Control Engineering Practice 46 (2016) 37–50

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

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

Stephan Rhode [a,*], Sanghyun Hong [b], J. Karl Hedrick [b], Frank Gauterin [a]

[a] Institute of Vehicle System Technology, Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany
[b] Department of Mechanical Engineering, University of California, Berkeley, CA 94720, USA

ARTICLE INFO

Article history:
Received 13 May 2015
Received in revised form
1 September 2015
Accepted 8 October 2015
Available online 23 October 2015

Keywords:
Robust
Poor excitation
Windup
Kalman filter
Vehicle

ABSTRACT

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.

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_{xv}) (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, Vahidi, Song, and Dawson, 2009; Rhode & Gauterin, 2012, 2013; Vahidi, Stefanopoulou, and Peng, 2005; Winstead and Kolmanovsky, 2005; Yu, Feng, Xiong, and Wu, 2011). 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

Abbreviation: LMS, least mean squares; KF, Kalman filter; LMS, least median squares; LS, least squares; LTS, least trimmed squares; MKF, M-Kalman filter; MME, multiple model estimation; PKS, polynomial Kalman smoother; RLS, recursive least squares; SGMKF, Stenlund–Gustafsson M-Kalman filter

* Corresponding author. Fax: +49 721 608 44146.
E-mail addresses: stephan.rhode@kit.edu (S. Rhode), shong@vehicle.berkeley.edu (S. Hong), khedrick@me.berkeley.edu (J.K. Hedrick), frank.gauterin@kit.edu (F. Gauterin).

http://dx.doi.org/10.1016/j.conengprac.2015.10.002
0967-0661/

Nomenclature

$\boldsymbol{A}$	measured input matrix
$\mathcal{A}$	state transition matrix
$\boldsymbol{a}$	measured inputs
A_V (m^2)	vehicle cross-sectional area
$\boldsymbol{b}$	measured output
$\hat{\boldsymbol{b}}$	estimated output
$\tilde{\boldsymbol{b}}$	output noise
c_x	longitudinal drag coefficient
d	number of outputs
δ	Huber tuning constant
$\Delta\boldsymbol{b}$	output correction
$\Delta\boldsymbol{x}$	parameter correction
det	determinant
diag $(\cdot)$	diagonal elements
$\mathbb{E}$	expectation
η	learning rate
f_r	coefficient of rolling resistance
R^1	covariance of output noise
F_{xV} (N)	vehicle tractive force
G	gear
g (m s^{-2})	gravitational constant
$\bigcirc$	Hadamard product
$\boldsymbol{I}$	identity matrix
i_D	differential ratio
i_G	gearbox ratio
I_{red} (kg m^2)	reduced moment of inertia
I_W (kg m^2)	wheel moment of inertia
j_W	wheel: 1-rear left, 2-rear right, 3-front right, 4-front left, 12-front wheels, 34-rear wheels
$\boldsymbol{k}$	Kalman gain
k	number of prediction steps
l	number of models
λ	forgetting factor
$\mathcal{M}$	model
m	samples
med	median
MEDSE	median squared error
m_V (kg)	vehicle mass
n	number of inputs
ω_E (rad s^{-1})	engine speed
ω_W (rad s^{-1})	wheel speed
$\boldsymbol{P}$	covariance matrix
p	probability
$\boldsymbol{P}_d$	desired $\boldsymbol{P}$
pdf	probability density function
ψ	influence function
ψ_a (rad)	air approach angle
$\boldsymbol{Q}$	covariance of parameter correction
$\hat{Q}$	estimated quantile
$\mathbb{R}$	rational numbers
ρ_a (kg m^{-3})	air density
ρ	ρ-function
r_W (m)	wheel radius
sgn	signum
$\hat{\sigma}$	estimated scale
t (s)	time
T_D (N m)	differential torque
T_E (N m)	engine torque
T_G (N m)	gearbox torque
θ (rad)	path angle
θ_r (rad)	road angle
T_R (N m)	rim torque
u	evaluation point
v_V (m s^{-1})	vehicle velocity
w_l	left window
w_r	right window
w	weight
$\boldsymbol{x}$	parameter
$\hat{\boldsymbol{x}}$	estimated parameter
$\bar{\boldsymbol{x}}$	true parameter
x_V (m)	vehicle longitudinal axis
$\mathbb{Z}$	integer numbers

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).

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 model while the inputs arise from a path angle model and vehicle sensor data.

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.

Section 4 introduces a novel robust and windup-stable Kalman filter, called Stenlund–Gustafsson M-Kalman filter (SGMKF) subsequently, 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.

In Section 5 multiple model estimation (MME) is introduced as a method to treat uncertainty in choosing $\boldsymbol{Q}$, 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