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Optimal traction control for heavy-duty vehicles

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A B S T R A C T

Heavy-duty vehicles such as tractors, bulldozers, certain construction and municipal vehicles, soil millers, forestry machinery etc. have a high demand for propulsion force and consequently a high fuel consumption. The current work presents a traction control approach based on motion dynamics estimation for optimizing propulsion force and energy efficiency according to a user-defined strategy. Unscented Kalman filter augmented with a fuzzy-logic system for adaptive estimation is used as the state observer. Simulation case study with an electrically driven tractor is presented. The new method of traction control showed considerable improvement of balancing energy efficiency and propulsion force.

1. Introduction

1.1. Problem description

Traction dynamics of a vehicle can be characterized by two factors—energy efficiency and propulsion force. The propulsion force is usually normalized by the vehicle mass to yield the so-called adhesion coefficient. Both the adhesion coefficient and energy efficiency are typically considered functions of the wheel slip ratio. Fig. 1 shows some typical characteristics along with the vehicle energy efficiency under various ground conditions. Further characteristics and a thorough description may be found in Söhne (1964).

It can be noticed from Fig. 1 that for the three selected offroad ground surface conditions – stubble, wet loam and muddy soil – the energy efficiency has a distinguished maximum in the range of the slip ratio of approximately 0.07 to 0.15. The adhesion coefficient characteristics corresponding to the three conditions increase with the slip ratio. The rate of increase is different for the range of a relatively low wheel slip (up to approximately 0.2) and that of a higher slip (above 0.2). In the first range, the rate of increase is high whereas in the second, the characteristic becomes more flat.

To improve vehicle performance it is important to achieve a reasonably high propulsion while keeping the energy efficiency close to the maximum. Unfortunately, this is not always possible since the adhesion coefficient and energy efficiency characteristics are not known. A possible solution is to define a set-point that would achieve a compromise between different ground conditions. For example, Renius (1985) recommended to keep the slip ratio at about 0.1 for all-wheel-drive machines. There is, however, a large potential for optimization of vehicle dynamics by adapting the slip set-point. The major objective of the current study is, therefore, to realize this optimization potential via assessment of the ground condition. The next section overviews some common approaches to traction control which is one of the most common means of improving vehicle's propulsion.

1.1.1. Traction control

In general, the machine's state can be adjusted both before and during the vehicle operation. Adjustment of the machine's state is addressed, for example, in the technique of traction prediction (Brixius, 1987; Freitag, 1965; Hegazy & Sandu, 2013; Maclaurin, 1990; Schreiber, Kutzbach, et al., 2008; Wismer & Luth, 1973). This technique focuses on deriving models of traction based on selected parameters of the ground and the propelling unit. The user may set up the parameters and compute a suggestion on the choice of the operation set-point for a particular operation. In contrast to the traction prediction, traction control is a method of adjusting the machine's state dynamically during the operation and is in the focus of the current section.

In the following, traction control algorithms for tractors are reviewed. The only difference to other heavy-duty machines is the point of application of an implement, if present. For instance, a tractor usually has an implement attached at the rear, while a bulldozer usually has a front implement. The two common methods of traction control are based on fuel injection quantity and implement adjustment (see Fig. 2).

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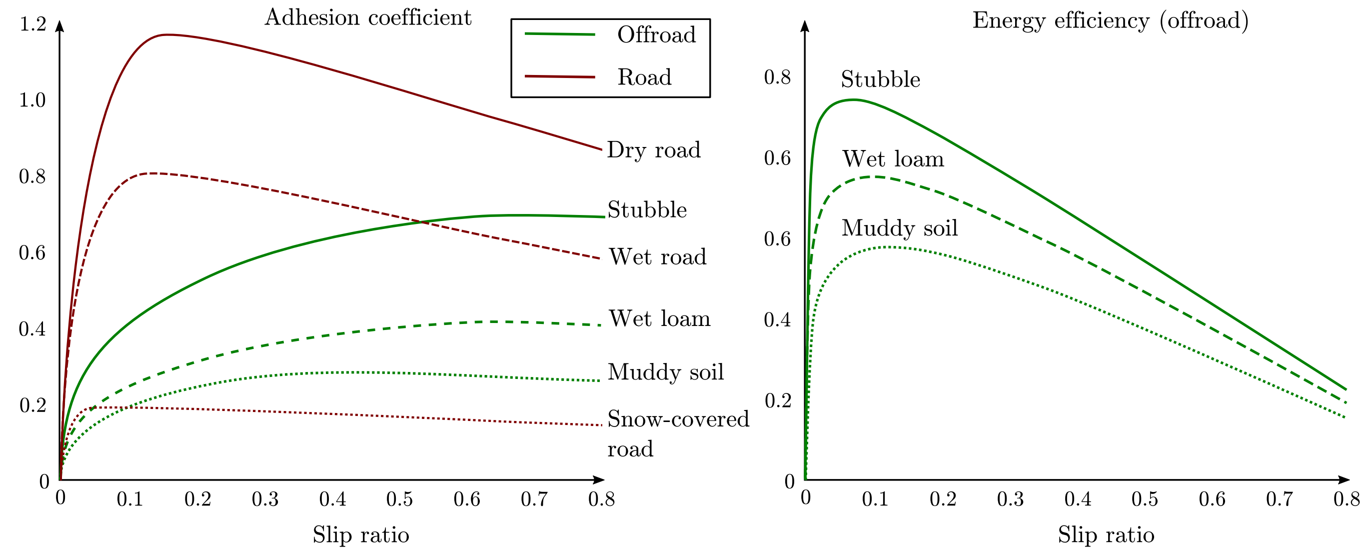

Fig. 1. Typical characteristics of the adhesion coefficient and vehicle energy efficiency. Based on Söhne (1964) and Kiencke and Nielsen (2005), p. 320).

