

Accuracy and Robustness of Parallel Vehicle Mass and Road Grade Estimation

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ABSTRACT

A variety of vehicle controls, from active safety systems to power management algorithms, can greatly benefit from accurate, reliable, and robust real-time estimates of vehicle mass and road grade. This paper develops a parallel mass and grade (PMG) estimation scheme and presents the results of a study investigating its accuracy and robustness in the presence of various noise factors. An estimate of road grade is calculated by comparing the acceleration as measured by an on-board longitudinal accelerometer with that obtained by differentiation of the undriven wheel speeds. Mass is independently estimated by means of a longitudinal dynamics model and a recursive least squares (RLS) algorithm using the longitudinal accelerometer to isolate grade effects. To account for the influences of acceleration-induced vehicle pitching on PMG estimation accuracy, a correction factor is developed from controlled tests under a wide range of throttle levels. The estimation approach is applied to data collected while driving on public roads under a variety of driving conditions, replicating several noise factors associated with daily driving. Thresholds are developed to isolate driving events that are likely to result in quick and accurate mass estimates, and an averaging filter is then applied to these converged values. The algorithm is shown to rapidly deliver estimates within 3% of true vehicle mass.

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INTRODUCTION

Inertial parameters of road vehicles have a significant influence on their handling, comfort, and energy efficiency. As the industry sees increasing automation of vehicle subsystems, accurate knowledge of inertial parameters is essential to ensuring passenger safety while enhancing vehicle performance. Vehicle mass and road grade represent two crucial parameters whose inertial effects influence a wide variety of vehicle dynamics, including longitudinal, lateral, and vertical motions [1]. Many vehicle control systems both in production and proposed in the literature assume an explicit knowledge of vehicle mass, or use an adaptive framework to compensate for parametric error. Accurate knowledge of vehicle mass is thus expected to facilitate optimal performance of current and future vehicle controls, including active safety and collision avoidance systems, adaptive cruise control and platooning, as well as energy management systems in hybrid and electric vehicles [2].

Without an accurate parameter estimate, a baseline value for vehicle mass must be assumed. However, common passenger and cargo loading conditions may cause variations in mass of up to 50% for small cars from trip to trip, while light trucks and cargo vans may vary in mass by up to 400% [3]. Various vehicle control systems may

employ adaptive algorithms to mitigate the effects of parameter uncertainty, but it is advantageous to have a single, accurate, on-line estimate of vehicle mass and road grade applied across controller platforms. This avoids redundant computations and conflicting parameter estimates that could compromise the performance of a supervisory controller coordinating the behavior of multiple subsystems [4]. While there have been numerous reported studies on inertial load estimation employing several prediction methods and modeling approaches [5, 6, 7, 8, 9], those that rely on production-grade sensors are most commonly based on longitudinal dynamics models due to the many common driving scenarios for which such models apply. Estimation approaches using longitudinal dynamics include recursive least squares (RLS) with multiple forgetting factors [3, 10, 11], extended Kalman filtering (EKF) [12], a dynamic grade observer (DGO) requiring only longitudinal acceleration and an estimate of powertrain torque [13], and a grade estimator using kinematic information provided by a longitudinal accelerometer [14]. Upon systematic evaluation of these methods under controlled conditions, it is found that the additional kinematic information provided by a production-grade longitudinal accelerometer facilitates accurate, parallel estimation of vehicle mass and road grade [15].

Since a longitudinal accelerometer is included in the standard vehicle sensor suite for today's vehicles, parallel mass and grade (PMG) estimation represents a viable strategy.

