Road Grade and Vehicle Parameter Estimation for Longitudinal Control Using GPS

Hong S. Bae[1], Jihan Ryu and J. Christian Gerdes

Abstract-- This paper demonstrates two methods for obtaining an estimate of road grade using a Global Positioning System (GPS) system on a ground vehicle. In the first method, two antennae are used to directly measure the attitude of the vehicle in the pitch plane; in the second method, the ratio of vertical to horizontal velocity at a single antenna is used to estimate road grade. Both methods are implemented experimentally and their relative sensitivities to corruption by vehicle pitch and bounce motion characterized. The resulting grade measurements are then used together with engine torque information to produce estimates of mass, rolling resistance and aerodynamic drag from a simple longitudinal force balance. The resulting mass estimation consistently converged to within ± 2 % of the true vehicle mass.

Index Terms-- Parameter estimation, GPS, pitch, road grade, command modification, automated highways, automated commercial heavy vehicles

I. INTRODUCTION

Longitudinal control systems such as Adaptive Cruise Control [7] or spacing control on an automated highway [8] require accurate models of a vehicle's longitudinal dynamics to achieve desired levels of safety and closed-loop performance. While basic models of longitudinal dynamics are well established and straightforward, the exact parameters of the models are rarely known. This uncertainty limits the accuracy of the system models and, ultimately, overall performance of closed-loop system. Since these parameters cannot be known in advance, they must be successfully identified while the vehicles are in operation in order to prevent such limitations. This is particularly important for automated highways where a number of vehicles may form a platoon and uncertainties can propagate as disturbances down the platoon.

Parameter variation plays an even larger role in automated control of heavy commercial vehicles (trucks, tractor-trailers and buses). Heavy vehicles generally exhibit larger variations in parameters such as vehicle mass (up to 500% differences between loaded and unloaded configurations) and aerodynamic drag than do passenger cars [4,5]. These facts highlight the need for estimation of mass and drag forces on a heavy vehicle.

Another variable that has a profound effect on vehicle performance is the road grade. Modest road grades may prove to be quite a challenge for vehicles with low power-to-weight ratio such as automated commercial heavy vehicles. Figure 1 shows the relative capability of a heavy truck engine and the demands from grade and aerodynamics as a function of speed. At highway speeds (about 20 m/s), a typical commercial heavy vehicle has little capability for acceleration in reserve since most of the engine output must go to counteract aerodynamic drag and rolling resistance. A 4% road grade can be a severe loading to such vehicles. This is why, in most cases, heavy vehicles have to slow down considerably going up steep grades, sacrificing speed in order to get more power from engine.

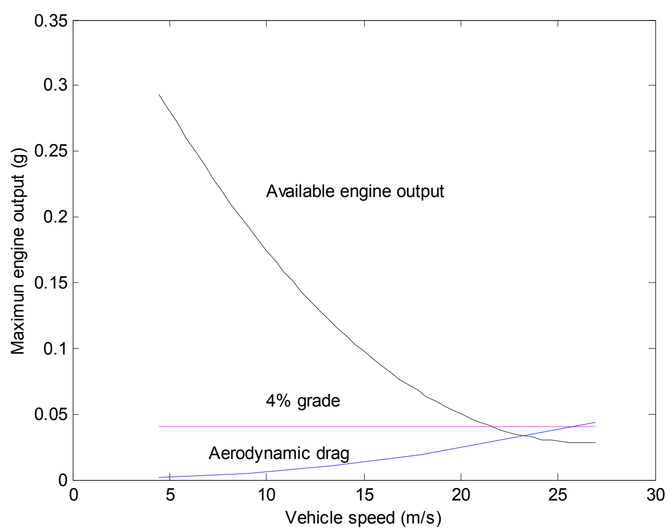

Figure 1. Comparison of forces in longitudinal heavy truck dynamics. Forces are normalized by weight and presented in units of acceleration for intuition.

