Title

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PARAMETER ESTIMATION AND COMMAND MODIFICATION FOR LONGITUDINAL CONTROL OF HEAVY VEHICLES

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Abstract

Commercial heavy vehicles, unlike passenger vehicles, display huge variation in parameters such as vehicle mass. Coupled with lower actuation authorities (engine and brake capabilities), these variations can induce actuator saturation even in moderately demanding maneuvers, presenting challenge to the task of maintaining string stability in a platoon formation of heavy trucks. A new control scheme is proposed to put on-line bounds, or artificial saturation, on command signals via parameter estimation such that all members in a platoon can follow the reference commands without saturating actuators, thereby, maintaining string stability.

This work also 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. 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.

Keywords: Parameter estimation, GPS, pitch, road grade, command modification, automated highways, automated commercial heavy vehicles, actuator saturation, string stability.

Executive Summary

Commercial heavy vehicles, unlike passenger vehicles, display huge variation in parameters such as vehicle mass. Coupled with lower actuation authorities (engine and brake capabilities), these variations can induce actuator saturation even in moderately demanding maneuvers. Thus, variations in the open-loop vehicle performance present a challenge to the task of maintaining string stability in a platoon formation of heavy trucks. A new control scheme is proposed to put on-line bounds, or artificial saturation, on command signals via parameter estimation such that all members in a platoon can follow the reference commands without saturating actuators. This report describes the rationale, structure and potential benefits behind such a scheme through comparisons with conventional (fixed gain and adaptive) controllers.

This report also describes methodology and results from actual implementation of online parameter estimation. Important vehicle parameters are estimated with recursive least squares estimation algorithm based on engine output from engine computer and road grade estimation from GPS. Two methods for obtaining an estimate of road grade are presented, 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.

1. Introduction

Advanced vehicle control systems (AVCS) and automated highway systems (AHS) -- with the goal of increasing traffic capacity of existing roads through intelligent coordination of vehicles and highway automation -- have seen significant progresses in the past decade. While previous efforts have been focused on automation of passenger cars, the efforts of AVCS and AHS research and development activity are now shifting towards commercial heavy trucks due to feasibility of implementation and economic benefits.

One of the most promising strategies for AHS is the concept of platoon operation [1-3]. A platoon consists of a number of vehicles traveling at a high speed, with a small inter-vehicle spacing. In addition to reduced driver fatigue due to automation, platoon operation of heavy trucks also provides an economic incentive in the form of lower fuel cost due to lower air drag resistance in a long stream of trucks. Moreover, the concept of a platoon is more feasible with heavy trucks than passenger cars since heavy trucks tend to spend a majority of travel time on highways and follow well-established routes [7].

In order for the platoon operation to be useful, the vehicles in the platoon should travel with a small inter-vehicle spacing for higher traffic throughput. Therefore, the longitudinal controller has to provide not only asymptotic stability - where relative speed and inter-vehicle spacing are ensured to go to zero - but also guarantee a property known as string stability. With string stability, disturbances in inter-vehicle spacing upstream in the platoon will be attenuated as they propagate downstream. Since it was established that constant inter-vehicle spacing cannot provide string stability without additional information [1], many inter-vehicle spacing policies have been devised. For example, inter-vehicle communication has been used to ensure string stability by transmitting the velocity and acceleration of the lead vehicle to followers [2]. Speed dependent spacing policies where time headway term provides more spacing at higher speeds have also been used [4]. Nonlinear spacing policies that place different weights on control gains based on measurements of relative speed or spacing have been suggested [7].

Controller design methods such as fixed or adaptive gain PID have proven useful in highway automation [2-7]. However, these are based on the assumption that the system to be controlled is constant, i.e. plant parameters are known and do not change much over time. Although controllers can be designed to tolerate some variances in vehicle parameters, typical ranges of parameter variations in commercial heavy vehicles are well beyond what conventional controllers are capable of handling and may saturate actuation capabilities (engine and brake) to the point where the platoon operation results in instability. The issue of actuator saturation is of a particular concern if the concept of highway automation is to be useful in the real world where a platoon is composed of heavy vehicles that may have different open loop capabilities. Such a situation arises fairly easily if the leading vehicle in a platoon has a larger engine than the following vehicles and/or the following vehicles are hauling heavier cargo.

It is proposed that a better way of implementing longitudinal control is to incorporate the knowledge of physical actuation limits in all members of a platoon through parameter estimation so that actuator saturation is avoided and, therefore, string stability is preserved. Importance of identifying operational parameters of heavy trucks is described in the following section.

2. Online Parameter Estimation

Four parameters play significant roles in the longitudinal dynamics of highway automation: vehicle mass, road grade, aerodynamic drag, and rolling resistance. Their qualitative characteristics are shown in Table 1. The first column lists the four parameters. The second column indicates the extent to which parameter changes produce performance variations and the third column lists parameter variation over time during the course of a trip. For example, the vehicle mass, while not changing very much once on the road, has a strong influence on the longitudinal dynamics. In comparison, road grade variations have a similar effect and may change quickly over time.

Among these parameters, vehicle mass is of the most importance since it has the most impact in longitudinal performance and potentially very large changes. It is not unusual to see the variation up to 500 % in operating mass (from unloaded mass of 7500 kg to fully loaded mass of 37000 kg, or from low density cargo to high density cargo). On the other hand, it is easiest to estimate the vehicle mass due to its slowly time-varying nature.

Table 1. Impact of Vehicle Parameters and Loads on Longitudinal Dynamics of Heavy Trucks.

Parameter	**Impact**	**Changes Over time**
Vehicle Mass	Large	Slow
Road Grade	Medium/large (0.08g)	Fast
Air Drag (C_d = 0.85-1.5, Area = 12 m^2)	Medium (0.02-0.04g)	Fast
Rolling Resistance	Small (0.01g)	Medium
Engine output at 55 mph (25 m/s)	0.035g	

Road grade changes are the second most important parameter to be estimated. For example, if the road grade information is not taken into account, the leading vehicle may out-accelerate the followers on an uphill road. Then, platoon formation may break down since the followers cannot maintain desired spacing from the leader. A modest road grade (4% uphill) can be a comparable load source compared to air drag and rolling resistance. An 8% uphill (maximum allowable grade in California highway construction) presents even stronger challenges [13]. This is equivalent to having a load of 0.08g (normalized to units of acceleration). Since the maximum acceleration of a typical loaded heavy vehicle is roughly 0.3g at low speed, road grade can be problematic in terms of avoiding engine output saturation, especially combined with uncertainty in the vehicle mass.

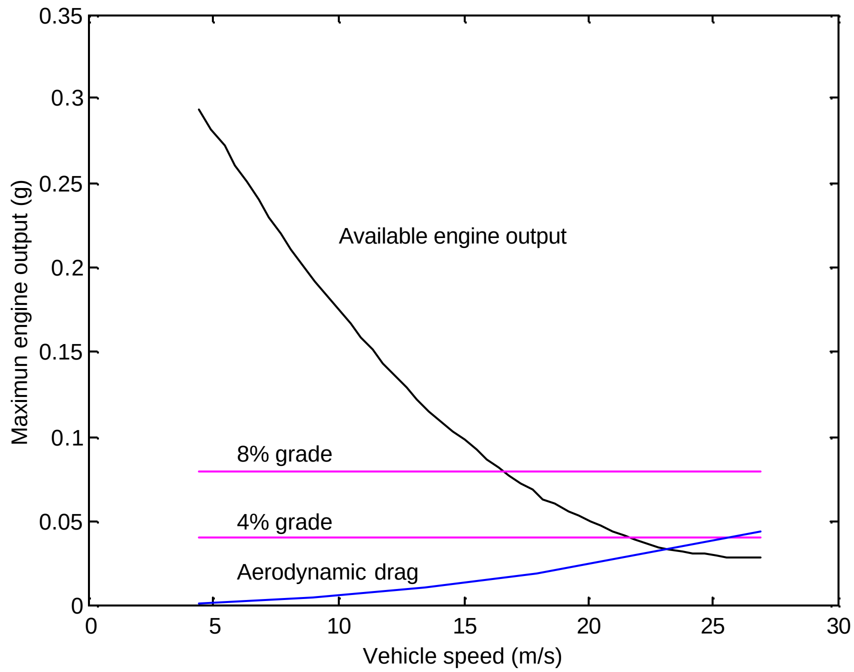

Figure 1. Typical maximum output of a heavy truck engine (500 hp) vs. vehicle speed. Note the low acceleration level at highway speeds (20-25 m/s).

The loads on heavy vehicles mentioned above are important issues because of relatively low reserve powers on heavy truck. When traveling at highway speeds, loaded heavy trucks often have 0.05g or less of acceleration capability as shown in Figure 1 [11] and approximated by the simple relationship:

$$P_{engine} = F_{engine} V \tag{2.1}$$

where

P_{engine} = engine power output,
F_{engine} = engine force output, and
V = vehicle speed.

