

Gradient and Mass Estimation from CAN Based Data for a Light Passenger Car

Robert Wragge-Morley and Guido Herrmann
University of Bristol

Phil Barber
Jaguar Cars

Stuart Burgess
University of Bristol

ABSTRACT

We present a method for the estimation of vehicle mass and road gradient for a light passenger vehicle. The estimation method uses information normally available on the vehicle CAN bus without the addition of extra sensors. A composite parameter estimation algorithm incorporating a nonlinear adaptive observer structure uses vehicle speed over ground and driving torque to estimate mass and road gradient. A system of filters is used to avoid deriving acceleration directly from wheel speed. In addition, a novel data fusion method makes use of the regressor structure to introduce information from other sensors in the vehicle. The dynamics of the additional sensors must be able to be parameterised using the same parameterisation as the complete vehicle system dynamics. In this case we make use of an Inertial Measurement Unit (IMU) which is part of the vehicle safety and Advanced Driver Assist Systems (ADAS). Therefore, a method using some filtering and supervisory logic is employed to give a sensible update behaviour for the vehicle mass estimation algorithm. The main function of the supervisor is to reject the mass estimate produced by unsuitable available data due to unmodelled loss forces. Good estimation results are obtained from data from a vehicle which was also fitted with some additional instrumentation including GPS sensors and a high quality IMU for scientific verification purposes.

CITATION: Wragge-Morley, R., Herrmann, G., Barber, P., and Burgess, S., "Gradient and Mass Estimation from CAN Based Data for a Light Passenger Car," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 8(1):2015, doi:10.4271/2015-01-0201.

1. INTRODUCTION

In the quest for increased vehicular functionality and autonomy, there is a requirement for more effective vehicle modelling in the context of control. Certain elements of a vehicle model may not be well known or easily determined by fitting inexpensive sensors to the vehicle system. Certain vehicle parameters are coupled mathematically by the vehicle dynamics so that sensor outputs include the influence of more than one vehicle or environmental parameter.

A pair of parameters to which this coupling applies are the focus of this paper, namely vehicle mass and road gradient. These are coupled by the Newtonian dynamics of the vehicle. Both are time varying from the vehicle's frame of reference, and both exhibit some dynamic behaviour, albeit with very different time scales and characteristics. Neither parameter is easy or especially inexpensive to measure directly in the context of current light duty passenger vehicle practice, but their estimation from existing vehicle bus data is complicated by the influence of other aspects of vehicle dynamics.

In this paper, we present a new set of results that demonstrate the effectiveness of a novel regressor-based data-fusion method for tackling a real estimation problem. We introduce two methods of supervised output filtering on the mass estimate to improve its robustness to certain types of error. The first method identifies periods of convergence of the estimate on an appropriate value and rejects estimates during events likely to generate errors. The second method makes use of a Kalman Filter which is controlled by the same type of data-rejection supervision to smooth the output; this method makes use of the ease with which a simple noise model may be identified for the mass parameter estimate. Data collected from practical vehicular experiments with a light passenger vehicle as part of a series of vehicle dynamics tests supporting several automotive projects is processed offline to demonstrate the effectiveness of these novel methods.

We begin by presenting an overview of the current state of the art in vehicle mass and road gradient estimation and also the background to this particular piece of work in light of the other methods found in the literature. We will then examine the mathematical context to the problem. This will encompass the methods used for vehicle

modelling, and the novel composite parameter estimation algorithm used at the core of the estimation method. The regressor data fusion method originally presented in [1] will then be reiterated in its latest form, as used for the work in this paper. The use of supervised output filtering to manage the mass estimate will then be presented and discussed along with results from experiments carried out using real vehicles.

2. A BRIEF OVERVIEW OF THE CURRENT STATE OF THE ART IN VEHICLE MASS AND ROAD GRADIENT ESTIMATION

A considerable amount of effort has been made by academic and industrial researchers into the online estimation of vehicle parameters that are either prohibitively difficult or expensive to measure directly. The most usual approaches are to use estimation based on the Recursive Least Squares algorithm [2] [3][4] or Kalman Filtering [2] [3][4] and many make use of data fusion from more than one source.

Vahidi *et al.* [5] make use of RLS methods to simultaneously estimate vehicle mass and road grade. Han *et al.* [6], Kim *et al.* [7] and Fathy *et al.* [8] among others have all used RLS methods to estimate vehicle mass, using various dynamics including lateral and roll dynamics. The extended RLS has been used to estimate a large number of vehicle parameters simultaneously in simulation by Bayani Khaknejad *et al.* [9] and expanded to include a total least squares approach to a similar problem by Rhode and Gauterin [10].

Kalman Filtering and Extended Kalman Filtering (EKF) based estimation methods are widely used in vehicle parameter estimation, by Sahlholm, Johansson and Jansson *et al.* [11][12][13]. Vahidi *et al.* [5] use a combination of Kalman Filtering and RLS methods in their approach, as does Raffone [14], while Sebsadji *et al.* [15] combine the Kalman Filtering of the vehicle dynamics with a Luenberger type observer for road gradient.

