Proceedings of IMECE'03
2003 ASME International Mechanical Engineering Congress
Washington, D.C., November 15–21, 2003

IMECE2003-43848

# EXPERIMENTS FOR ONLINE ESTIMATION OF HEAVY VEHICLE'S MASS AND TIME-VARYING ROAD GRADE

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## ABSTRACT

In this paper application of recursive least squares with multiple forgetting factors is explained for online estimation of Heavy Duty Vehicle mass and road grade. The test data is obtained from highway experiments with a Freightliner truck. The experimental setup is explained in detail. This data is used to validate the longitudinal dynamics model of the truck. Then two distinct driving cycles are used to investigate the performance of the mass and grade estimation scheme. In the first scheme no gear shift occurs and the only concern is persistence of excitations. It is shown that if the excitations are persistent, mass and time-varying grade are estimated with good accuracy. In the second cycle gearshifts occur and the challenge is the unmodelled dynamics during gearshifts which cause large overshoots in the estimates. A method is proposed to circumvent this problem and good estimation results are shown with this provision.

## Introduction

Strong federal initiatives for increasing the efficiency and safety of today's vehicle, and also marketing strategies in industry, has fuelled extensive research for automation of part of the human driver tasks. Control strategies have been developed along with improvements in sensor technology. Issues like ergonomics and legal barriers have also been studied. Heavy duty vehicles have received particular attention due to the higher impact that automation has on the fleet efficiency and fuel economy. Strategies like platoonning for a fleet of HDV's have been experimented and have shown promising outcomes. However closed loop experiments [1] indicate that longitudinal controllers with fixed gains have limited capability in handling large parameter variations of an HDV. An adaptive control approach with an implicit or explicit online estimation scheme for estimation of unknown vehicle parameters can ensure a much better performance [2–4]. Examples of adaptive controllers for vehicle control applications can be found in the work by Liubakka et al. [5], Ioannou et al. [6], and Oda et al [7].

Among the parameters that largely influence a vehicle's performance, mass and road grade are the most important. The mass varies largely from trip to trip and mild grades can be serious loadings for an HDV. It is therefore important to estimate mass and road grade explicitly or implicity. In addition to the speed controller, many other controllers like the transmission control unit and the anti-lock brake system can benefit from these estimates. The vehicle mass can be accurately estimated by conventional parameter-adaptive algorithms as long as the road grade information is available (e.g., driving on a road with zero grade, using road map information and satellite communication, or using a GPS antenna to estimate the grade [2], [8]). In [9] using an onboard accelerometer is proposed for grade estimation. The mass is then estimated based on this estimate of the grade. The adaptive scheme proposed in [3] provides simultaneous mass and road grade estimation without additional sensors or measurements of the grade under the assumption of constant road grade.

In a previous paper, the authors proposed a recursive least square scheme with forgetting for online estimation of mass and time-varying grade and showed good results in simulation [10]. The scheme uses vehicle's longitudinal dynamics, engine torque

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and vehicle speed available through the CanBus for simultaneous estimation of mass and grade. To capture the time variations of grade, different forgetting factors for grade and mass were introduced in the recursive least square scheme.

In this paper we demonstrate the performance of this algorithm with experimental data. The formulation of problem is discussed briefly in the next section and the rest of the paper is dedicated to application of the algorithm to experimental data. The data is obtained during two days of highway tests with an experimental HDV owned by California PATH [1]. The measured data, its sources and available standards to interpret the raw data are discussed. Identification of unknown parameters like rolling resistance and drag coefficient based on the test data is explained next and the model of the longitudinal dynamics of the truck is validated with the test data. Then recursive least square with vector-type forgetting is applied to the data for estimation of mass and grade. New challenges, compared to estimation with simulated data, include lack of persistent excitations during normal cruise and model mismatch during gearshift. Ways to avoid these problems are proposed. Good estimation results are shown with experimental data in two driving cycles, with and without gearshifts. Sensitivity of these estimates to other vehicle parameters is also analyzed.