Because of this low actuation authority, loading conditions that are not issues to passenger cars become a challenge for heavy trucks. The amount of variation in the road loads can exceed the overall actuation capability of the engine at highway speeds. Engine outputs can thus be easily saturated if commands are not properly generated or maneuvers not carefully coordinated to reflect these limits. When actuators saturate, the followers may not be able to keep with the leader, dropping back significantly. This in turn would cause overshoots in relative spacing and velocity, resulting in string instability and possibly a collision. Therefore, avoiding actuator saturation is especially important in heavy truck platooning. Although smart nonlinear control schemes such as in [6,7] may reduce integrator windup and controller overshoot, actuator saturation cannot be systematically avoided without careful planning of vehicle maneuvers.

In short, heavy trucks are more susceptible to actuator saturations that may cause instability in platooning. Parameter estimation can provide a better understanding of the system limits and loads, enabling the modification of raw trajectory commands into a reachable set of commands.

The main concept behind such command modification through parameter estimation follows next. Comparisons are drawn between conventional MRAC (model reference adaptive control) and the proposed approach with differences illustrated qualitatively. Advantages of parameter estimation and command modification are then shown in simulation, first with fixed gain controllers, and then with adaptive gain controllers.

3. Command Modification

The basic idea in command modification is intuitive: limit the command signals (speed, acceleration, and/or jerk) to a level by creating an artificial saturation point so that all members in a platoon can execute without saturating actuators. For example, the modification module may lower the peak acceleration in a lead vehicle maneuver from 0.03g to 0.02g based upon the capabilities of the followers.

The artificial saturation can be represented in a simple mathematical statement as in Equation (3.1).

$$\ddot{x}(t) = \min\left[\ddot{x}(t), \ddot{x}_{Limit}(\hat{m}(t), F_{\substack{road\\grade}}(t))\right] \qquad (3.1)$$

where

$\hat{m}(t)$ = estimated vehicle mass, and

$F_{\substack{road\\grade}}(t) = \hat{m}(t) g \sin q(t)$ = load from road grade, $q(t)$

The acceleration limit in Equation (3.1) is a function of vehicle parameters. The vehicle parameters, in turn, may also be a function of time as mass and road grade change.

3.1 Command Modification in Adaptive Control Framework

Adaptive control techniques have been used in longitudinal control of heavy vehicles since uniform closed-loop performance can be achieved even with the varying open-loop characteristics of commercial heavy trucks [6,7,9]. In other words, the adaptive controller compensates for different open-loop dynamics and places the closed-loop poles of each vehicle identically.

Figure 2 demonstrates a basic structure for such a controller. It follows the standard MRAC scheme in the sense that the controller gains are updated through an adaptive mechanism that takes as an error signal the difference between the desired output from the reference model and the actual system output.

Typical MRAC controllers are based on the assumption of time invariant reference models. The limitation of this approach, however, is that fact that the parameters of the reference model are still fixed. Therefore, similar problems as other fixed gain controller exist with respect to saturation. If the reference model is not chosen properly (i.e. the desired closed-loop system is too aggressive), the physical system may saturate actuators in an attempt to reduce the error between the actual system output and the reference model output.

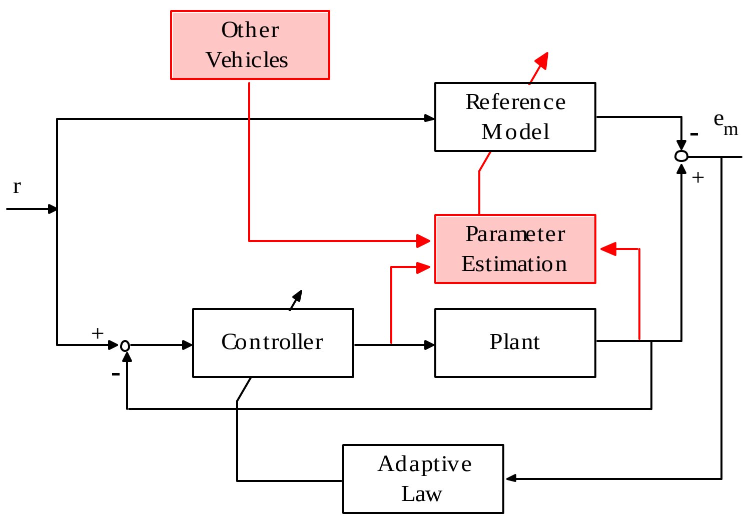

Figure 2. Conventional MRAC with Active Model Adjustment.

In the context of platoon operation of commercial trucks, it is desired to have one reference model for all members in a platoon so that closed-loop performances are uniform throughout the formation. Therefore, it is possible to assign an unreachable reference model to less capable members in a platoon if the model selection process is not aware of performance variations. If this happens, the leading vehicle may still command trajectories that are not reachable by other members in a platoon. One method to get around this problem is to choose a conservative reference model, i.e. based on the worst possible situation where all vehicles are assumed to carry maximum gross weight at all times and have arbitrarily lower engine performance. However, as discussed previously, this may result in using only 10-20% of the acceleration capability of a well-matched platoon of trucks.

The essence of the proposed approach is a new parameter estimation block in the lead vehicle that incorporates information about all vehicles in the platoon. Based on the information, the reference model can then be adjusted so as to generate reasonable command signals that are reachable by all members in a platoon without actuator saturation.

Figure 3 shows the actual block diagram used in the simulations shown in this report. As in Figure 2, controller gains are updated according to an adaptive law, and input/output properties of plant are used for parameter estimation. The difference lies in the command modification module. The estimated vehicle characteristics of all vehicles are used to update performance limit information in the command modification module. This performance limit, or artificial saturation, compares the incoming command with the given limit and provides a minimum of the two values so that the modified commands are within the performance bounds of all vehicles. Benefits of command modification will be shown with simulation in Section 5.

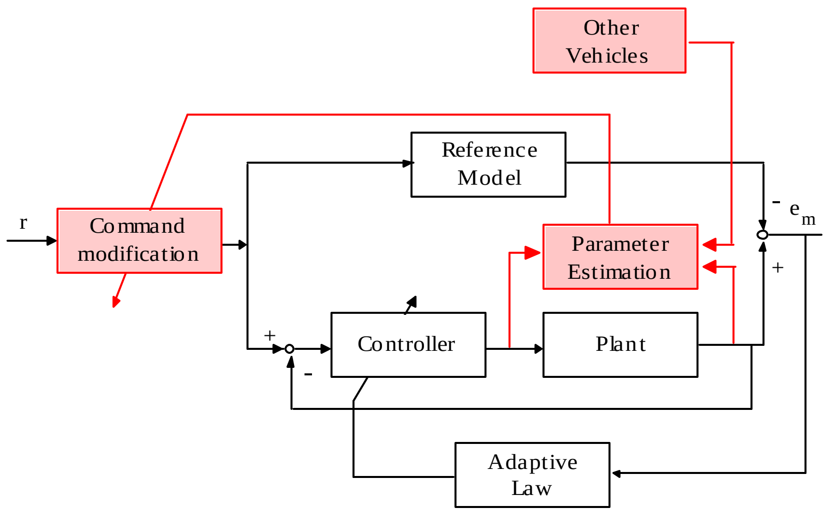

Figure 3. Modified MRAC for command modification.

3.2 Vehicle-to-Vehicle Communication

Information sharing of the most conservative reference model is based on the assumption of some inter-platoon communication. Every member in a platoon should be able to receive and send information. However, as most communication for parameter information and model updates occurs at the beginning phase of platoon formation when the leader collects information of all members in a platoon and broadcasts the reference model selected, low bandwidth communication is required. This could also be achieved through communication with a fleet headquarters or roadside rather than directly between vehicles.

4. Implementation

4.1 Sensors

The parameter estimation scheme in this report is based on physical sensors that measure speed, acceleration, engine output and grade. With such sensing capabilities, the estimation of mass and other parameters becomes a matter of finding the best fit to a polynomial equation. It is also possible to extract the parameter information such as vehicle mass through indirect MRAC scheme [9]. Direct parameter estimation may be preferable, however, since it does not require loop closing with adaptive controllers. Therefore, normal open-loop operation of heavy trucks would suffice to generate data for mass estimation. This would be beneficial due to reasons described in the previous paragraph.