To bridge the gap between academic investigations and industry implementation of an accurate and reliable vehicle mass estimation scheme, a thorough robustness study of PMG estimation is undertaken. The goals are to identify and address impediments to accurate estimation, assess estimator robustness and accuracy under a wide range of driving conditions, and use the findings to improve estimator performance. First, a longitudinal dynamics model is introduced. Then, the details of parallel mass and grade estimation are presented. The grade estimator compares the kinematic data acquired by a longitudinal accelerometer with the acceleration as calculated from a numerical differentiation of vehicle speed, while the mass estimation portion uses a single variable recursive least square (RLS) formulation. A deeper evaluation of PMG estimation is performed using data gathered on public roads with the algorithm being applied to short segments of data in order to study the influence of specific driving conditions and events on estimator performance. Results from this study are then used to motivate the application of thresholds on acceleration or weighting factors based on acceleration signal magnitude. Finally, sensitivities to various parametric uncertainties are discussed, and concluding remarks discuss possible extensions of the presented work.

LONGITUDINAL DYNAMICS MODEL

Longitudinal motion dominates for typical driving scenarios, and hence its measurement provides near-continuous data that may be used for real-time estimates of vehicle mass and road grade. Fig. 1 depicts forces that influence a vehicle's longitudinal dynamics. The propulsive tractive force due to tire-road interactions is denoted by F_w . A no-slip condition is assumed, so tractive force may be expressed as $F_w = T_w/r_w$, where T_w is wheel torque and r_w is the effective tire radius. Other forces influencing longitudinal motion include aerodynamic drag F_{aero} , rolling resistance F_μ , inertial forces F_{grade} due to road grade, and braking tractive forces F_{fb} .

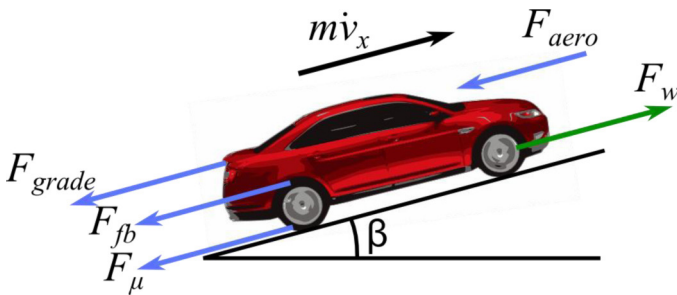


Figure 1. Forces influencing the longitudinal motion of a vehicle.

From these assumptions, the longitudinal dynamics of a vehicle may be expressed through Newton's 2nd law as:

$$m\dot{v}_x = \frac{T_w}{r_w} - \frac{1}{2}\rho C_d A_f v_x^2 - mg(\mu + \sin \beta) \quad (1)$$

where m is vehicle mass; v_x is longitudinal velocity; ρ is the density of air; C_d is the vehicle's drag coefficient; A_f is the vehicle's frontal area, g is the gravitational constant, μ is the vehicle's rolling resistance, and β is road grade. In this study, the propulsive wheel torque T_w is determined by using a magneto-elastic torque sensor on the transmission output shaft [16] and multiplying this signal by the final drive ratio.

$$T_w = T_{sensor} * f_{dr} \quad (2)$$

If the vehicle is equipped with a longitudinal accelerometer, road grade may be computed by comparing measured acceleration a_x with the differentiated longitudinal velocity $\dot{v}_x$. When the accelerometer is tilted from the horizontal plane by an angle β , the component of gravity projected onto its measurement axis is $g \sin(\beta)$ [14, 17].

$$a_x = \dot{v}_x + g \sin(\beta) \quad (3)$$

The parallel mass and grade (PMG) estimation method takes advantage of this relationship to independently estimate vehicle mass and road grade [15]. The kinematic information provided by a longitudinal accelerometer allows direct extraction of road grade information according to eq. (3). Substitution of eq. (3) into eq. (1) eliminates the explicit road grade angle β from the longitudinal model.

$$m(\dot{v}_x + g(\mu + \sin \beta)) = \frac{T_w}{r_w} - \frac{1}{2}\rho C_d A_f v_x^2 \quad (4)$$

$$m(a_x + \mu g) = \frac{T_w}{r_w} - \frac{1}{2}\rho C_d A_f v_x^2 \quad (5)$$

Denoting the right-hand side of equation (5) by ϕ , and isolating for vehicle mass gives:

$$m = \frac{\phi}{a_x + \mu g} \quad (6)$$

Vehicle mass estimates are updated using eq. (6) and a single-variable recursive least squares algorithm with a forgetting factor γ chosen close to $\gamma = 1$, reflecting the fact that vehicle mass is considered to be a constant parameter over the course of a trip [18].