## The Estimation Scheme

The estimation algorithm relies on a model of vehicle longitudinal dynamics. The dynamics of engine rotational speed, $\omega$, can be described as follows:

$$r_g^2\dot{\omega} = (T_e - T_{fb} - T_{aero} - J_e\dot{\omega})\frac{1}{M} - \frac{gr_g^2}{\cos\beta_\mu}\sin(\beta+\beta_\mu) \qquad (1)$$

where $r_g = \frac{r_w}{g_d g_f}$, $r_w$ is the wheel radius, $g_d$ is the gear ratio and $g_f$ is the final drive ratio. $J_e$ is the engine crankshaft inertia, $M$ is the total mass of the vehicle, $\mu$ is the coefficient of rolling resistance and $g$ is the acceleration due to gravity. $T_e$ is the engine torque. The torque due to aerodynamic resistance is given by

$$T_{aero} = C_q v^2 r_g = C_q r_g^3 \omega^2,$$

in which $C_q$ is the aerodynamic drag coefficient. The engine speed is proportional to the vehicle speed, i.e. $v = \omega r_g$ as long as the wheels do not slip and the gear is fixed. $\beta$ is the road grade, $\beta = 0$ corresponds to no inclination, $\beta > 0$ corresponds to uphill grades. $\beta_\mu$ is defined by $\tan\beta_\mu = \mu$. We can rewrite Eq. 1 in the following linear form,

$$y = \phi^T\theta, \quad \phi = [\phi_1 \;\; \phi_2]^T, \quad \theta = [\theta_1 \;\; \theta_2]^T \qquad (2)$$

[1] Partners for Advanced Transit Highways

where

$$\theta = [\theta_1, \theta_2]^T = [\frac{1}{M}, \quad \sin(\beta+\beta_\mu)]^T$$

is the parameter of the model to be determined and

$$y = r_g^2\dot{\omega}, \quad \phi_1 = T_e - T_{fb} - T_{aero} - J_e\dot{\omega}, \quad \phi_2 = -\frac{gr_g^2}{\cos\beta_\mu}$$

can be calculated based on measured signals and known variables.

In the classical recursive least square with forgetting $\theta$ is selected such that it minimizes the following loss function:

$$V(\theta,k) = \frac{1}{2}\sum_{i=1}^{k}\lambda^{k-i}\left(y(i) - \phi^T(i)\theta(k)\right)^2 \qquad (3)$$

where $\lambda$ is a positive parameter smaller than 1 and is called the forgetting factor. It is introduced to discard older information in favor of newer information. The recursive solution is [11]:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + L(k)\left(y(k) - \phi^T(k)\hat{\theta}(k-1)\right) \qquad (4)$$

where

$$L(k) = P(k)\phi(k) = P(k-1)\phi(k)\left(\lambda I + \phi^T(k)P(k-1)\phi(k)\right)^{-1}$$

and

$$P(k) = \left(I - L(k)\phi^T(k)\right)P(k-1)\frac{1}{\lambda}.$$

The least-square method with exponential forgetting, as described above, is suitable for keeping track of parameters varying with similar rates. It was shown in [10] that least square with a single forgetting does not converge when the grade is constantly changing. There we proposed using two distinct forgetting factors one for mass and one for grade. We employ a vector-type forgetting scheme [12–14] in updating the covariance matrix, $P(k)$, which bypasses the limitation of a single forgetting factor [10]. In this scheme the covariance matrix $P$ is updated in the following way:

$$P(k) = \Lambda^{-1}\left(I - L(k)\phi^T(k)\right)P(k-1)\Lambda^{-1} \qquad (5)$$

where $\Lambda = diag(\sqrt{\lambda_1}, \sqrt{\lambda_2})$ and $\lambda_1$ and $\lambda_2$ are the forgetting factors for the first and second parameters respectively. Choosing two values for $\lambda_1$ and $\lambda_2$ will allow more degrees of freedom in the update of the two entries of $L(k) = [L_1(k), L_2(k)]$ and enhances the stability of the classical method quite noticeably. In the next sessions this algorithm is used with test data to estimate vehicle mass and road grade.