Due to the importance of sensing in this estimation, some discussion of the feasibility is necessary. Vehicle speed can be deduced from wheel speed sensors or directly from carrier phase GPS [10]. For example, multiple antenna GPS can measure trailer pitch to within 0.4 ° with a one-meter baseline, or a single antenna GPS could be used as long as the vehicle is in motion. Hence grade can be obtained within the accuracy of the assumption of a single grade value beneath the vehicle. If a vehicle travels on a known route, position information from single antenna GPS can also be used to provide grade information by comparing the current location with pre-mapped database of road information. Acceleration can be obtained through a fusion of accelerometers (which necessarily include tire and suspension modes) with differentiated GPS and wheel speed velocities.

Measurements of engine output in modern engines can be obtained by accessing the engine control unit (ECU). While there is admittedly some error in these static maps, the scheme here does not require transients to obtain information for estimation. Hence, the engine maps can be used in their more accurate steady-state range.

4.2 Online Parameter Estimation

As discussed earlier, mass change in a heavy vehicle is the single most important factor in longitudinal performance because of actuator saturation. In addition, the mass estimation requires only modest bandwidth.

This section 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.

Equation 4.1 presents a simple longitudinal vehicle model.

$$m\ddot{x} = F_{engine} - F_{drag} - F_{\substack{rolling\\resistance}} - F_{\substack{road\\grade}} \qquad (4.1\ 3)$$

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 [16]. However, the remaining unknown, road grade, has been mainly ignored in previous research. An exception to this has been an estimation scheme by [9] 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.

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 4 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 *?*) and the pitch of the car (angle *?*) 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

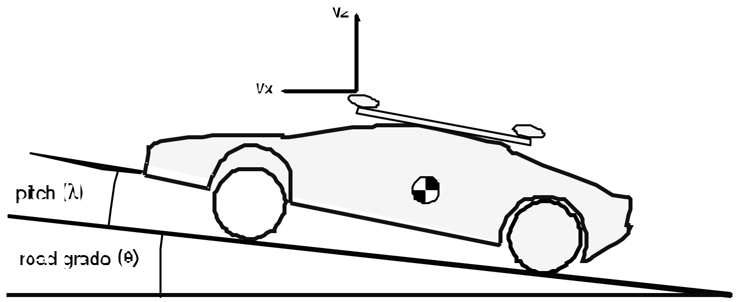

Figure 4. Two-antenna GPS setup on a car to measure vehicle pitch angle. Note two-antenna system measures road grade (?) and vehicle pitch angle (?) combined.

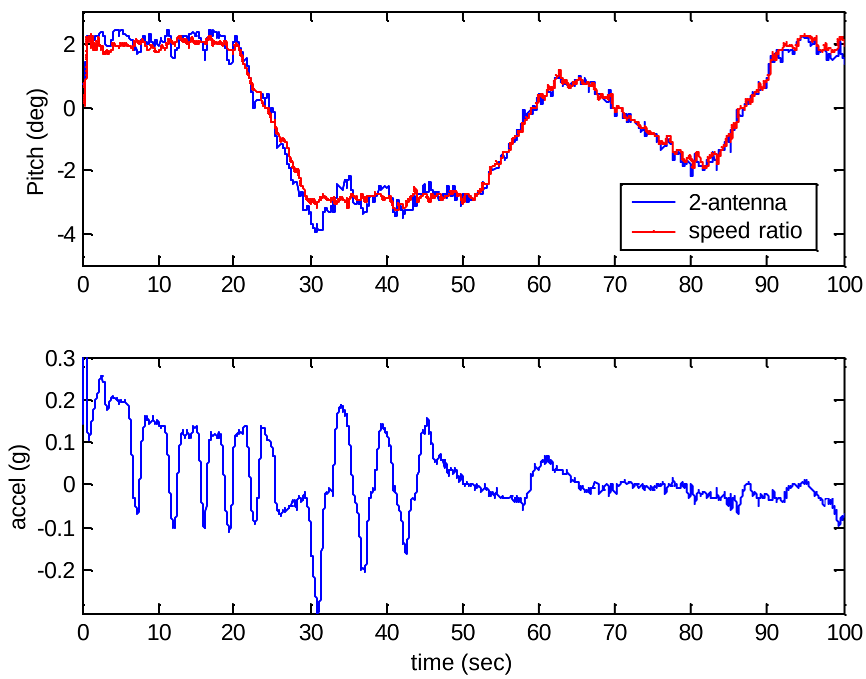

Figure 5. Plot of filtered (2-pole, 0.5 Hz Butterworth) pitch-derived road grade (Highway 280) using two-antenna GPS setup and speed ratio-derived road grade on a passenger car. Velocity ratio-based grade estimation shows less influence from contamination by pitch.

Figure 5 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.

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 6, 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.

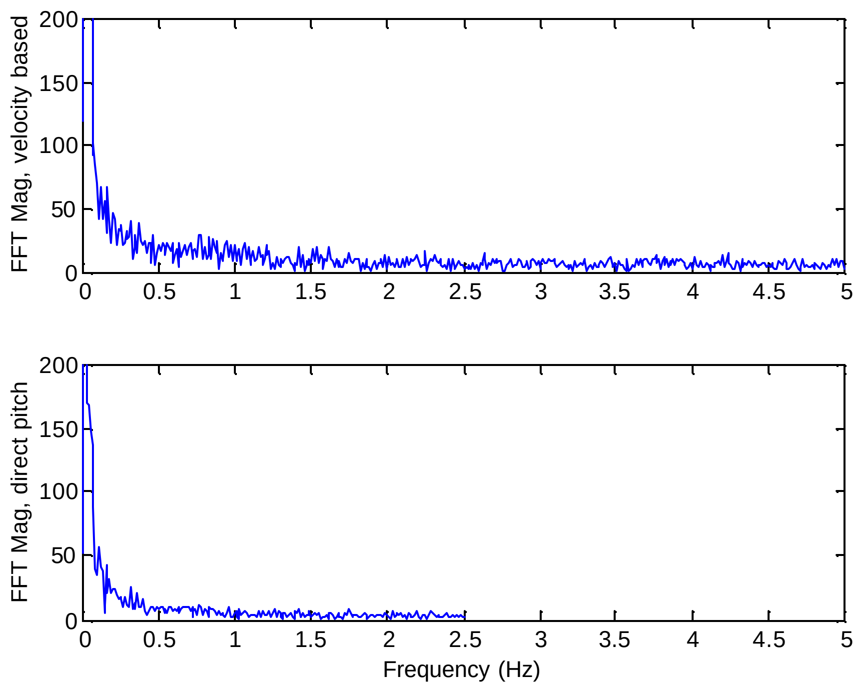

Figure 6. Frequency contents of road grade estimation (velocity-based, sampled at 10Hz and direct pitch, sampled at 5Hz) from GPS readings before filtering. Note that, as expected, most energy is concentrated at low frequencies (below 0.5 Hz).

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 multi-path 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).

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.

Estimation of Individual Unknowns

In this work, 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 4.2.

$$F_{engine} = \frac{T_{engine} \cdot N_{\substack{torque\\converter}} \cdot N_{transmission} \cdot N_{differential} \cdot f_{\substack{mechanical\\loss}}}{R_{tire}} \qquad (4.2)$$

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 7, 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.

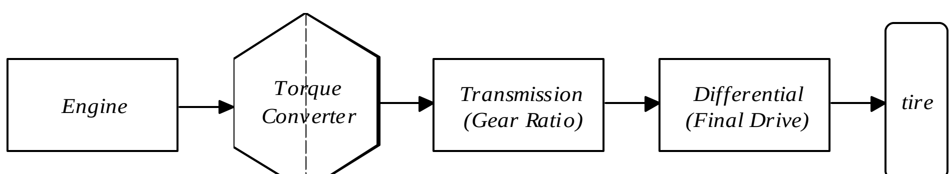

Figure 7. Engine torque flow diagram. Force on car is determined by several cascaded components.

To separate effects of aerodynamic drag from rolling resistance, aerodynamic drag can be modeled as in Equation 4.3 where constants (air density, frontal area, and coefficient of drag) are lumped in C_{df} (drag factor),

$$F_{drag} = \frac{1}{2} ?AC_d V^2 = C_{df} V^2 \qquad (4.3)$$

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

$$F_{\substack{road \\ grade}} = mg \sin \theta \qquad (4.4)$$

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

$$F_{engine} = \begin{bmatrix} \ddot{x} + g \sin \theta & V^2 & 1 \end{bmatrix} \cdot \begin{bmatrix} \hat{m} \\ \hat{C}_{df} \\ \hat{F}_{roll} \end{bmatrix} \qquad (4.5)$$

For n data points, therefore,

$$z = H\hat{x} + noise \qquad (4.6)$$

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 [12]. 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.

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.

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.

Algorithm and Data Processing

The signal flow is shown in Figure 8. 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.