The concept of reserve acceleration further motivates the need for parameter identification. The acceleration capability of a heavy vehicle can be used for several purposes: overcoming road loads (grade, rolling resistance and aerodynamic drag), maneuvering (trajectory following) and correcting for spacing or parameter errors (control authority). Since grade is set by the road, the vehicle has no choice but to devote sufficient capacity to overcome this load. Thus knowledge of the grade and appropriate command modification are essential to ensure that platoons do not separate when encountering this load [1]. To maintain the maximum ability to maneuver or compensate

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for errors, the acceleration required to compensate for parameter mismatches should be minimized. This, in turn, can be achieved if the mass, rolling resistance and drag can be estimated while the vehicle is in operation.

This paper presents a system for estimating the road grade, mass, rolling resistance and aerodynamic drag of a ground vehicle using values of engine torque calculated by the engine map, a Global Positioning System (GPS) receiver and, optionally, wheel speed or inertial sensors. Two different approaches for obtaining the grade measurement are presented: using two GPS antennae to calculate the pitch angle of the vehicle and using a single GPS antenna to calculate the ratio of the vehicle's vertical velocity to its horizontal velocity. Both methods are demonstrated to produce reasonable measures for road grade variations experimentally. Using this grade estimate, it is straightforward to estimate mass and drag terms and – if sufficient variation in vehicle velocity exists – separate this latter term further into aerodynamic drag and rolling resistance.

II. PARAMETER IDENTIFICATION

A. Estimation Outline

Equation 1 presents a simple longitudinal vehicle model.

$$m\ddot{x} = F_{engine} - F_{drag} - F_{\substack{rolling \\ resistance}} - F_{\substack{road \\ grade}} \qquad (1)$$

Given measurements of longitudinal acceleration, engine output and road grade, the mass and the sum of the drag and rolling resistance can be identified by a simple least-squares fit to the experimental data. Acceleration can be obtained from an accelerometer or – in regions of low tire slip – through numerical differentiation of wheel speed sensors. In this work, GPS velocity is used for grade estimation and numerical differencing may be used to obtain acceleration directly from this measurement. The measurement of the force produced by the engine is obtained directly from the engine map inside the engine controller and represents the "stock" estimate available on the vehicle.

Aerodynamic drag and rolling resistance cannot be distinguished in this approach if the vehicle moves at a constant speed. Since aerodynamic drag is a function of velocity, some variations in velocity are necessary to obtain an accurate estimation of drag coefficient. This would, in turn, produce a better estimate of rolling resistance.

Isermann demonstrated that the vehicle mass, aerodynamic drag and rolling resistance could be obtained on flat ground from measurements of acceleration and engine output [3]. However, the remaining unknown, road grade, has been mainly ignored in previous research. An exception to this has been an estimation scheme by [4] which estimates mass and grade while the vehicle is braking. As shown in Figure 1, forces from road grade play a major role in uphill sections, particularly for heavy trucks. Since road grade has the potential of completely overwhelming the engine capability of heavy trucks, particularly at highway speeds, knowledge of the grade is crucial in its own right for control of longitudinal vehicle dynamics in addition to being necessary for parameter estimation. A good estimate of the grade can be obtained with the addition of a GPS receiver.

B. Road grade estimation with GPS

GPS can be used to estimate road grade in two different ways, depending upon whether the system has a single antenna or two antennae. Figure 2 illustrates two GPS antennae mounted longitudinally on the roof of a passenger car, with a fixed baseline between antennae. By tracking the carrier phase at each antenna, the angle of this baseline relative to the horizontal can be measured. Since the antennae are fixed to the roof of a car, the angle measured by the antenna is the sum of road grade (angle θ) and the pitch of the car (angle λ) which changes in response to acceleration, deceleration and high frequency road irregularities. Since the road grade changes much less rapidly than the pitch motion of the vehicle, the low frequency part of this signal can be assumed to be grade (with a constant bias due to antenna orientation). Alternately, the ratio of vertical velocity to horizontal velocity – both obtained from the GPS receiver – can be used to estimate grade. While the same low frequency assumptions hold, the velocity method is unbiased and can be implemented with a single GPS antenna