## Experimental Setup

We planned experiments on a Freightliner truck owned by California PATH [2]. The signals are measured through different interfaces. The vehicle CanBus is responsible for communication between the engine and powertrain controllers. Many of the signals are obtained by accessing the CanBus. The signals are transferred under certain standards set by SAE [3]. Currently the J1939 [15] and its extensions like J1939-71 [16] are standard for heavy duty vehicles. Older equivalents are SAE J1587 for powertrain control applications. Other sources of data are EBS, GPS and customized sensors installed by PATH staff. The EBS is the electronic brake control system and measures signals like wheel speed. A GPS antenna is available on the PATH truck that provides, longitude, altitude and latitude coordinates as well as the truck's cruise speed. A few sensors had been installed on the truck including accelerometers in x, y and z directions, tilt sensors,and pressure transducers for measuring brake pressure at the wheels.

The real time QNX operating system was used for data acquisition. The system was wired to the Canbus and other sensors and data was sampled at 50 Hz. A computer specialist monitored the flow of data and logged the instructions and actions by the driver and other researchers in a text file that was available to us after the test. The whole test was carried out open-loop except for some periods when cruise control was activated. Each run concentrated on gathering data required for identification of one or more components such as service brakes, compression brake, gear scheduling, etc. For successful identification we made sure that the dynamics is sufficiently rich, many times by asking the driver to pulse the commands like throttle and braking. To generate different loading scenarios, the loading of the trailer was decreased gradually from full to empty in stages during the test. At each stage the total mass of the truck was known. Abundant amount of data in distinct driving scenarios was obtained during two days of test. In the next sections we explain how the data was used for system identification and parameter estimation.

## Measured Signals

Numerous signals are recorded during the experiments, using different sensors, each with certain degree of accuracy, and different levels of noise. The update rates and sampling rates for the signals might also vary from one to the other based on the sensors and the port they are read from. In this section we discuss the source and accuracy of data. Then we proceed to estimate the parameters based on this measured data.

Velocity is available from J1939 as well as the EBS sensors which measure the wheel speed. GPS also provides an accurate measure of the velocity. Engine speed is known from J1939 with good accuracy. Engine torque, compression brake and transmission retarder torques are available through the J1939 port. These engine and compression braking torques are calculated based on static engine maps and do not reflect the very fast dynamics of the engine. However they are fast enough for our purpose. Also J1939 provides an approximate value for torque losses. This value is used to calculate the net engine torque. Pressure transducers are installed to measure brake pressure at the wheels. Determining the actual force developed by service brakes will depend on a model that translates the pressure into a torque. At this stage we do not have such a model and therefore in our analysis we will dismiss portions of data in which service brakes were activated. The transmission status is available form J1939. That determines if the driveline is engaged and whether the torque convertor is locked or if a shift is in process. The driveline is always flagged engaged when not in neutral. The torque convertor was shown locked whenever the vehicle was in the third or a higher gear. Shift in process denotes the period of a gear shift when the transmission controller is in effect. The gear number could not be accessed through J1939 at the time of the test. So the J1587 port was used to get the gear numbers. Each gear ratio and the final drive ratio were available from the transmission manufacturer and were verified by comparing the engine and wheel speed.

The signals recorded from the accelerometers were noisy and therefore we decided not to use these signals for obtaining accelerations. Also the signals recorded from tilt sensors had a small signal to noise ratio and therefore we could not investigate possibility of using tilt sensors for measuring the road grade. The actual road grade was extracted from the profile plans of the road.

## Road Grade

The road tests were carried out on a part of the HOV lane of Interstate 15 north of San Diego. Within the two days of test, various driving cycles were completed in a number of round trips on a twelve kilometer stretch of highway. The test route included some overpasses with steep grades. This grade was later determined using the road plans and served as a comparison with the estimated grade. Although the GPS elevation signal was available in the test-run, the information was often noisy or corrupted as shown in the upper subplot of figure 1. The most accurate source for the road grade is the as-built plan available for roads and highways. Therefore we obtained the profile plans of the experiment route from CALTRANS[4]. We then carefully digitized

[2]Partners for Advanced Transit and Highways
[3]Society of Automotive Engineers
[4]California Department of Transportation

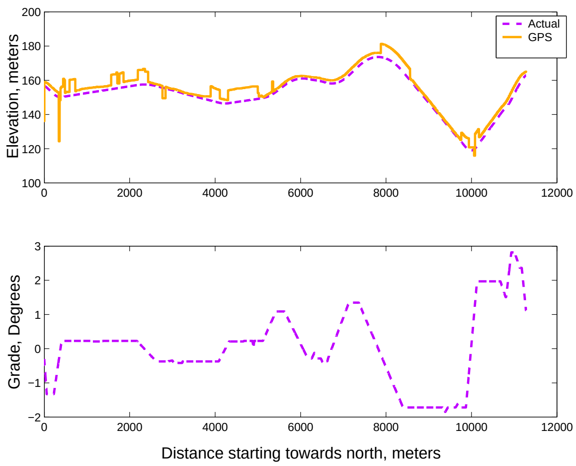


Figure 1. Digitized road elevation and grade.