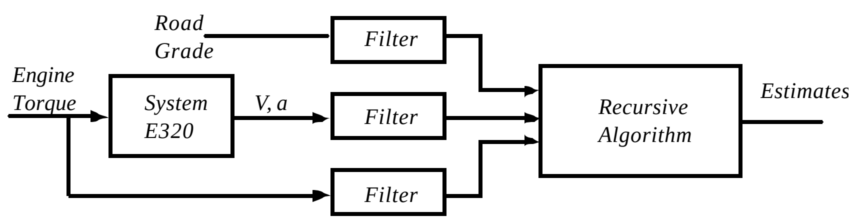

Figure 8. Input-output representation of signal flow.

Since GPS receivers may lose solution integrity while going under-path or experiencing severe multi-path 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.

Discussion of Online Estimation Results

The speed profile for parameter estimation is shown in Figure 9. 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 10 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.

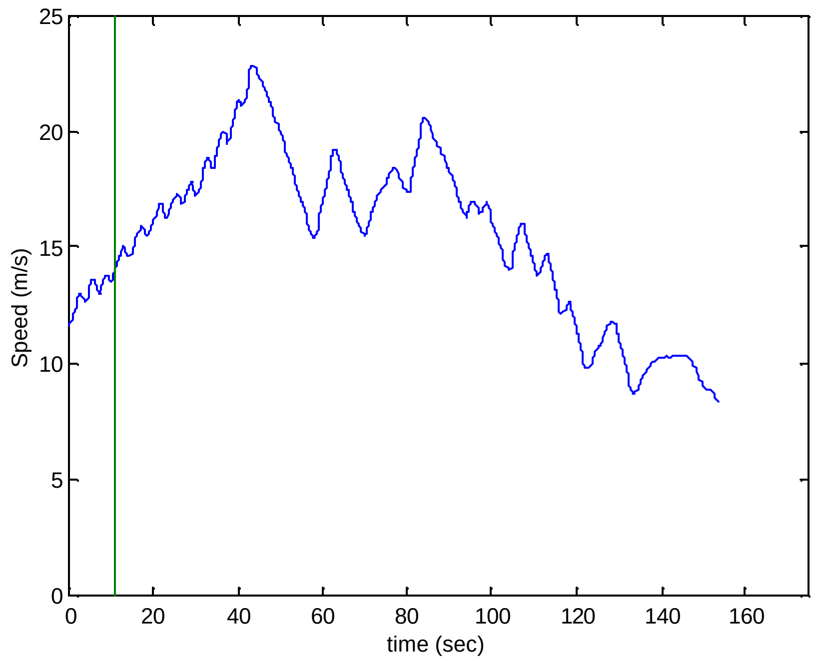

Figure 9. Horizontal speed profile for mass estimation. Note the repetition of acceleration and deceleration although estimated vehicle mass converged quickly (by t = 12 s) through recursive estimation algorithm.

As Figure 10 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).

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 7) 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.

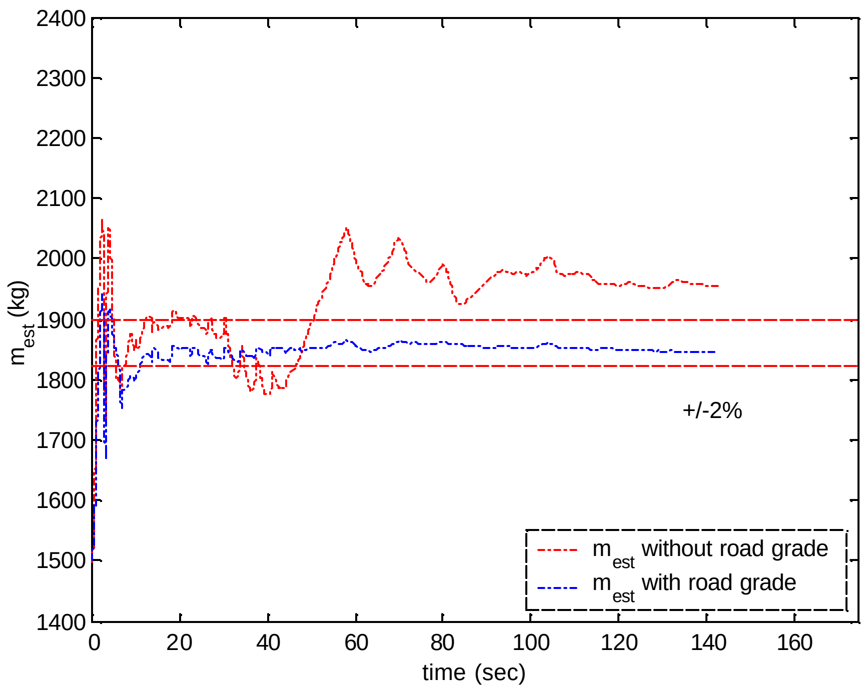

Figure 10. Recursive estimation of vehicle mass. The mass estimate converged to 2% of final value in 12 s.

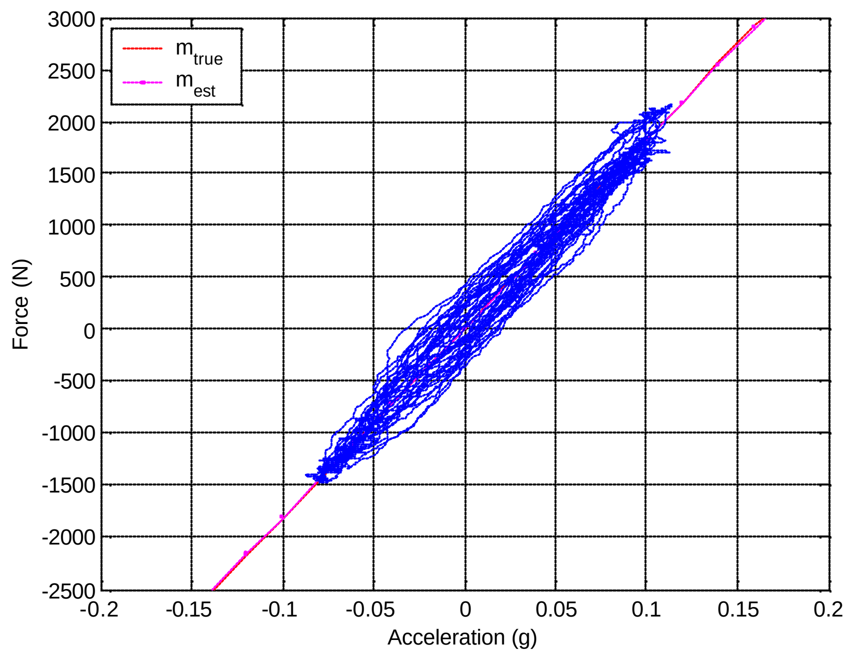

Figure 11. Plot of F_{engine} vs. acceleration. The filtered data are scatted in a cigar-like shape. The best fit in the sense of least squares is shown as a line going through the data points. The estimation error is about 2%.

Figure 11 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 12) 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, r = 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.

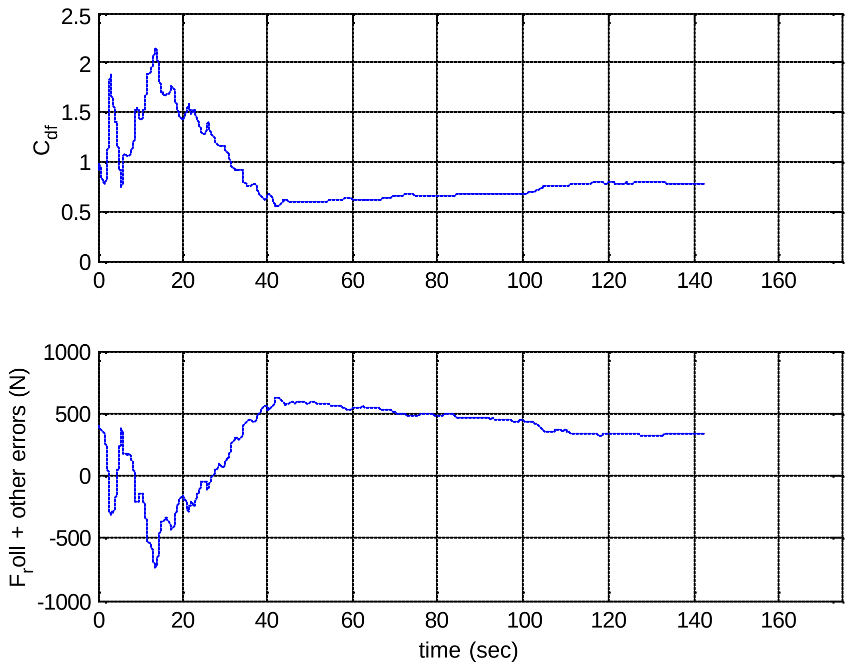

Figure 12. Estimation of C_{df} and F_{roll}. Note the complementary nature of two plots.