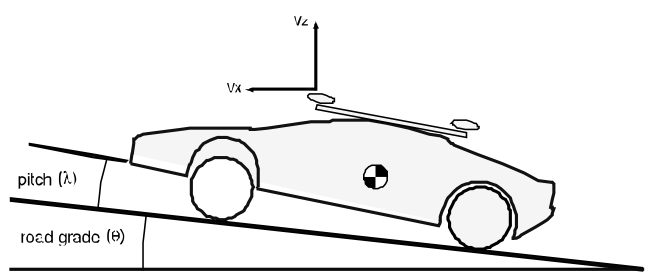

Figure 2. Two-antenna GPS setup on a car to measure vehicle pitch angle. Note two-antenna system measures road grade (θ) and vehicle pitch angle (λ) combined.

Figure 3 shows estimates of road grade for a section of Highway 280 in California using both of these methods. Several things can be clearly seen in this plot. First, the characteristic frequency at which road grade is changing is substantially slower than the frequencies associated with motion of the suspension. Hence, this data supports the claim that grade information can be obtained from the low frequency content of either of the GPS measurements. The two methods also produce rather similar results overall, though they differ in terms of how much oscillation in the measurement is produced by vehicle motion. During the first 45 seconds, the grade estimate from vehicle pitch measurement shows more pronounced oscillations than the estimate based upon velocity. This is a function of the large amount of vehicle pitch in the first part of this test produced by rapid periods of acceleration and deceleration. The second plot shows that the oscillations in pitch correlate with the acceleration of the vehicle. Since the other method is based upon velocity measurement, it exhibits much less sensitivity to these motions.

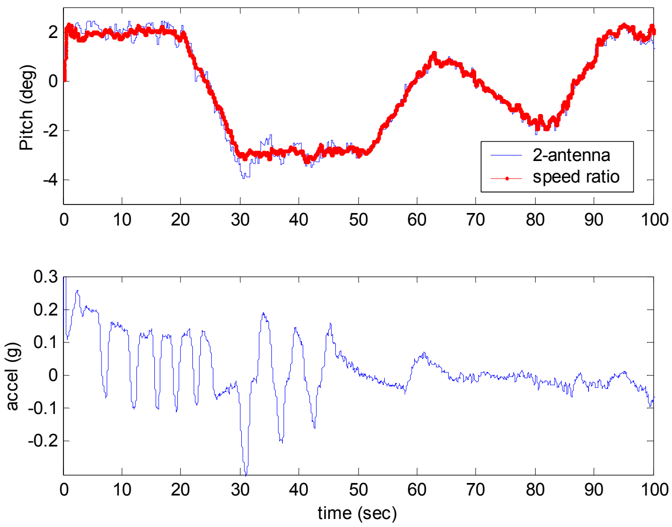

Figure 3. Plot of filtered (2-pole, 0.5 Hz Butterworth) pitch-derived road grade (Highway 280) using two-antenna GPS setup and speed ratio-derived road grade on a passenger car. Velocity ratio-based grade estimation shows less influence from contamination by pitch.

However, after the acceleration commands become more moderate (from 50 to 100s), the estimate based on velocity exhibits more variability. This is more clearly illustrated in Figure 4, which shows a Fourier transform of both signals during another test run representing normal driving. As can be seen, there is more power associated with higher frequency motions (0.5 – 2.5 Hz) in the velocity based estimate. This follows from the fact that the pitch based measurement is insensitive to vertical motions of the vehicle, which appear as common mode disturbances, while the velocity based measurement assumes such motions are actually grade changes. From a performance standpoint, the choice of method represents a tradeoff between rejecting disturbances caused by vehicle bounce and those caused by vehicle pitch.

In addition, there are several other considerations in the choice of grade estimation approach. First, a single GPS antenna can be positioned anywhere on the roof while restrictions exist for a two-antenna system due to the baseline requirement. Second, a single antenna system is more robust to problems with multipath or loss of satellite visibility since it does not need to resolve integer ambiguity like a two-antenna system. Third, a single antenna system is more cost effective not only because merely one antenna is required, but also since a lower cost receiver can be used. Finally, calculating grade from a single antenna using velocity eliminates the bias that arises from the installation of the two antennae (e.g. a heavy load in a wagon which causes a constant tilt along the pitch axis).