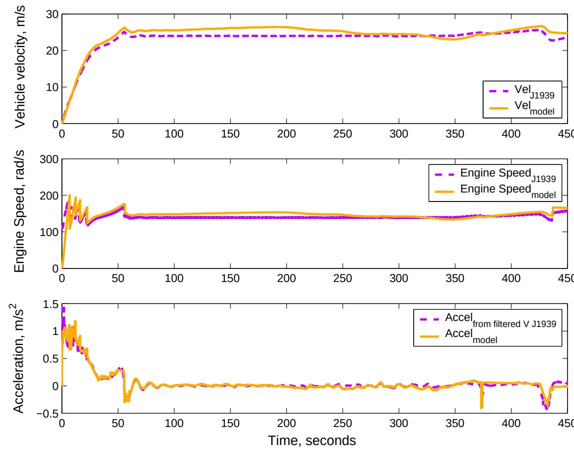


Figure 2. Comparison of the model and real longitudinal dynamics.

the plans and determined the grade based on the elevations. Figure 1 shows the digitized elevation and grade. Note that the grade is either constant or varies linearly with distance. That is a natural result of highway design where the transition between slopes are parabolic. We used the information from GPS to determine the starting point of each test run on the digitized elevation map.

## Determining Unknown Parameters

A range for values of drag coefficient and coefficient of rolling resistance for different vehicles is available in handbooks of vehicle dynamics (e.g. [17]). To select the values that fit our available data we used longitudinal dynamics equation (1) and tuned the parameters of the model to make the outcomes match the experimental data as closely as possible. The model used the engine or the retarder torque, the road grade and the selected gear that were recorded during the test and based on these inputs the accelerations were calculated. The accelerations were compared to the accelerations obtained from the test data. The drag coefficient and rolling resistance were tuned in the feasible range so that calculated and actual accelerations roughly matched each other. We found coefficient of rolling resistance of 0.006 and drag coefficient of 0.7 suitable candidates that result in good match between experiments and simulation. The calculated values are within the reasonable range defined in vehicle handbooks. Figure 2 shows a typical test run with good match between test data and simulation results for most part of the trip. During gear changes experiments and simulation results do not have a good match. This is due to the fact that gear shift dynamics is not considered in the longitudinal dynamics model. In the model we have assumed that velocity and engine speed are always proportionally related and that transmission is always engaged. These assumptions only result in local mismatch between model and experiments and in general the model represents the longitudinal dynamics adequately well. We see that the steady-state speed predicted by the model is slightly larger than the actual speed at steady-state. That could be due to assuming locked status for the torque converter in the model at all times. This will result in overestimating the speed.

Having identified the model of vehicle longitudinal dynamics, we now can use this model for mass-grade estimation.

## Performance of the Estimator with Experimental Data

In the previous sections of this paper, the estimation problem was formulated and a solution was proposed. In [10] the authors had shown that this scheme works well with simulated data. In a real scenario the situation can become more challenging due to higher level of uncertainties. The signals are potentially delayed and many times the signals are noisy and biased in one direction rather than being only affected by pure white noise. Moreover, the delay or noise level in one signal is normally different from the other signals. Finally, note that what is available from sources like J1939 is normally not the true value of an entity but an estimate of the true value through the vehicle/engine management system. Unmodelled dynamics of the system might result in poor estimation.

The signals in a natural experimental cycle may not always be persistently exciting. As discussed before lack of good excitation results in poor estimates or even cause estimator windup. In our case, if the acceleration is constant and there is no gear change, we are not able to observe enough to determine both mass and grade. In this case the longitudinal dynamics equation represents essentially a single mode, making it literally impossible to estimate the two unknowns. Therefore it is important that in online estimation, rich pieces of data are detected and used for estimation of both parameters. Once a good estimate for mass which is constant is obtained tracking of variations of grade would be possible even during low or constant levels of acceleration.