5. Benefits of Command Modification

In the following section, the potential benefits of this design are illustrated through simulation. Parameter estimation uncertainties are not included; only the limiting cases of known and unknown parameters are included. The longitudinal dynamics of the vehicle used in the simulations are represented in Equation (5.1) to (5.6).

$$m\ddot{x} = F_{engine} - F_{brake} - F_{\substack{air\\drag}} - F_{\substack{rolling\\resistance}} - F_{\substack{road\\grade}} \tag{5.1}$$

$$F_{\substack{air\\drag}} = \frac{1}{2} r_{air} C_d A V^2 \tag{5.2}$$

$$F_{\substack{rolling\\resistance}} = 0.0041mg \tag{5.3}$$

$$F_{\substack{road\\grade}} = mg \sin q \tag{5.4}$$

$$F_{engine} - F_{brake} = u + u_{feedforward} \tag{5.5}$$

$$u_{feedforward} = \hat{F}_{\substack{air\\drag}} + \hat{F}_{\substack{rolling\\resistance}} + \hat{F}_{\substack{road\\grade}} \tag{5.6}$$

where

r_{air} = density of air,
C_d = drag coefficient,
A = vehicle frontal area,
V = vehicle speed,
m = vehicle mass,
q = road grade, and
u = control input (engine or brake) to the vehicle,
$u_{feedforward}$ = feedforward control input, and
$\hat{F}_{\substack{air\\drag}}$ = estimate of air drag, etc.

Engine output and brake forces are assumed to be directly available as control inputs. The maximum engine output is given in Equation (2.1) and in Figure 1 as a function of vehicle speed only, assuming a constant power output. The maximum braking output with nominal vehicle mass is set to be 0.6g. Actual nonlinear engine, drivetrain and brake dynamics are ignored.

The mass is the only parameter estimated in this simulation. Road grade is assumed to be available without estimation. Forces by wind are assumed negligible, so air drag force is a function of vehicle speed only. In addition, reduction in air drag through drag coefficient changes as the following vehicle gets closer to the leading vehicle, is also neglected.

A two-vehicle platoon is simulated, which is sufficient for demonstration of the concept. In this scenario, the leader and the follower are assumed to have identical nominal vehicle parameters (e.g. engine/brake limits) except for masses: the follower weighs 30,000 kg while the leader weighs only 20,000 kg. Therefore, the nominal mass for the controller is 20,000 kg until the actual mass information is available upon the completion of mass estimation. The acceleration profile for the leader has been adjusted to keep the engine output near its maximum level in order to simulate demanding conditions. The minimum inter-vehicle spacing is set to 2 m. Relative spacing error less than –2 m indicates inter-vehicle collision.

5.1 Fixed Gain Controllers

A fixed gain nonlinear PIQ (proportional-integral-signed quadratic) controller is used for this simulation [6,7]. Instead of dealing with two control variables, the relative vehicle speed and spacing error are combined into one error variable as shown in Equation (5.7) [7].

$$e = v_r + k_d d \qquad (5.7)$$

where

v_r = relative vehicle speed,

d = relative spacing error (difference in current spacing and desired spacing), and

k_d = spacing error gain.

Control input is then defined as,

$$u = k_p e + k_i \int e dt + k_q e|e| \qquad (5.8)$$

where k's are control gains. The last term is the signed quadratic part that provides improved performance over derivate control [7].

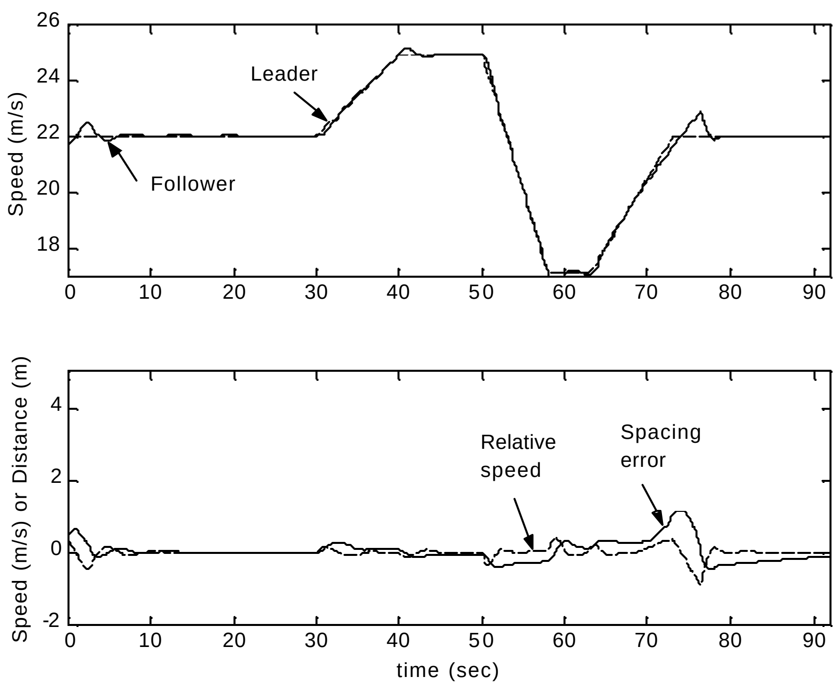

Figure 13. Fixed gain controller with nominal mass and zero road grades. Gains are chosen to provide acceptable closed-loop performance. The follower is maintaining small speed and spacing errors.

The performance of the base controller in the nominal parameter setting is shown in Figure 13. In this case, the actual vehicle mass is the same as the nominal mass and road grade is set to zero. The leading vehicle is traveling at 22 m/sec and the following vehicle starts a little slower, but still close to the leader. The following vehicle shows good tracking performance in terms of maintaining small speed and spacing errors. The first plot shows velocity profiles of leader and follower. The leader's velocity profile can be thought of as command signals for the follower. The second plot shows two control variables: relative speed and spacing error. The control goal is simplified into keeping the combination of these variables small through spacing policies using time headway and separation error gain.

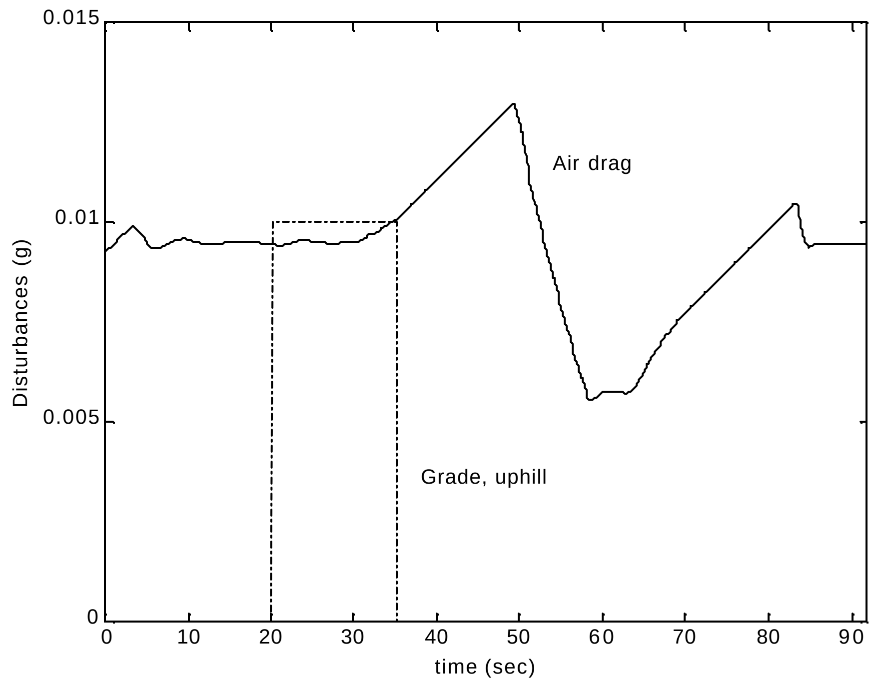

Figure 14. Loads from air drag and road grade. Changes in air drag as a function of vehicle speed is shown. Road grade presents 0.01g load between 20 and 35 sec.

The following simulations use loads from air drag and road grade, shown in Figure 14. The air drag profile roughly follows that of vehicle speed in Figure 13 since the air drag is a function of vehicle speed only with a constant drag coefficient in Equation (5.2).

Small changes in vehicle mass and road grade turn out to have a large effect on the performance of a fixed gain controller. The 10 % difference in vehicle mass was enough to cause spacing error of larger than 2 m (Figure 15 and 7). The performance worsens when the effects of nonzero road grade come in (Figure 16) in terms of larger spacing and relative speed errors.