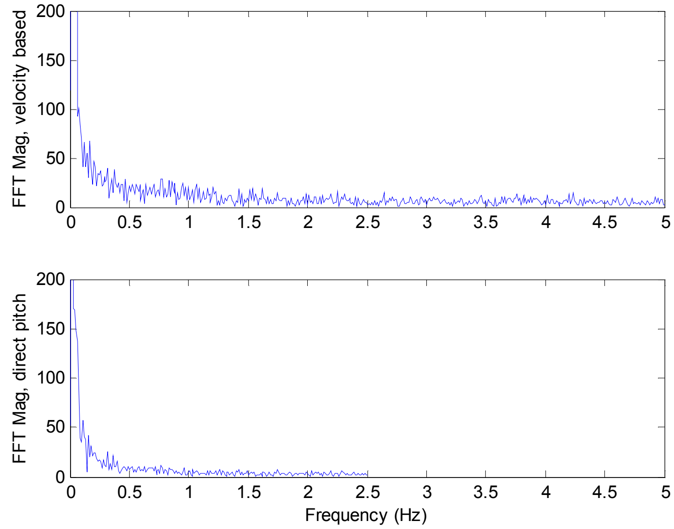

Figure 4. Frequency contents of road grade estimation (velocity-based, sampled at 10Hz and direct pitch, sampled at 5Hz) from GPS readings before filtering. Note that, as expected, most energy is concentrated at low frequencies (below 0.5 Hz).

Of course, both methods could be combined (e.g. through Kalman filters) to produce a measurement which balances sensitivity to pitch and bounce motions. Furthermore, if higher frequency grade information is desired, a Kalman filter structure could also be used to decouple the pitch motion from the longitudinal acceleration. As Figure 4 demonstrates, however, the road grade variation is concentrated at low frequencies (below 0.5 Hz). Thus simple low frequency filtering was deemed sufficient for this work.

C. *Estimation of Individual Unknowns*

In this paper, acceleration is derived through numerical differentiation of longitudinal velocity from GPS as well as front wheel speed. The engine force can be calculated from the engine output torque as in Equation 2.

$$F_{engine} = \frac{T_{engine} \cdot N_{\substack{torque\\converter}} \cdot N_{transmission} \cdot N_{differential} \cdot f_{\substack{mechanical\\loss}}}{R_{tire}} \quad (2)$$

The output torque should be adjusted with torque converter amplification ratio, transmission ratio, final differential ratio, tire radius and total mechanical efficiency, as illustrated in Figure 5, to find the force exerted on the car. The test vehicle used in this research had the torque converter ratio and the current gear available on the databus. The remaining ratios were determined from the vehicle specifications while the mechanical efficiency was adjusted experimentally, as described later.

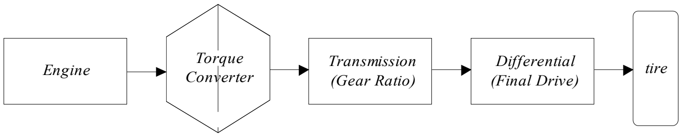

Figure 5. Engine torque flow diagram. Force on car is determined by several cascaded components.

To separate effects of aerodynamic drag from rolling resistance, aerodynamic drag can be modeled as in Equation 3 where constants (air density, frontal area, and coefficient of drag) are lumped in C_{df} (drag factor),

$$F_{drag} = \frac{1}{2}\rho A C_d V^2 = C_{df} V^2 \tag{3}$$

Force from road grade is based on the GPS grade angle:

$$F_{\substack{road\\grade}} = mg\sin\theta \tag{4}$$

Rearranging the equations in a linear estimation format for one data point yields

$$F_{engine} = \begin{bmatrix} \ddot{x} + g\sin\theta & V^2 & 1 \end{bmatrix} \cdot \begin{bmatrix} \hat{m} \\ \hat{C}_{df} \\ \hat{F}_{roll} \end{bmatrix} \tag{5}$$

For n data points, therefore,

$$z = H\hat{x} + noise \tag{6}$$

Then, z is n x 1 vector of F_{engine} and H is n x 3 matrix of acceleration, road grade and speed squared. In the current setup, m, C_{df} (drag factor), and F_{roll} are estimated, while the grade angle is measured directly with a GPS receiver. The estimates can be calculated in a batch process where a pseudo inverse of H is multiplied to z. A recursive method was used since it translates to on-line estimation of the parameters easily.