### Modification for Reducing Signal Noise Effect

Direct implementation of (1) in least square estimation requires differentiation of velocity and engine speed signals. If the measurements are prone to noise, differentiation is not very appealing. It will magnify the noise levels to much higher values and the differentiated data may not be useable. In order to circumvent this problem we will first integrate both sides of (1) over time and apply the estimation scheme to the new formulation. Assuming that mass and coefficient of rolling resistance are constant, integration of both sides yields:

$$v(t_k) - v(t_0) = \frac{1}{M}\int_{t_0}^{t_k}\left(\frac{T_e(t)-J_e\dot{\omega}(t)}{r_g(t)} - F_{fb}(t) - F_{aero}(t)\right)dt - \frac{g}{\cos(\beta_\mu)}\int_{t_0}^{t_k}\sin(\beta+\beta_\mu)dt \tag{6}$$

where $t_k$ is the current time. We can rewrite the above equation in the form of (2),

$$y = \phi^T\theta, \quad \phi = [\phi_1, \phi_2]^T, \quad \theta = [\theta_1, \theta_2]^T$$

where this time,

$$y(k) = v(t_k) - v(t_0)$$

$$\theta = [\theta_1, \theta_2]^T = [\frac{1}{M}, \quad \frac{\int_{t_0}^{t_k}\sin(\beta+\beta_\mu)dt}{(t_k - t_0)}]^T$$

and

$$\phi_1 = \int_{t_0}^{t_k}\left(\frac{T_e - J_e\dot{\omega}}{r_g} - F_{fb} - F_{aero}\right)dt, \quad \phi_2 = -\frac{(t_k - t_0)g}{\cos(\beta_\mu)}$$

Notice that $\phi_2$ is multiplied by $(t_k - t_0)$ and $\theta_2$ is divided by it. This is to keep the unknown parameter $\theta_2$ away from growing fast with time. In this fashion if the grade, $\beta$, is constant, $\theta_2$ will remain constant as well. $\phi_1$ is calculated recursively at each sampling time using its previous value and trapezoidal integration for the last sampling period. Employing integration instead of differentiation helped avoid some serious issues related to signal noise.

### Estimation in Normal Cruise: No Gearshift

We first evaluate the estimation scheme with experimental data when the gear is constant. A batch of data is used in the first few seconds of estimation to initialize the estimation scheme. Good initial estimates are obtained only when the chosen batch is rich in excitations. Better estimates can be obtained with a smaller batch when the acceleration has some kind of variation during the batch. The RLS with vector-type forgetting was used during the rest of the travel for estimation and tracking.

To reduce the high frequency noise, the torque and velocity signals were passed through a second order butterworth filter before they were used in the estimation. The sampling frequency is 50 Hz, and therefore the Nyquist frequency is 25 Hz. We use the cutoff frequency of 25 Hz for the filter, to ensure that aliasing will not occur. Figure 3 shows the estimation results for more than five minutes of continuous estimation. The gear was constant throughout this period. The initial four seconds of data was processed in a batch to generate the initial estimates. For the recursive part, forgetting factors of 0.95 and 0.4 were chosen for mass and grade respectively. The forgetting factors are chosen based on the anticipated rate of change of parameters. When parameters vary with different rates it is important to reflect their relative rate of change in the size of forgetting factors. Small forgetting factor for the grade reflects its faster rate of variation. Since mass is constant forgetting factor of 1 would be suitable. However the forgetting factor of 0.95 acts as a damping effect on the older information and makes the mass estimate a little more responsive to new information. This showed to result in further convergence of mass to its true value. In this estimation the root mean square (RMS) error in mass is 350 kg and the maximum error is 2.8%. During the recursive section the error in mass reduces down to a maximum of 1.7%. The RMS error in grade is 0.2 degrees. It can be seen that grade is estimated well during its