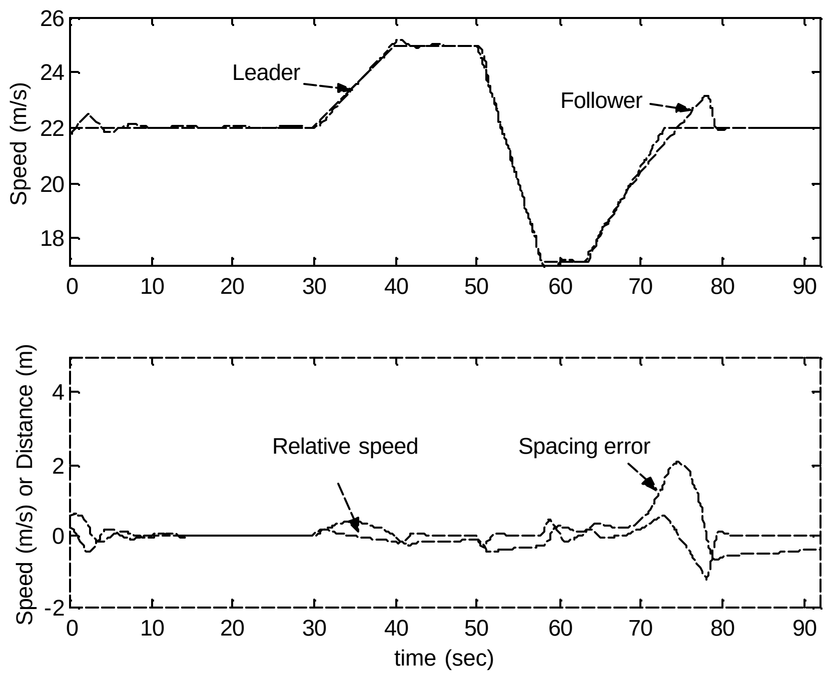

Figure 15. Fixed gain PIQ with 10% more vehicle mass and zero grade. Note larger errors compared to Figure 13.

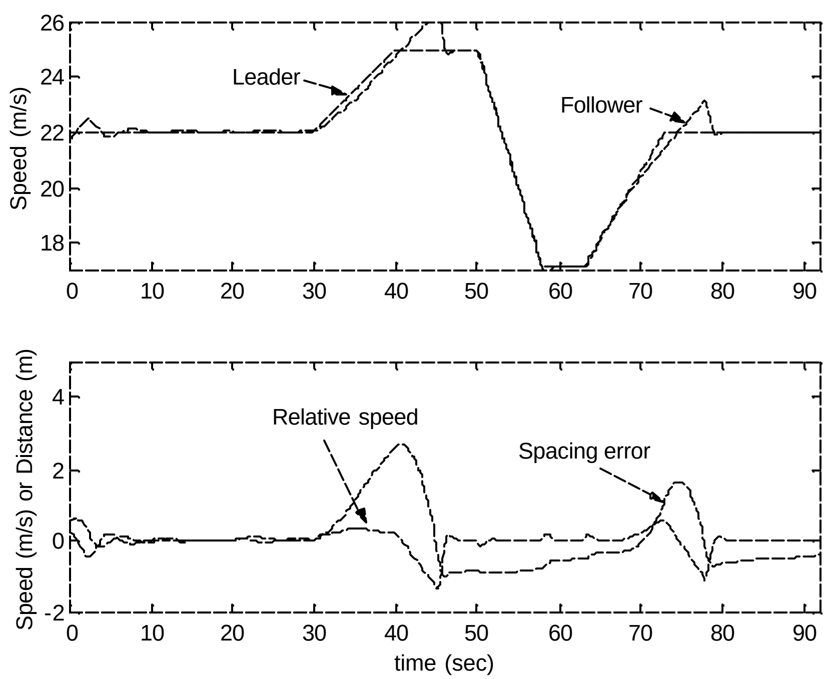

Figure 16. Fixed gain PIQ with 10% more vehicle mass and road grade changes as shown in Figure 14. More errors are evident in relative speed and vehicle spacing.

The same fixed gain controller finally becomes unstable when the nominal and actual vehicle masses differ by more than 30 %. Figure 17 shows the problems associated with fixed gain controllers without parameter estimation when the actual vehicle mass is 50 % more than the nominal value. The follower can easily catch up with the leader at the beginning and the spacing error and the relative speed go to zero. At t = 30 sec, however, the leader decides to accelerate to about 24 m/sec at a certain rate (0.02g). However, the follower cannot accelerate as fast as the leader because of its lower acceleration limit due to larger mass of the follower and road grade load. Actuators on the follower saturate, which results in overshoot in velocity profile (t = 45 sec) due to integrator windup. This in turn causes an inter-vehicle collision around t = 53 sec when the relative spacing becomes negative (spacing error more than – 2 m).

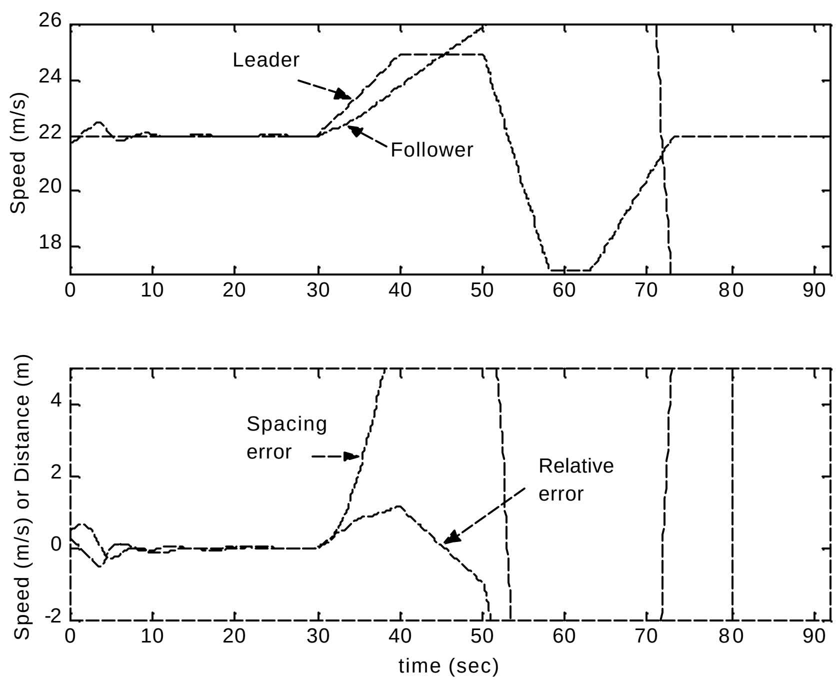

Figure 17. Fixed gain controller without parameter estimation. The leader is generating acceleration profiles that the follower cannot execute. This results in a collision around t = 53 sec when the spacing error decreases to – 2 m.

Figure 18 shows the advantages of parameter estimation and command modification. A fixed gain PIQ controller is again used. The first plot shows a third velocity profile in addition to previous two profiles. The new profile is the modified velocity profiles of the leader, given updated parameter values through estimation. It is assumed that the mass estimation is finished and the command modification module is informed of the updated value at t = 5 sec. The slopes on the modified leader velocity are lowered from t = 20 to 45 sec and t = 65 to 75 sec so the follower can execute the command. Therefore, the velocity profiles of the modified leader and the follower are almost exactly the same except for the overshoots in follower velocities. Since saturation is avoided, the fixed gain controller can easily keep the control variables near zero as shown in the second plot.

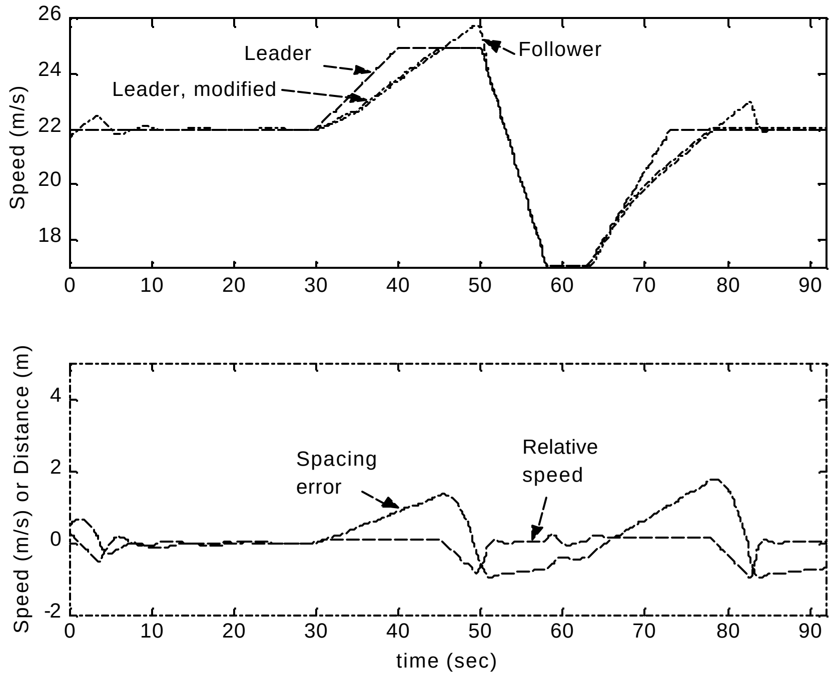

Figure 18. Fixed gain controller with parameter estimation and command modification. Acceleration profile of the leader is now modified to reflect the lower actuation limits of the follower. Closed-loop system is now stable since saturation is avoided.