A number of approaches also use nonlinear observer structures. McIntyre *et al.* [16] and Rajamani *et al.* [17] both make use of Lyapunov based estimators, the latter using roll dynamics for mass estimation, a theme shared with Kim *et al.* [7] who use multiple observer synthesis to combine the results of their longitudinal and lateral dynamics based estimators.

Many of the approaches to the simultaneous mass and road gradient estimation problem already mentioned are model based to some greater or lesser degree. Some model based approaches such as that of Mangan *et al.* [18] make use purely of the Newtonian dynamics of the vehicle system to estimate, in this case, road gradient, whilst others introduce more complex effects. Bae *et al.* [19] uses a model based approach to introduce GPS data to the system, whilst Reineh *et al.* [20] use autoregressive moving average (ARMAX) models and Winstead and Kolmanovsky [21] make use of Model Predictive Control (MPC) and Kalman Filtering to produce their estimates.

As we have already seen, numerous methods in the literature, as well as our own [1] make use of data fusion from additional sensors that are attached to but not necessarily part of the vehicle system.

Numerous methods including those of Sahlholm *et al.* [11][12] and Bae and Gerdes [22] have made use of GPS in addition to vehicle sensors. The work of Jansson *et al.* [13] also includes altitude measurements using a barometer, while Caron *et al.* [23] and Sukkariah *et al.* [24][25] both incorporate data from both GPS and IMU/INS systems. It is beneficial to include additional data sources because this reduces the reliance on excitation and accuracy from a single source, thus producing a more reliable and robust estimate. The work of Reineh [20], Kim [7] and Fathy [8] using the results of a relatively decoupled set of vehicle dynamics to reinforce their mass estimates may also be regarded as a form of data fusion. Current practical results for passenger vehicles provide mass estimates within 10% accuracy with a usual settling time of the estimate of more than ~100 seconds [14] [21].

In this paper we will introduce the application of supervisory control methods for selecting appropriate data to drive our estimation methods. Supervisory control is a broad field and different aspects of it are applied to similar problems in the literature, including the use of multiple models for different gearbox ratios by Raffone [14] and selective use of available data by Fathy [8].

The work presented in this paper is a development of a parameter estimation project within the dynamics and control group at the University of Bristol. Vehicular estimation for mass, road gradient and other parameters was begun using standard estimation methods and adaptive observers from the literature by Chan and Foreman *et al.* [26][27]. A composite estimation algorithm [presented in the mathematical context of this paper] was developed by Na *et al.* [28] and applied to vehicular systems by Mahyuddin *et al.* [29][30]. This algorithm has subsequently been modified to include a novel data fusion method by Wragge-Morley *et al.* [1]

3. MATHEMATICAL CONTEXT

3.1 Vehicle Modelling

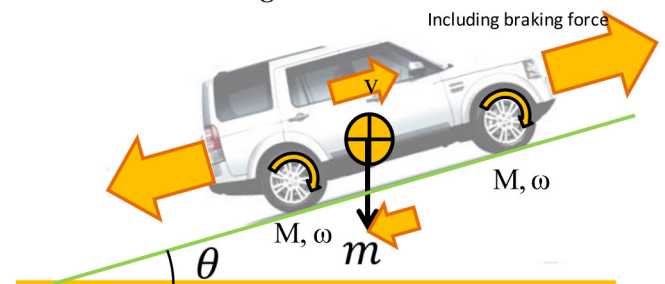


Figure 1. Free body diagram expressing the significant driving and loss forces in longitudinal vehicle dynamics for a vehicle on a fixed road grade.

For the purposes of this paper, we need to consider our model of the vehicle dynamics. We use a simple longitudinal dynamics model incorporating the main resistance forces, but without including too much detail to increase computational speed and simplicity. Within the algorithm, the vehicle dynamics model is incorporated into the observer (10), so it is essential that it be computationally light.

In addition, some inaccuracies in the model may be tolerated by the robust estimation method employed, although there is scope for including certain extra loss force. The main forces on the vehicle are shown on the free body diagram [Figure 1](#). In addition it is important to consider rotational inertias of certain drivetrain components and the torque required to accelerate them. Thus the Newtonian force balance for the main vehicle dynamics is derived as:

$$m\ddot{x} = F_{drive} - mg \sin \theta - C_{\mu} mg \cos \theta - \frac{\rho C_d A_f}{2} \dot{x}^2 \operatorname{sgn} \dot{x} \quad (1)$$

where θ is road gradient, C_{μ} is the coefficient of rolling resistance, ρ is density of the air, and C_d is the aerodynamic drag coefficient of the vehicle body whose frontal area is A_f . Vehicle mass is represented by m and the gravitational constant by g . Meanwhile the states $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x \\ \dot{x} \end{bmatrix}$ are respectively the displacement and speed of the vehicle.