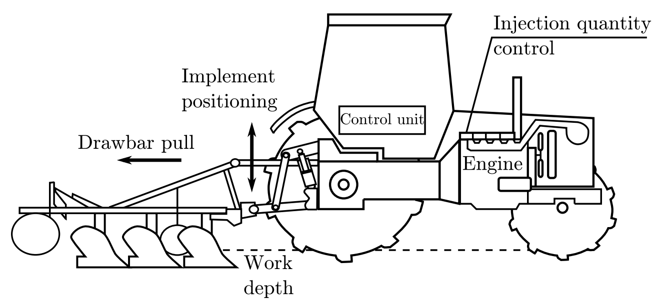

Fig. 2. Illustration of implement positioning and injection quantity control in a tractor.

Concrete methods differ in implementation of traction control. For example, Ishikawa, Nishi, Okabe, and Yagi (2012) suggested to measure the ground speed with a GPS antenna, to compute the slip ratio and to elevate the implement when the slip ratio exceeds a predefined threshold. When the implement is elevated, the drawbar pull decreases followed by a slip ratio decrease. A similar approach to traction control was proposed by Pranav, Tewari, Pandey, and Jha (2012) for two-wheel drive tractors where the ground speed could be determined from the non-driven wheel rotation frequency. Automatic traction control was developed by Volvo Group to prevent slip ratio from rising beyond a preset condition (see, for example, Sjögren, 2012). Pandey, Caruthers, Skiba, et al. (2008) used traction control for an electrically driven commercial vehicle such as a wheeled/track type tractor or a construction machine. This approach was based on a ground condition selector allowing setting the operating point to improve traction or reduce fuel consumption. Pohlenz and Bailly (2013) used the transmission gear ratio as a mean to control the slip ratio. A gear-neutral transmission constituted the basis of the approach. Henderson and Cebon (2015) used a sliding mode controller to adjust the slip ratio during a braking phase of a heavy-duty vehicle. Adhesion coefficient characteristic curve was estimated before the operation via repeated measurement. Callaway and Farmer (2013) used the driveline acceleration versus the ground acceleration of the vehicle to determine the slip ratio. Kelly (2014) used implement positioning applied to the excavation blade where raising and lowering the implement served as a mean to control the slip ratio.

1.1.2. Selected approaches for estimation of the vehicle's dynamics

None of the above methods fully address the problem of balancing vehicle propulsion and energy efficiency in an optimal way. Either they are essentially offline methods that lack adaptation to dynamically changing ground conditions or they are based on a fixed set-point setting and use no optimization. In contrast, the current work is concerned with a method of traction control that is optimal and dynamically adapts itself to ground conditions. The approach uses state estimation and relevant approaches in the context of traction control are briefly reviewed in the following.

Estimation of the adhesion coefficient is one of the main concerns in traction control. A variety of methods were suggested to assess the adhesion from the measured signals in a vehicle. Nakakuki, Shen, and Tamura (2008) used an adaptive traction control in which the adhesion coefficient was estimated. They demonstrated shorter braking distances using the slip ratio control. Rajamani, Phanomchoeng, Piyabongkarn, and Lew (2012) used recursive least squares (RLS) for the adhesion coefficient estimation. Villagra, D'Andréa-Novel, Fliess, and Mounier (2011) applied a differentiator filter for this purpose. Matuško, Petrović, and Perić (2008) used artificial neural networks. Baffet, Charara, and Lechner (2009), Dakhlallah, Glaser, Mammar, and Sebsadji (2008), Turnip and Fakhrurroja (2013) and Zhu, Qiu, Guo, and Zhang (2011) based their identification approaches on the extended Kalman filter (EKF), whereas Antonov, Fehn, and Kugi (2011) and Hamann, Hedrick, Rhode, and Gauterin (2014) suggested to use a superior variant of the EKF – the unscented Kalman Filter (UKF). The UKF (Van Der Merwe, Wan, & Julier, 2004; Wan & Van Der Merwe, 2000) uses the so called sigma points to characterize the mean and covariance of the probability distribution and propagates them directly via the system model instead if linearizing it, as it is done in the EKF. Both the EKF and UKF, however, suffer from divergence issues if not properly tuned (Fitzgerald, 1971). For examples of adaptation of KF, refer to Herrera and Kaufmann (2010); Mohamed and Schwarz (1999); Soken and Hajiyev (2009). One of the adaptation techniques uses fuzzy logic (Abdelnour, Chand, & Chiu, 1993; Escamilla-Ambrosio & Mort, 2000; Havangi, Nekoui, & Teshnehlab, 2010; Tian, Cao, & Chen, 2011). Fuzzy logic is used to assess performance of the KF using parameters such as a degree of matching between the estimated and theoretical covariance of the predicted and measured system output (also called innovation sequence). This degree of matching was used, for example, to adjust the noise covariances of the KF that are fixed parameters in the standard set-up. Such techniques are especially beneficial in addressing the uncertainty in the state noise covariance that is difficult to estimate.

1.2. Structure and contribution of this work

The key contribution of the present study is addressing the wheel–ground contact parameter assessment by means of system identification