depending on different soil surfaces. The Pacejka's empirical models (Pacejka, 2006) are usually used for the $\mu(s)$ -curve. Here, it is modified to give

$$\mu(s) = a - pa \exp^{\alpha_1 s} - a(1-p) \exp^{\alpha_2 s}, \quad (18)$$

where a, p, α_1, α_2 are the μ -model parameters (refer to (Osinenko and Streif, 2017, Fig. 8) for example of parameter values). For alternative models, refer to Pacejka (2006); Schreiber and Kutzbach (2007).

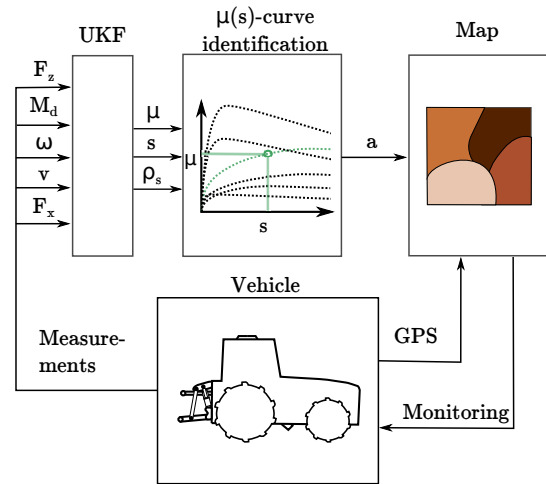


Fig. 4. Flowchart of identification and mapping.

Fig. 4 illustrates this works identification and mapping algorithm schematically. In the first step of the $\mu(s)$ -characteristic identification, a set of typical μ -curves, whose parameters a, p, α_1, α_2 are known, is generated. It was observed that for similar kinds of surface, e. g., road or soil, the three parameters p, α_1, α_2 may be fix, while only the parameter a can be varied to cover a spectrum of ground conditions. This parameter is used in the second step to generate a set of shape-similar $\mu(s)$ -curves with only one changing parameter a , see Fig. 5.

As mentioned above, the AUKF-FS identifies μ, ρ_s and s . With the estimated pair of μ and s and the known parameters p, α_1, α_2 the parameter a can be calculated.

Now, as the identification measures are done, proceed to the mapping of ground condition parameters.

4. MAPPING

The identified parameters are determined at certain discrete instances during the vehicle motion on the working

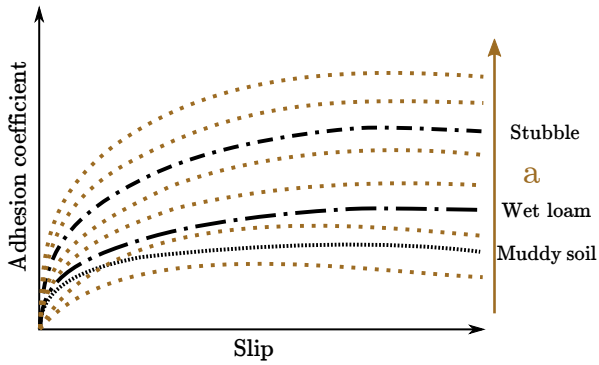


Fig. 5. Three similar ground types are displayed. Parameters for (18) are fitted to "stubble". The colored curves are generated by changing one parameter a .

area, e. g., a field. Since soil properties are usually similar in a vicinity, interpolation is suggested to generate a map from those discrete estimates. The parameters $p_{\text{soil}} = a, p, \alpha_1, \alpha_2, \rho_s$ are known and connected to their respective coordinates, which can be measured through, e. g., a GPS. The map is initialized as an empty matrix. The fetched GPS coordinates are first transformed in such a way that the origin of the measurement coordinate system aligns with the first entry in the map-matrix. Depending on the resolution of measurements and of the map, there are cases where multiple measurements are available for the same map entry. In this case, saving the mean value is a reasonable choice. Since heavy-duty vehicles usually operate at comparably slow speeds, saving measurements at a rate of 10 Hz is used in this study. The map-matrix M has the dimensions w, l, h , where w is width, l is length and h is the number of parameters in p_{soil}

$$M_{i,j} = p_{\text{soil } i,j}, \quad (19)$$

where i and j denote the matrix indices.