Parameters are assumed to be constants and the H matrix be noise free. While the vehicle mass and the drag factor are constants, rolling resistance is a nonlinear function of speed [2]. However, the estimation results show little effect from this simplification. Note also that F_{roll} in Equation 1 contains not only the rolling resistance forces but also any unmodeled dynamics such as aerodynamic forces from wind gust, engine friction, etc.

D. Experimental Setup

Engine-related information (F_{engine}) is essential to parameter estimation. A Mercedes-Benz E320 wagon was used for this experiment. Since this vehicle incorporates various sensors for advanced vehicle stability control system, the information necessary for this work is available through the CAN (control area network) bus. In this experiment, engine torque (T_{engine}), torque converter amplification ratio, front wheel speeds, and gear number (converted to gear ratio) are read from CAN.

In addition, a NovAtel Beeline two-antenna GPS system and a Millenium receiver with a single antenna were used for road grade estimation. The integrity of pitch information from GPS receivers has to be checked since the receiver may send erroneous data if, for example, signals from GPS satellites are blocked by buildings, etc. This is especially true for a two-antenna system since maintaining relative position data of two antennae (thus, an angle with respect to a level surface) is more difficult than getting position fix from one antenna. The Beeline receiver outputs data at 5 Hz and the Millenium at 10 Hz. Other variables such as engine information are read at 100 Hz. A single board computer was used to run on-line estimation algorithm and record data in Mathworks xPC real-time operating environment.

E. Experimental Procedures and Assumptions

The vehicle was driven as straight as possible because the engine torque was assumed to be used only for longitudinal motion. Excessive wheel spins, such as tire slip during hard acceleration, were also avoided. Deceleration by pressing the brake pedal was avoided since the measurement of braking force was not available.

F. Algorithm and Data Processing

The signal flow is shown in Figure 6. Engine torque is the input to the system to be identified while speed and acceleration are the outputs. All measurements are filtered through a second order Butterworth low pass filter with the cut-off frequency at 0.5 Hz in order to remove any unmodeled high frequency dynamics such as hydrodynamic coupling in torque converter. This is consistent with the understanding that the engine map is really only valid in steady-state operation. A recursive algorithm estimates vehicle mass, drag factor and rolling resistance, based on the filtered version of input/output data and road grade.

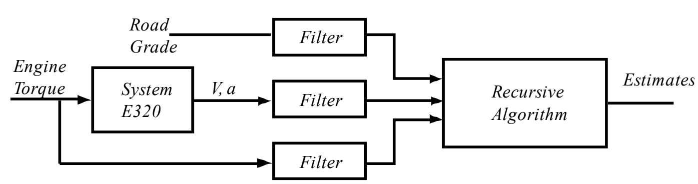

Figure 6. Input-output representation of signal flow.

Since GPS receivers may lose solution integrity while going under-path or experiencing severe multipath interference, the integrity of road grade from GPS is monitored continuously and invalid grade data is rejected. When a data point is rejected, no updates of estimates are performed.

G. *Results and Discussion*

The speed profile for parameter estimation is shown in Figure 7. A mix of acceleration of the vehicle followed by deceleration (letting the accelerator pedal up without engaging foot brake pedal) was repeated to simulate real world situations and generate excitation for judging the stability of the estimate. As Figure 8 illustrates, the mass estimate converged to a final value very quickly (by t = 12 s as shown by a vertical line), negating the need for long periods of persistent excitation in the vehicle. The maneuver executed during the first 12 seconds would be similar to merging on a highway. This shows that mass estimation can be performed successfully with normal operation of a vehicle.