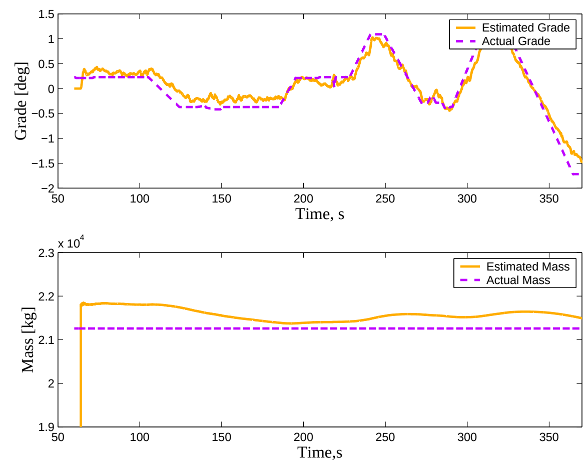


Figure 3. Estimator's performance during normal cruise when the gear is constant. Forgetting factors for mass and grade are 0.95 and 0.4 respectively. RMS error in mass is 350 kg and RMS grade error is 0.2 degrees.

variations.

Next we will remedy the estimation problem when gear changes occur.

## Estimation Results During Gearshift

In the longitudinal dynamics Eq. (1) we assume that engine power passes continuously through the driveline to the wheels. This assumption is valid only when the transmission and torque convertor are fully engaged. During a gear change, transmission disengages to shift to the next gear and during this time the flow of power to the wheels is reduced and in the interval of complete disengagement no torque is passed over to the wheels. Moreover the assumption that vehicle speed is proportional to the engine speed by some driveline ratio is not in effect during this transition and engine speed goes through abrupt changes while the change in vehicle velocity is much smoother. Therefore relying on (1)

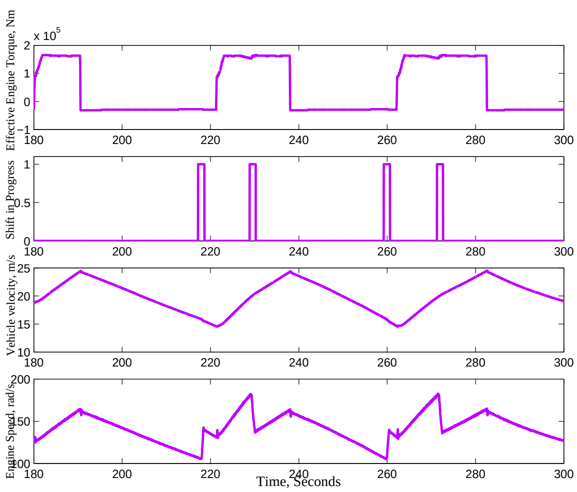


Figure 4. The response during a cycle of pulsing the throttle

for estimation will result in very big deviations during gearshift. The bigger the deviations are the longer it takes the estimator to converge back to the true parameter values.

Modelling the dynamics during a shift is not simple due to natural discontinuities in the dynamics. Besides the period when the transmission is in control does not take more than two seconds and therefore it is not really necessary to estimate the parameters during this short period. Therefore we decided to turn off the estimator at the onset of a gearshift and turn it back on a second or two after the shift is completed. The estimates during the shift are set equal to the latest available estimates. Also the new estimator gain is set equal to the latest calculated gain. This approach proved to be an effective way of suppressing unwanted estimator overshoots during gear shift. Figure 4 shows the engine torque, shift status, vehicle velocity and engine speed during part

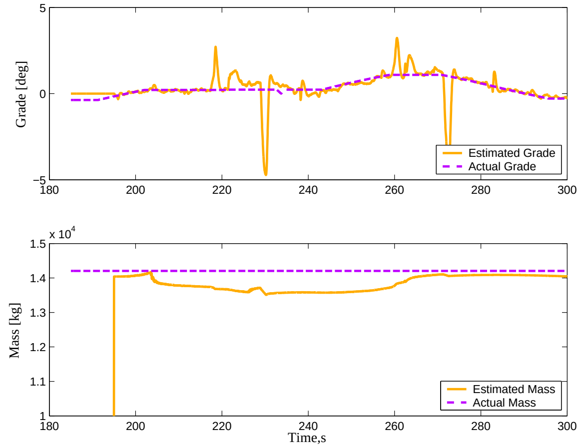


Figure 5. Estimator's performance when it is always on. Forgetting factors for mass and grade are 0.95 and 0.4 respectively. The RMS errors in mass and grade are 420 kg and 0.77 degrees respectively.