The next step involves the interpolation/extrapolation of the data into the close vicinity of each non-empty map entry. First, three search thresholds $\varepsilon_{\text{low}} > \varepsilon_{\text{mid}} > \varepsilon_{\text{high}}$ with weights $w_{\text{low}} < w_{\text{mid}} < w_{\text{high}}$ are introduced. The distance d between two entries in the map-matrix $M_{i,j}$ and $M_{e,f}$ is defined as

$$d = |e - i| + |f - j|$$

which is also known as the Manhattan distance. Starting with $M_{i,j} = M_{1,1}$, the mean of all entries with a distance $\varepsilon_{\text{low}} \geq d > \varepsilon_{\text{mid}}$ is calculated and weighted with w_{low} . This is repeated for w_{mid} and w_{high} . The sum of all weighted mean values is the new extrapolated value for the particular entry $M_{i,j}$. This procedure is repeated for the whole map and every parameter in p_{soil} .

5. RESULTS AND DISCUSSION

The model equations and algorithms introduced in the previous sections were implemented in a Matlab/Simulink environment. Measurement noise is simulated as white noise. For the case study, a model of an electrified tractor was used (please refer to Osinenko et al. (2014) for comprehensive details). It has 80 kW total drive-train power, 6300 kg unloaded mass including four wheels with 160 kg each. The ground is chosen as a flat plane with three different soil types. The vehicle accelerates to a desired

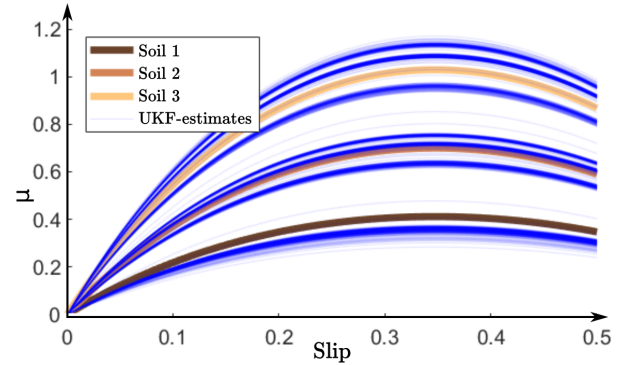


Fig. 6. The brown lines represent the true traction characteristics in the simulation. The blue lines show the characteristics identified by the AUKF-FS.

speed and then cruises at it. The search thresholds were set as $\varepsilon_{\text{low}} = 10$, $\varepsilon_{\text{mid}} = 5$, $\varepsilon_{\text{high}} = 1.5$ meter and the weights were chosen as $w_{\text{low}} = 0.1$, $w_{\text{mid}} = 0.5$, $w_{\text{high}} = 4$.

The adhesion coefficient is calculated using (4) and compared to the UKF estimates, see Fig. 6. A visual evaluation shows a good fit. Whenever the soil's traction properties change, the AUKF-FS adapts the estimated values to track the true physical one. The average absolute estimation error is within 5%. For every ground condition an average representative $\mu(s)$ -characteristic was calculated from the UKF-estimates. These representatives were compared to the true $\mu(s)$ -characteristic using R-squared. This gave R-squared values of $R^2 = 0.857$, $R^2 = 0.996$ and $R^2 = 0.983$ for soil 1, 2 and 3 respectively. Fig. 7 shows the map generated from the algorithm suggested in this work. The background and the identified tiles align well, the AUKF-FS successfully detects changes in soil properties (see the transition between different soils) and identifies parameters reasonably well.

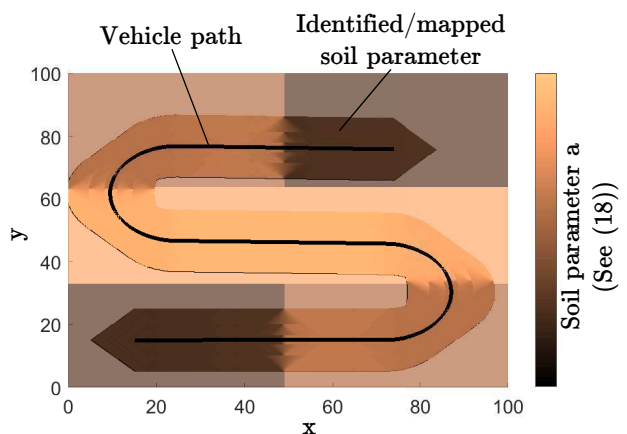


Fig. 7. In a simulation a vehicle (black line) drove over a field (transparent background) and simultaneously identified traction parameters (opaque tiles).

6. CONCLUSION

This work demonstrated a method of identification of ground condition parameters combined with their mapping. These parameters are crucial in determining optimal set-point for operation of heavy-duty vehicles. A case

study with a single-wheel drive moving on a field with three different soil types showed promising capabilities of the mapping algorithm. The latter may be used, e.g., in intelligent traction control algorithms or condition monitoring systems.

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