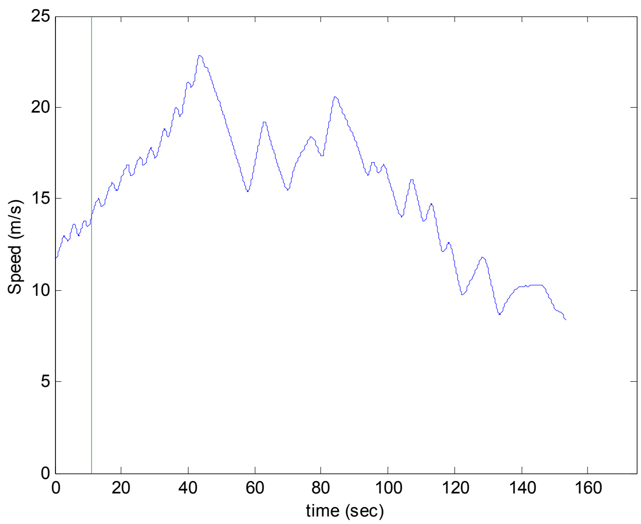

Figure 7. Horizontal speed profile for mass estimation. Note the repetition of acceleration and deceleration although estimated vehicle mass converged quickly (by t = 12 s) through recursive estimation algorithm.

As Figure 8 shows, the estimated mass converges to within ± 2% error of the measured mass value. The 2% error range was chosen to be the threshold for good estimation since mechanical losses (e.g., torque converter loss, transmission loss, errors in engine map data, etc) cannot be accounted for perfectly. Obtaining this level of accuracy required scaling the mechanical loss factor to match the overall efficiency of the drivetrain (a value that would be known at least approximately by the manufacturer). To determine the amount of error that could arise due to changes in this value, the total mechanical loss factor was varied from 0.9 to 0.98 and a final value of 0.96 chosen. Different data sets with a fixed mechanical loss factor showed strong consistency with standard deviation in errors of less than 1%. Furthermore, the total estimation error stayed within ± 5% as the loss factor was varied within this range. The initial conclusion based upon this test vehicle is that mass estimation within 5% is clearly feasible with this method and that results within 2% are possible if some estimation of overall efficiency is available (from design data or periodic calibration with actual vehicle weight, for instance).

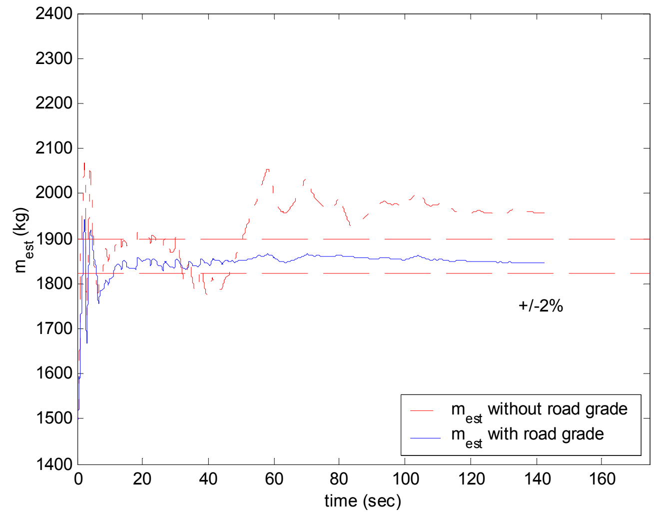

Figure 8. Recursive estimation of vehicle mass. The mass estimate converged to 2% of final value in 12 s.

On the same plot, vehicle mass estimation without road grade information is also shown. Even the modest road slopes (maximum magnitude of 3º in Figure 3) were large enough to cause significant errors in mass estimation of a passenger vehicle. Without grade information, estimation of vehicle parameters using this method would contain an unacceptable level of error for control.