The advantages of command modification can be seen more easily in Figure 19 where various accelerations are compared explicitly. As indicated in the figure, the upper dotted line is maximum acceleration. Changes in deceleration are omitted since the adjusted maximum braking is more than the maximum braking command at 0.1g. The maximum acceleration is lowered at 5 and again at 20 seconds as the command modification module receives updated mass and grade information. Since the actual mass of the vehicle is found to be 50 % more than the nominal mass, the acceleration limits are lowered. Increases in acceleration limits between 55 – 65 sec are due to the engine model as function of vehicle speed. As the vehicle slows down, more engine output is available (see velocity profiles around t = 55 sec in Figure 18).

Comparisons of the two acceleration commands at 30, 45 and 65 seconds reveal the most important aspect of this figure. At 30 sec, the unmodified command acceleration is above the maximum available acceleration capability of the follower (dotted line). This corresponds to the case where the leading vehicle out-accelerates the following vehicle.

On the other hand, the modified command signal stops at the artificial limits of acceleration and deceleration, staying within the two dotted lines. In these simulations, the artificial acceleration limits are set to be the same as the physical acceleration limits. However, lower artificial limits should be used if some reserve acceleration capability is desired.

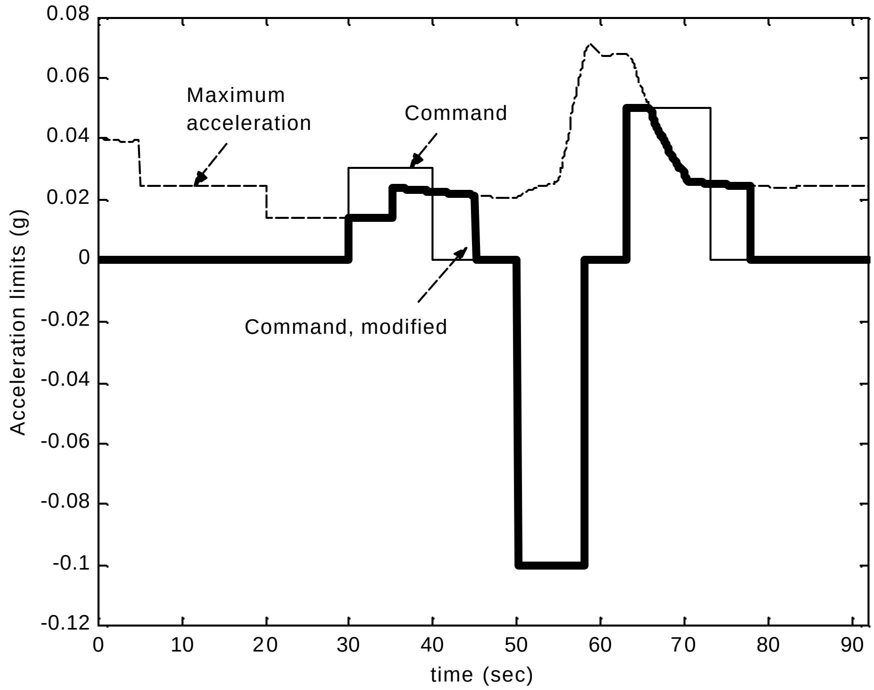

Figure 19. Maximum acceleration and deceleration limit changes as a function of mass estimation. Two reductions in maximum acceleration at 5 and 20 sec are due to updated mass and road grade information, respectively. The modified command is now within maximum limits.

5.2 Adaptive Gain Controllers

The same form of PIQ controller is again used for these simulations. However, the gains on PIQ controller are now continuously varied through a set of adaptive laws. The adaptive laws based upon Lyapunov stability were taken from [7].

The control laws are similar to Equation (5.8), except for adaptively changing gains.

$$u = \hat{k}_p e + \hat{k}_i + \hat{k}_q e|e| \qquad (5.9)$$

Using a linear vehicle model,

$$\dot{v}_f = a(v_r + kd) + bu + d \qquad (5.10)$$

substituting (5.9) into (5.10) gives

$$\dot{v}_f = \left(a + b\hat{k}_p\right)e + b\hat{k}_i + b\hat{k}_q e|e| + \bar{d} \qquad (5.11)$$

for the motion of the vehicle. With the following reference model and Lyapunov function to design adaptive control laws,

$$\dot{v}_m = a_m(v_l - v_m + kd) + q_m(v_l - v_m + kd)|e| \qquad (5.12)$$

$$V = \frac{1}{2}\left(e_r^2 + b\frac{\tilde{k}_p^2}{g_p} + b\frac{\tilde{k}_i^2}{g_i} + b\frac{\tilde{k}_q^2}{g_q}\right) \qquad (5.13)$$

$$e_r = v_f - v_m \qquad (5.14)$$

$$\tilde{k} = k - \hat{k} \qquad (5.15)$$

where

v_f = follower speed,
v_m = reference model speed,
$\tilde{k}$ = adaptive gain error, and
k = true adaptive gain

stability of the closed-loop system can be shown with,

$$\dot{V} = -a_m e_r^2 - q_m|e|e_r^2 \le 0 \qquad (5.16)$$

by choosing

$$\dot{\hat{k}}_p = \mathrm{Proj}[-g_p e_r e] \qquad (5.17)$$

$$\dot{\hat{k}}_i = \mathrm{Proj}[-g_i e_r]$$

$$\dot{\hat{k}}_q = \mathrm{Proj}[-g_q e_r e|e|]$$

The convergence to the true values of the adaptive gains is ensured by the projection operator, Proj[·]. a_m and q_m are closed-loop pole and gain parameters, thus positive design variables. g' s are also design parameters that control the speed of adaptation. For detailed development of Equations (5.9) to (5.17), refer to [7].

Performance of adaptive controller for a nominal case is shown in Figure 20. As expected, spacing and relative speed errors are smaller than those in the case of fixed gain controller (Figure 13).

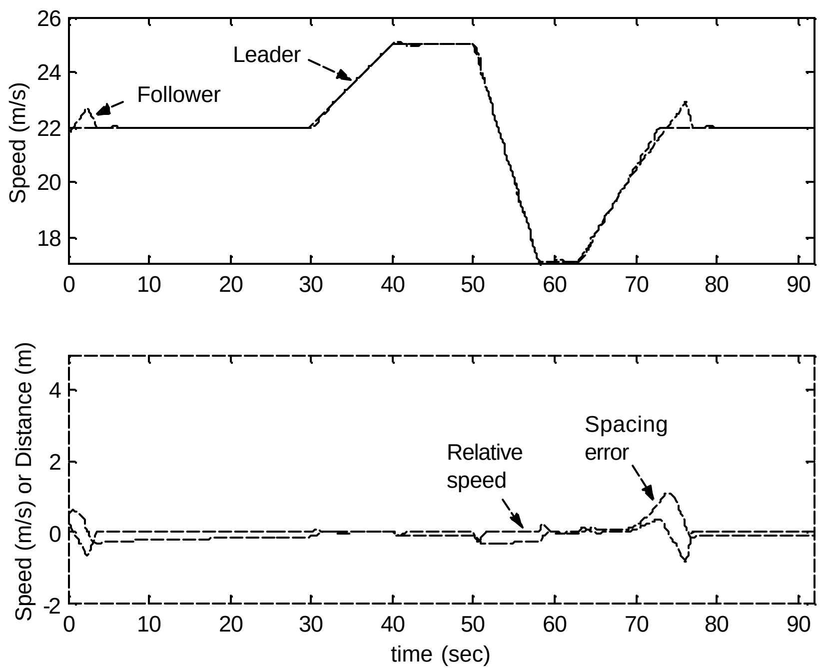

Figure 20. Adaptive controller with nominal mass and zero road grades. Gains are varied continuously through a set of adaptive laws to provide acceptable closed-loop performance. The follower is maintaining smaller speed and spacing errors compared to fixed gain controllers in Figure 13.