DATA COLLECTION PROCEDURE AND ESTIMATOR EVALUATION STRATEGY

To enable an evaluation of the proposed mass estimation method, data is collected on a 2014 Ford F-150 at Ford's Dearborn Development Center and surrounding public roads in Dearborn, MI. The vehicle is equipped with a magneto-elastic torque sensor mounted to the output shaft of the transmission, while the longitudinal accelerometer is part of the standard inertial sensor suite. Signals from the powertrain control module (PCM) and controller area network (CAN) are collected and stored using a data acquisition module and ATI Vision, then processed offline in

MATLAB. All offline computations are causal, reflecting the constraints of real-time estimation. The test route along public roads in Dearborn is shown in Fig. 2, with the green and red circles indicating start and end locations, respectively, and the blue line showing the route followed. The route features segments on local streets, arterial roads and a freeway. The corresponding velocity profile is depicted in Fig. 3. The velocity profile shows periods of uninterrupted high speeds on freeway and arterial road segments, as well as acceleration and braking events due to traffic lights and stop signs on local roads. The vehicle parameters required for application of PMG are presented in Table 1. Drag and rolling resistance coefficients are obtained from coast-down tests at Ford's Dearborn Development Center, while the wheel radius is calculated by comparing accelerometer measurements with vehicle velocity measurements.

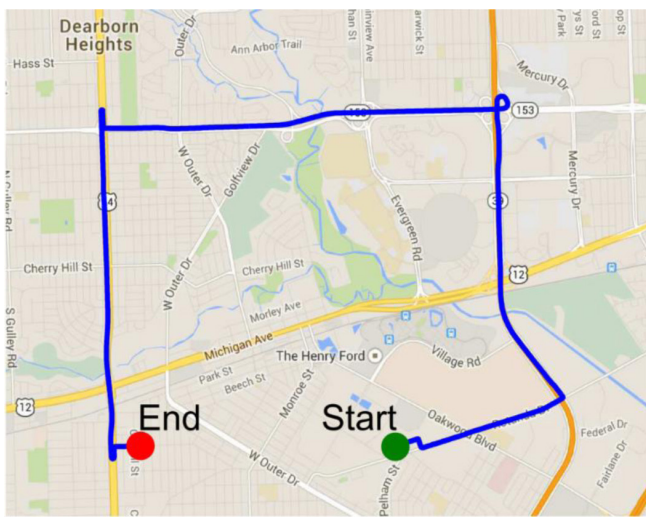


Figure 2. "Drive-around" route in Dearborn, MI. Green and red circles indicate start and end locations, respectively.

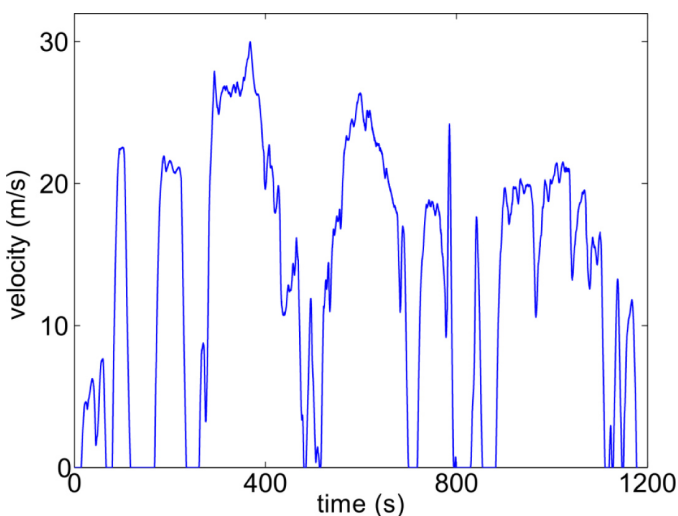


Figure 3. Velocity profile for route shown in Fig. 2.