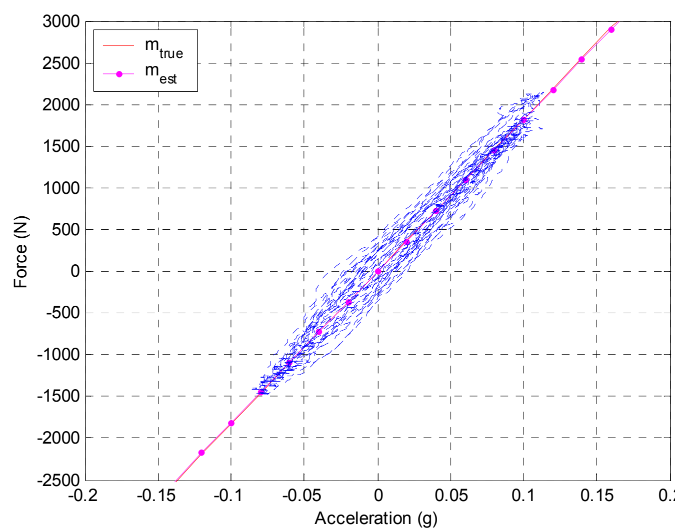

Figure 9. Plot of F_{engine} vs. acceleration. The filtered data are scatted in a cigar-like shape. The best fit in the sense of least squares is shown as a line going through the data points. The estimation error is about 2%.

Figure 9 shows a force vs. acceleration graph, assuming constant C_{df} and F_{roll}. The slope of a straight line going through data points is the vehicle mass. Two straight lines on the plot indicate the true mass (measured with a scale) and an estimated mass. In the frequency range examined, therefore, any unmodeled dynamics appear to be insignificant as far as mass estimation is concerned.

Unlike mass, estimates of drag factor and rolling resistance did not converge to constant values (Figure 10) although the estimates have the right orders of magnitude. With C_{df} of 0.7, C_d (drag coefficient) for the experimental vehicle with two GPS antennae on the roof is about 0.42 if A = 1.7x1.5 m^2, ρ = 1.25 kg/m^3 while C_d provided by the manufacturer is 0.34. As noted before, it is difficult to separate the drag and rolling resistance terms when the vehicle operates in a narrow speed range so these values will not exhibit the same accuracy as mass estimation under this approach. Obtaining more accurate measurement of the aerodynamic drag and rolling resistance by incorporating additional models represents an avenue for future work.

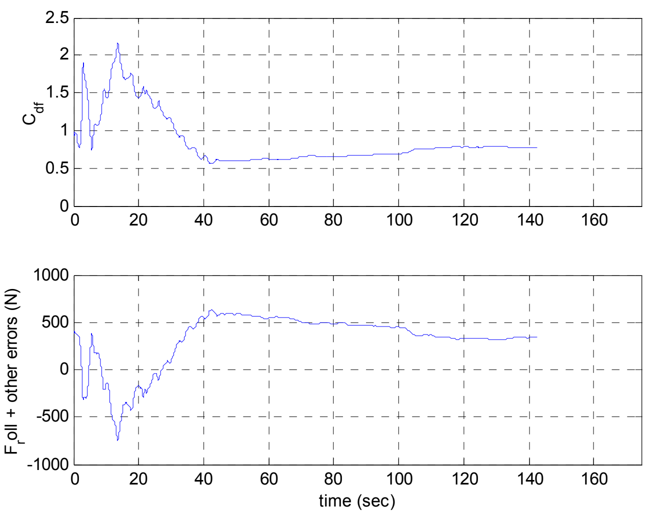

Figure 10. Estimation of C_{df} and F_{roll}. Note the complementary nature of two plots.

III. SUMMARY

Automated vehicles require sufficiently accurate system models in order to achieve a desired level of closed-loop performance. Parameters of the models are one of the important factors that determine the accuracy of system modeling and eventually overall performance of closed-loop system.

Current GPS sensing technology enables estimation of road grade and, consequently simple treatment of parameter estimation from a static mass balance. An on-line recursive parameter estimation scheme based on this idea has been developed and demonstrated experimentally with a passenger vehicle. Both methods for estimating road grade from GPS produced a rapidly converging mass estimate that fell within ±2% of the measured value. As a future step, this system will be implemented in a heavy truck and the estimates incorporated into a longitudinal control scheme.

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