On the other hand, without command modification through parameter estimation, adaptive controllers are not any better than the fixed gain controllers in maintaining stability since the problem of actuator saturation still exists. The 10 % difference in vehicle mass alone was enough to cause instability in performance of the PIQ adaptive controller. In Figure 21 and 13, it is obvious that the follower cannot keep up with the leader due to its weak control authority. This is an intuitive result since fundamental physical limitation such as actuator saturation cannot be overcome by the adaptiveness in a controller. While the bandwidth of adaptation may be lowered for the sake of closed-loop stability, it will degrade the usefulness of adaptive filters if it has to adapt slowly. As before, overshoots in follower's velocity and vehicle collision are noted.

What is important to realize through these simulations is that, regardless of the types of controllers, physical limits must be incorporated into controller designs. Simply tweaking controllers will be fruitless unless physical saturation of actuators is explicitly accounted for. Large parameter changes in heavy truck operation, combined with low power-to-weight ratio, make parameter estimation essential in terms of identifying actuator limits. As seen in Figure 18, once true operating parameters are known with sufficient accuracy, a fixed gain controller could perform quite well without the need for more complicated (software- and hardware-wise) controller design such as adaptive controllers.

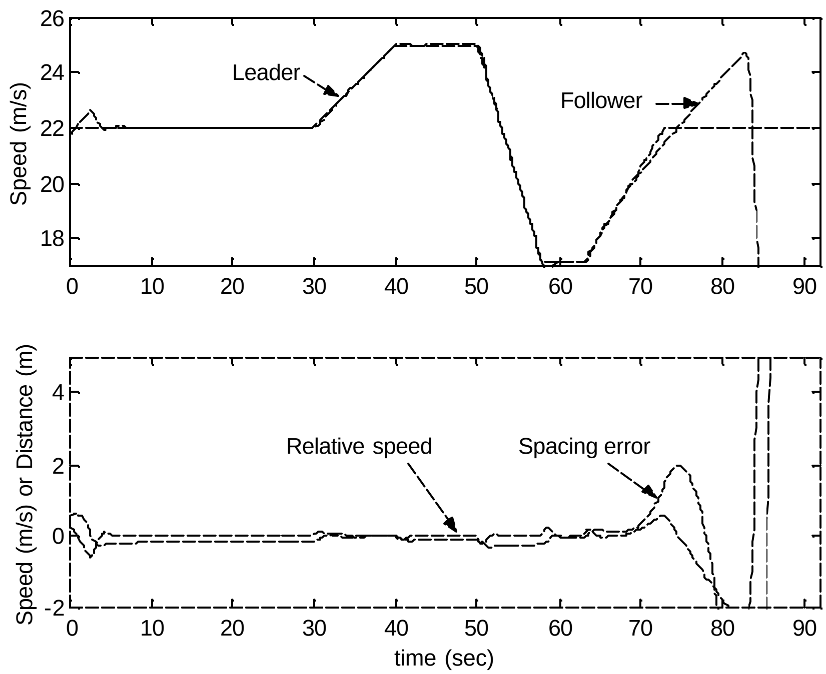

Figure 21. Adaptive PIQ with 10% more vehicle mass and zero road grades. Adaptive controller tuned for one operating conditions may be very sensitive to different operating conditions and therefore may perform much worse than a fixed gain controller once actuators are saturated.

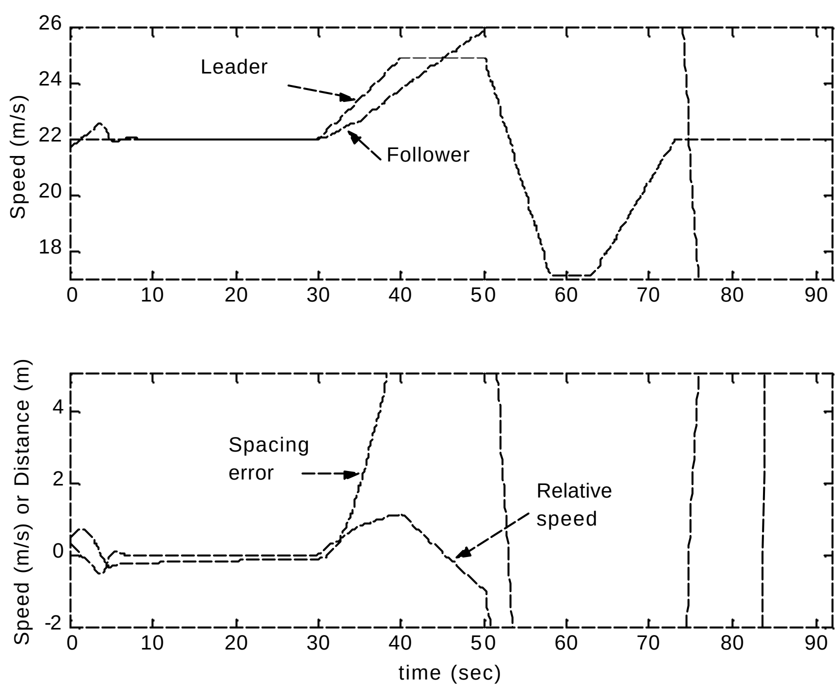

Figure 22. Adaptive PIQ without parameter estimation for 50 % mass difference and non-zero road grade case. The closed-loop system is unstable due to actuator saturation.

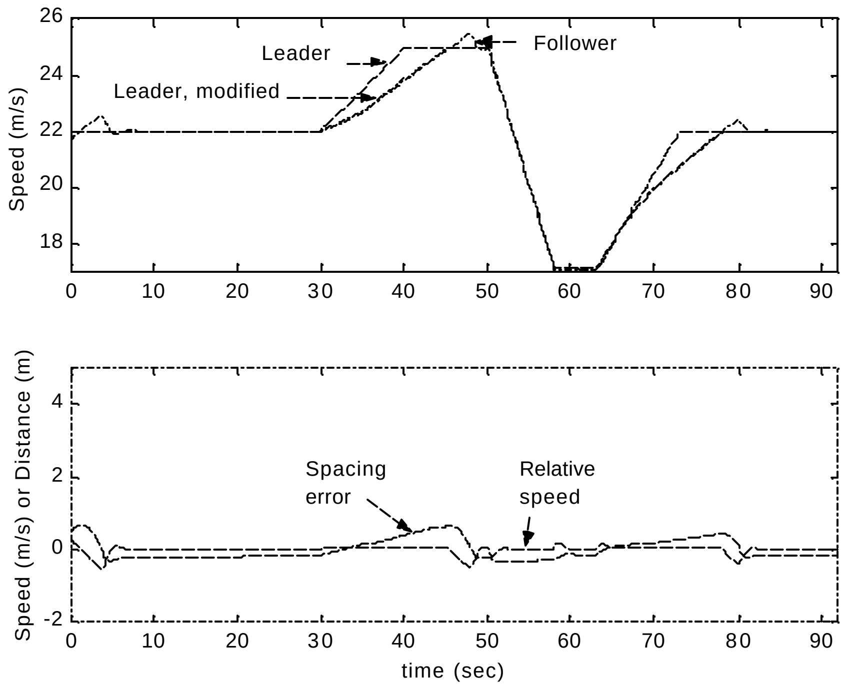

Figure 23. Adaptive PIQ with parameter estimation and command modification. The closed-loop system is stable and shows improved tracking performance over fixed gain controllers.

The same adaptive PIQ controller with command modification shows a stable trajectory following results with smaller overshoot and errors in Figure 23. The tracking performance of the adaptive controller is much better in that the modified command trajectory and the actual follower trajectory are indistinguishable, except for when the follower overshoots. As expected from the tight velocity tracking, spacing error and relative speed are smaller than fixed gain case during the entire simulation period. In addition, due to adaptiveness in the controller, overshoots are smaller than the case with fixed gain controller and as a consequence, spacing errors in the second plot are a factor of 2-3 lower than in Figure 18.

6. Conclusion

Avoiding actuator saturation is of a particular interest in highway automation for commercial heavy-duty vehicles. For the idea of highway automation to be practical, it is reasonable to assume that vehicles in a platoon will have different open-loop characteristics. Given the possibility of a leading vehicle with higher performance compared to following vehicles due to combination of engine/brake capabilities and parameter differences, it is important to know the limits of performance in a platoon as a single entity. In other words, 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.

Fundamentally, the saturation problem must be treated explicitly. The amount of variability in mass and road loads relative to actuator authority makes the idea of command modification essential for actual deployment of automated commercial vehicles. 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.

With the actual vehicle parameters obtained, raw commands can be modified to a reasonable set of trajectories that can be executed by other members in a platoon without actuator saturation. String stability can then be guaranteed by any of the existing results in this area once the threat of saturation has been eliminated.

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