Table 1. Vehicle longitudinal model parameters.

$\frac{1}{2} \rho C_d A_f [kg \cdot s^{-1}]$	μ	$\frac{fdr}{r_w} [m^{-1}]$
0.541	0.012	8.90

To identify how different driving events influence estimation accuracy, the data is segmented into smaller periods of time and estimates during each of these short segments are evaluated separately. After each period t_{est} the RLS estimator for vehicle mass is re-initialized by resetting the initial estimate and covariance. The grade estimation portion of PMG is unaffected by the segmentation of data into intervals since it requires no initialization. Mass estimation is enabled under the following conditions, where eq. (1) is assumed to govern the vehicle's longitudinal motion:

1. $v > v_{min}$: Vehicle speed above minimum threshold.
2. Brakes not applied.
3. Gear shift not in progress.
4. $\delta < \delta_{max}$: Steering angle below a maximum threshold.

Since the grade estimation portion of PMG relies purely on kinematic data and is continuously updated, it is not subject to the constraints described above.

PRELIMINARY RESULTS AND CORRECTION OF ACCELERATION-INDUCED VEHICLE PITCHING

In order to observe preliminary trends regarding the accuracy PMG estimation, the estimates obtained after each short interval t_{est} following the route shown in Fig. 2 are plotted as histograms in Fig. 4. Fig. 4a shows values to which the RLS algorithm converges at the end of each estimation interval of duration $t_{est} = 5s$, and the true vehicle mass of 2984 kg is indicated by the dashed vertical line. Fig. 4b shows the average grades over 1-second intervals. These preliminary results indicate that mass is generally under-estimated over the chosen estimation intervals. While instrumentation to precisely measure road grade is not available in the test vehicle, it appears that the road grade is overestimated with a mean value near 1%, rather than near 0 as would be expected along the mostly flat route.

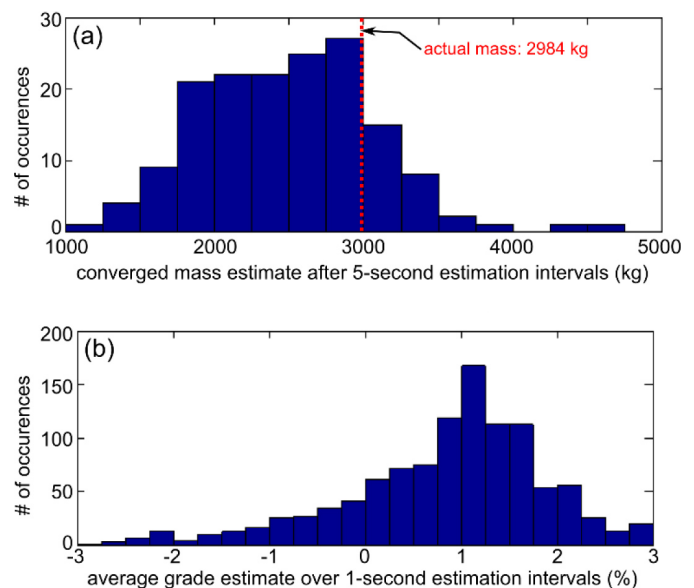


Figure 4. Histograms of (a) converged vehicle mass estimates after each 5s interval and (b) average grade estimate over 1s intervals. Data is collected from test whose route is shown in Fig. 2. Red line shows true vehicle mass (2984 kg).