Vehicle tractive force prediction with robust and windup-stable Kalman filters

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A B S T R A C T

Vehicle control systems need to prognosticate future vehicle states in order to improve energy efficiency. This paper compares four approaches that are used to identify the parameters of a longitudinal vehicle dynamics model used for the prediction of vehicle tractive forces. All of the identification approaches build on a standard Kalman filter. Measurement signals are processed using the polynomial function approximation technique to remove noise and compute smooth derivative values of the signals. Experimental results illustrate that the approach using multiple Stenlund–Gustafsson M-Kalman filters (multiple robust and windup-stable Kalman filters) reaches the best performance and robustness in predicting the vehicle tractive forces.

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1. Introduction

Recent vehicle look-ahead controllers aiming at reduced fuel consumption and energy-efficient driving strategies require a prediction of vehicle tractive force (\( F_x \)) (Back, 2005, pp. 47–49; Ganji, Kouzani, and Khayyam, 2011; Hellström, Ivarsson, Åslund, and Nielsen, 2009; Khayyam et al., 2011; Radke, 2013, pp. 11–18; Shakouri and Ordys, 2014; Wahl and Gauterin, 2013). The vehicle tractive force acts in the longitudinal direction of the body-fixed vehicle coordinate system and is the force that is required to propel the vehicle to the desired speed. Moreover, the vehicle tractive force determines the fuel consumption of vehicles driven by combustion engines and the range of electric and hybrid electric vehicles (Denis, Dubois, Gil, Driant, and Desrochers, 2012; Grewal and Darnell, 2013). All references mentioned above model the vehicle tractive force by linear white-box models that result from differential equations of the vehicle longitudinal and lateral motion and contain time-invariant vehicle parameters, such as the vehicle mass, longitudinal drag coefficient, and coefficient of rolling resistance. However, the vehicle parameters indeed vary with time and depend on environmental conditions. Therefore, recursive estimators are required to provide online estimates for the temporally varying vehicle parameters.

1.1. Related work

Motivated by driver assistance systems and safety controllers, numerous research efforts have been undertaken to estimate vehicle parameters and in particular the vehicle mass (Bae, Ryu, and Gerdes, 2001; Fathy, Kang, and Stein, 2008; Han, Kim, Jo, and Huh, 2009; Hong, Lee, Borrelli, and Hedrick, 2014; McIntyre, Ghotikar, Gerdes, 2001; Fathy, Kang, and Stein, 2008; Han, Kim, Jo, and Huh, 2009; Hong, Lee, Borrelli, and Hedrick, 2014; McIntyre, Ghotikar, Gerdes, 2001; Fathy, Kang, and Stein, 2008; Han, Kim, Jo, and Huh, 2009; Hong, Lee, Borrelli, and Hedrick, 2014; McIntyre, Ghotikar, Gerdes, 2001; Fathy, Kang, and Stein, 2008; Han, Kim, Jo, and Huh, 2009). Furthermore, De Bruyne, Van der Auweraer, Diglio, and Anthonis (2011) provide a recent survey of vehicle mass estimation literature.

Our work reported here, however, was ultimately aimed at predicting the state: vehicle tractive force. Note that there is a substantial difference between (vehicle) parameter estimation and (vehicle) state prediction. Parameter estimation seeks for unbiased estimates based on given data that are referred to as training data. The goal in state prediction, however, is to reduce errors of prediction for a horizon of unseen data, called validation data. Splitting of data into training data and validation data is known as cross-validation.

To the best of our knowledge, the only reference that focuses...
on predicting the vehicle tractive force is Rhode (2016), which serves as the basis of this work.

1.2. Contribution & outline

The problem studied herein is how to design a model that provides accurate predictions of the vehicle tractive force from standard vehicle sensor data that contain outliers and periods of poor system excitation. Outliers cause breakdown of non-robust estimators (Zoubir, Koivunen, Chakhchoukh, and Muma, 2012), and poor excitation results in an ill-posed problem that causes windup (Evestedt and Medvedev, 2006). Subsequently, to recursively solve the random-walk output error model in the presence of outliers and periods with poor excitation.

Section 2 introduces a vehicle longitudinal dynamics model that provides the vehicle tractive forces as model outputs using the states as model inputs. These outputs are given by a drivetrain filter, called Stenlund–Gustafsson M-Kalman filter (SGMKF) subsequent, to recursively solve the random-walk output error model in the presence of outliers and periods with poor excitation. Starting with the well known Kalman filter (KF), Section 4 explains all the required modifications to add robustness and windup stability. Moreover, a novel robust recursive scale estimator with low computationally load is introduced. The presented SGMKF algorithm can be applied to any linear parameter estimation problem, where the parameters vary on different rate, the measurements are corrupted by outliers, and the observed system shows periods with poor excitation. Therefore, SGMKF is a general estimator and not specifically designed for vehicle tractive force prediction, which is studied herein.

Section 3 provides a recursive estimator, called polynomial Kalman smoother (PKS), for local polynomial function approximation which is used to smooth noisy vehicle signals and give their derivatives as well as smooth path angle estimates. PKS is ideally suited for vehicle signal smoothing, because PKS preserves the signal level (flat magnitude filter), exhibits a well-defined delay, and gives smooth derivatives. The latter property is unique, because common signal filters (Butterworth, or FIR filters) do not deliver signal derivatives. To the best of our knowledge, the recursive polynomial function approximation has not been applied elsewhere to vehicle signals.

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In Section 5 multiple model estimation (MME) is introduced as a method to treat uncertainty in choosing Q, which is the covariance of the assumed Gaussian sequel that determines the rate of variation of the vehicle parameters and is an important tuning input in Kalman filters. Multiple model estimation gives the result with highest probability from a bank of parallel robust and
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