We wish to consider this model in a standard, state space form shown below in order to allow it to be treated like a set of first order dynamics for the purposes of facilitating the linearisation of the model.

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}_1 \mathbf{u}_1 + \mathbf{B}_2 f(\mathbf{x}, \mathbf{u}_2) + \boldsymbol{\zeta} \quad (2)$$

The linearisation makes use of the following known and unknown parameters ϕ and Θ to re-write the dynamics in the form:

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \end{bmatrix} = \mathbf{A} \begin{bmatrix} x \\ \dot{x} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \underbrace{\phi \Theta}_{=f(\mathbf{x}, \mathbf{u}_2)} - \underbrace{\begin{bmatrix} 0 \\ C_{\mu} \cos \theta \end{bmatrix} g - \begin{bmatrix} 0 \\ \frac{\rho C_d A_f}{2m} \end{bmatrix} \dot{x}^2 \operatorname{sgn} \dot{x}}_{=\boldsymbol{\zeta}} \quad (3)$$

where the known regressor ϕ is:

$$\phi = \begin{bmatrix} -g & F_{drive} \end{bmatrix} \quad (4)$$

the unknown parameters Θ are:

$$\Theta = \begin{bmatrix} s \\ b \end{bmatrix} = \begin{bmatrix} \sin \theta \\ \frac{1}{m} \end{bmatrix} \quad (5)$$

and $\mathbf{B}_1 \mathbf{u}_1 = 0$. The known parameters are gravity and the powertrain estimate of vehicle driving force, and the unknown parameters which we wish to estimate describe road grade and vehicle mass.

3.2 Filtering

It is undesirable for the purposes of this estimator to derive accelerations directly from the wheel-speed sensor outputs. However, this situation is avoided by applying a filter to the information sources. The second state equation of the vehicle dynamics is:

$$\dot{x}_2 = \bar{B}_2 \phi \Theta + \zeta_2 \quad (6)$$

where the term $\phi = \bar{B}_2 \phi$ is created for convenience of notation. First order filters are applied of the form (7) where k is the filter constant. It is significant that this allows us to re-write the derivative of wheel-speed in terms of the measured and filtered wheel-speed (8).

$$\begin{aligned} k\dot{x}_{2f} + x_{2f} &= x_2, & x_{2f}(0) &= 0 \\ k\dot{\phi}_f + \phi_f &= \phi, & \phi_f(0) &= 0 \\ k\dot{\zeta}_{2f} + \zeta_{2f} &= \zeta_2, & \zeta_{2f}(0) &= 0 \end{aligned} \quad (7)$$

$$\dot{x}_{2f} = \frac{x_2 - x_{2f}}{k} \quad (8)$$

This allows the second state equation to be re-written as:

$$\frac{x_2 - x_{2f}}{k} = \phi_f \Theta + \zeta_{2f} \quad (9)$$

3.3 Novel Observer-Based Parameter Estimation Method

Part of the estimation structure is dependent on an observer using the parameterised vehicle dynamics [equation \(3\)](#):

$$\dot{\hat{\mathbf{x}}} = \mathbf{A}\hat{\mathbf{x}} + \mathbf{B}_1 \mathbf{u}_1 + \mathbf{B}_2 \phi \Theta + \mathbf{L}(\mathbf{y} - \mathbf{C}\hat{\mathbf{x}}) \quad (10)$$

The key elements of the estimation structure developed by Na, Mahyuddin *et al* [28][29][30] are a gradient descent type of algorithm based on the observer error and a regressor-driven structure R made up of terms responsible for finite and exponential time convergence. They are effectively driven by the parameter error, due to a relationship discussed later in this paper.

$$\dot{\hat{\Theta}} = \Gamma \left[\underbrace{\phi^T F(\mathbf{y} - \mathbf{C}\hat{\mathbf{x}}) - R(t)}_{\text{ObserverError}} \right] \quad (11)$$

$$R(t) = \underbrace{M(t)\omega_1 \Omega \frac{M(t)\hat{\Theta} - N(t)}{\|M(t)\hat{\Theta} - N(t)\|}}_{\text{FiniteTimeConverging}} + \underbrace{M(t)\omega_2 \Omega (M(t)\hat{\Theta} - N(t))}_{\text{ExponentialTimeConverging}} \quad (12)$$

where M is a filtered regressor-based matrix

$$\dot{M}(t) = -k_{ff} M(t) + k_{ff} \phi_f^T(t) \phi_f(t), \quad M(0) = 0 \quad (13)$$

and N is the corresponding filtered regressor-based vector

$$\dot{N}(t) = -k_{ff} N(t) + k_{ff} \phi_f^T(t) \kappa, \quad N(0) = 0 \quad (14)$$