of an experiment. We had asked the driver to pulse the throttle off and on and therefore as seen in the torque plot, the torque is either at its maximum or drops down to zero. Also two gear shifts occur during this time window. As mentioned before the variations in velocity are smooth but the engine speed has jump discontinuities both during gear shift and during the throttle on/off. Upon using the estimator with no on/off logic we observed big overshoots in the estimates during both the gearshift and the throttle on/off. The results are shown in Figure 5. The root mean square error in mass is 420 Kilograms and the RMS grade error is 0.77 degrees which is a large error. We then used the estimator with

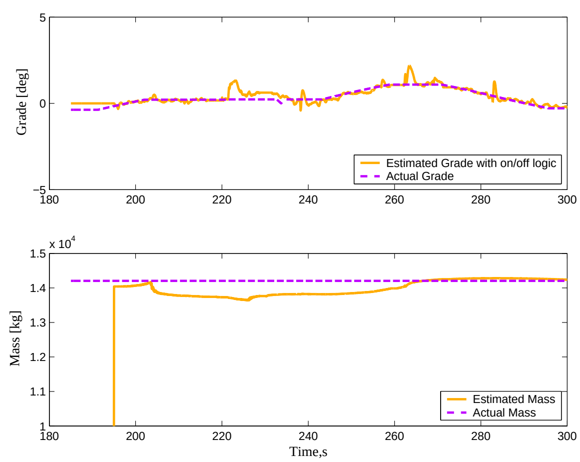


Figure 6. Estimator's performance when it is turned off during shift. Forgetting factors for mass and grade are 0.95 and 0.4 respectively. The RMS errors in mass and grade are 310 kg and 0.24 degrees respectively.

the on/off logic. The results are shown in figure 6. The estimation has improved considerably due to the estimator deactivation during the shifts. The deviations due to throttle pulsation exist as before but the magnitude of these deviations are small and they fade away quickly. In this estimation the root means square error in mass is 310 kilograms and the RMS grade error is 0.24 degrees which are quite improved due to the employed estimator logic.

## Sensitivity Analysis

Earlier in this paper the coefficient of rolling resistance and the drag coefficient were calculated based on matching the model outcomes and experimental results. We mentioned that these estimates are rough estimates that meet our needs. We are in general interested to know how much the mass and grade estimation results are sensitive to these parameters. In other words we want to analyze the sensitivity of the estimation scheme with respect to these parameters.

For this analysis, the rolling resistance and drag coefficient are varied one at a time and observe the performance of the estimates and based on these results provide a sense on the sensitivity of the system. We perform the analysis with the experimental set of data used in previous sections of this paper. Figure 7 shows the sensitivity of the estimates with respect to drag coefficient and rolling resistance. Variations in the coefficient of rolling resistance only affect the grade estimate. That is because the rolling resistance and grade affect the longitudinal dynamics in the same way. In a realistic range, a 50% variation of the coefficient of rolling resistance caused, in the worst case, less than 25% change in the RMS error of grade estimates. The drag coefficient selection influenced both mass and grade estimates. Here 25% change in drag coefficient within a feasible range, cause less than 25% change of error in grade and mass estimates.

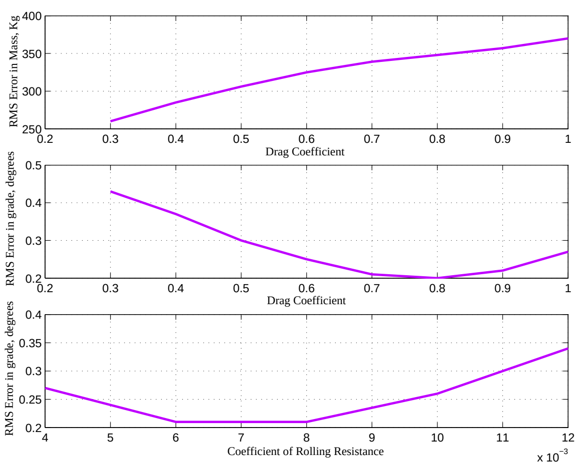


Figure 7. Sensitivity of the estimates with respect to drag coefficient and rolling resistance. Forgetting factors for mass and grade are 0.95 and 0.4 respectively. Nominal mass is 21250 kg.

## Conclusions

Results of simultaneous online estimation of a heavy vehicle mass and road grade with experimental data are shown in this paper. The test data was obtained from experiments that were carried out on Interstate 15 in San Diego in the August of 2002 with an experimental heavy duty vehicle. The experiment setup, the measured signals and their source and issues like sampling rate and accuracy are briefly discussed. Using this data we first verify that the vehicle model captures the longitudinal dynamics accurately for most part of travel. The RLS with multiple forgetting, proposed by the authors in a previous paper, proved effective with the experimental data. The real life issues like lack of persistent excitations in certain parts of the run or difficulties of parameter tracking during gear shift are explained and suggestions to bypass these problems are made. Without gear shift and in the presence of persistent excitations mass and grade are estimated with good precision and variations of grade are tracked. When gearshifts take place, the estimator shows large overshoots and it takes a few seconds for these deviations to damp out. We proposed turning off the estimator during and shortly after a gearshift. The estimation results are improved by this provision. Sensitivity analysis demonstrates that estimation is not overly sensitive to uncertain parameters of the system including drag coefficient and rolling resistance.

## Acknowledgement

This research is supported in part by the California Department of Transportation through the California PATH Program under TO 4234.

## REFERENCES

[1] D. Yanakiev, J. Eyre, and I. Kanellakopoulos. Longitudinal control of HDV's: Experimental evaluation. Technical Report MOU 293, PATH, 1998.

[2] H.S. Bae and J. Gerdes. Parameter estimation and command modification for longitudinal control of heavy vehicles. *Proc. of International Symposium on Advanced Vehicle Control*, 2000.

[3] M. Druzhinina, L. Moklegaard, and A. Stefanopoulou. Compression braking control for heavy-duty vehicles. *Proceedings of American Control Conference*, 2000.

[4] Y. Tan, A. Robotis, and I. Kanellakopoulos. Speed control experiments with an automated heavy vehicle. *Proceedings of the 1999 IEEE*, 1999.

[5] M.K. Liubakka, D.S. Rhode, J.R. Winkelman, and P.V. Kokotovic. Adaptive automotive speed control. *IEEE Transactions on Automatic Control*, 38, 7:146–156, 1993.

[6] P. Ioannou and Z. Xu. Throttle and brake control systems for automatic vehicle following. *PATH Research Report UCB-ITS-PRR-94-10*, 1994.

[7] K. Oda, H. Takeuchi, M. Tsujii, and M. Ohba. Practical estimator for self-

tuning automotive cruise control. *Proceedings of the American Control Conference*, pages 2066–2071, 1991.

[8] H.S. Bae, J. Ryu, and J. Gerdes. Road grade and vehicle parameter estimation for longitudinal control using GPS. *Proc.of IEEE Conference on Intelligent Transportation Systems*, 2001.

[9] H. Ohnishi, J. Ishii, M. Kayano, and H. Katayama. A study on road slope estimation for automatic transmission control. *JSAE Review*, 21:322–327, 2000.

[10] A. Vahidi, M. Druzhinina, A. Stefanopoulou, and H. Peng. Simultaneous mass and time-varying grade estimation for heavy-duty vehicles. *Proc. of American Control Conference*, 2003.

[11] A. Astrom and B. Wittenmark. *Adaptive Control*. Addison Wesley, second edition, 1994.

[12] J.E. Parkum, N.K. Poulsen, and J. Holst. Selective forgetting in adaptive procedures. *Proceedings of the 11th Triennial World Congress of the IFAC*, 2:137–142, 1990.

[13] Steiner Saelid, Olav Egeland, and Bjarne Foss. A solution to the blow-up problem in adaptive controllers. *Modeling, Identification and Control*, 6, 1:36–39, 1985.

[14] Steiner Saelid and Bjarne Foss. Adaptive controllers with a vector variable forgetting factor. *Proceedings of the 22nd IEEE Conference on Decision and Control*, pages 1488–1494, 1983.

[15] *Recommended Practice for a Serial Control and Communications Vehicle Network*. Society of Automotive Engineers, 1998.

[16] *Surface Vehicle Recommended Practice; Vehicle Application Layer*. Society of Automotive Engineers, 1998.

[17] J.Y. Wong. *Theory of ground Vehicles*. John Wiley and Sons, third edition, 2001.