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Examensarbete

Adaptive Vehicle Weight Estimation

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Adaptive Vehicle Weight Estimation

Thesis for Degree of Master of Science
Department of Electrical Engineering
Division of Vehicular Systems
Linköping University
by

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Adaptive Vehicle Weight Estimation
Adaptiv skattning av fordonsvikt

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Emil Ritzén

Sammanfattning
Abstract

The functionality of vehicle engine control systems is getting more and more complex due to new emission laws and increasing demands from customers. More computing power results in possibilities to use more advanced algorithms. An example is the possibility to estimate parameters that are not directly measurable, often because of economical reasons, which can be used to make control systems work better. One important parameter affecting the dynamics of the vehicle is the weight, especially concerning heavy trucks where the load varies a lot. If the weight is known, enhancements in the behavior of the vehicle can be achieved.

Here, a method for estimating the weight of a vehicle during driving is developed by comparing the acceleration of the vehicle and the estimated torque from the engine. The method is based on measurements from standard automotive sensors and can be applied to any vehicle, and it is implemented and successfully validated in heavy truck field trials. In on-line experiments an accuracy of about ±10% without a trailer and ±20% with a trailer connected is obtained. The deterioration in accuracy when using a trailer is probably due to the vehicle shuffle caused by the play between the truck and the trailer. Nevertheless, the accuracy is enough to obtain a substantial improvement in performance of control systems.

Nyckelord
Keywords

vehicle, driveline, modeling, weight estimation, truck

Abstract

The functionality of vehicle engine control systems is getting more and more complex due to new emission laws and increasing demands from customers. More computing power results in possibilities to use more advanced algorithms. An example is the possibility to estimate parameters that are not directly measurable, often because of economical reasons, which can be used to make control systems work better. One important parameter affecting the dynamics of the vehicle is the weight, especially concerning heavy trucks where the load varies a lot. If the weight is known, enhancements in the behavior of the vehicle can be achieved.

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Contents

1

Introduction

Modern vehicles consist of increasingly sophisticated control systems, which contain a growing number of control algorithms needing even more parameters. The weight of the vehicle is one parameter that is significant to many algorithms, but since the vehicle's weight is seldom known, control algorithms are not designed to take advantage of it. If the weight could be estimated during driving, greater performance of the algorithms could be expected. One example of this is the cruise controller. In order to gain better comfort and lessen the fuel consumption the algorithm should act a bit differently if the truck is unloaded or if it is driven with full load. Knowledge of the weight is also fundamental when deriving control algorithms that reduce driveline oscillations with engine control [12].

The goal of this thesis is to develop and implement a method that estimates the vehicle's weight during driving without using any kind of balance. The basic idea of the method is to treat the vehicle as one rigid body that, according to Newton's second law, achieves a certain acceleration when driven with a certain force.

1.1 Outline

The experiments are performed on Scania heavy trucks described in Chapter 2 along with their internal data buses.

In Chapter 3, a first order model of a truck drivline is developed.

Chapter 4 develops two different methods of identifying the model parameters from measured data; estimating during acceleration and estimation during gear shifting.

The algorithm development is considered in Chapter 5, which includes treatment of measuring vehicle acceleration and estimating engine torque.

Chapter 6 covers the experiments with weight estimation and the experimental equipment.

Finally, Chapter 7 contains the conclusions.

2

The Experimental Vehicles

The trucks used for the experiments are three Scania heavy duty trucks from the 4-series. They have different engines and weight, and one of the trucks can be driven with or without trailer.

2.1 The Trucks

Scania 144L 6x2

Figure 2.1 *Scania 144L 6x2 truck.*

Weight: 24400 kg (+ 32000 kg)

The Scania 144L 6x2 (six wheels, two driven) is a truck with a 14 liters V8-engine. The fuel system is based on an in-line injection pump system [1], and the transmission is equipped with an automatic gear shift system called OptiCruise [2]. A trailer is available for this truck with a weight of 32000 kg.

Scania 124L 6x2

Figure 2.2 *Scania 124L 6x2 truck.*

Weight: 18000 kg

The Scania 124L 6x2 is powered by a six-cylinder 12 liters engine, and the fuel injection is handled by a unit-pump system [1]. Also, this truck is equipped with OptiCruise.

Scania 124L 4x2

Figure 2.3 *Scania 124L 4x2 truck.*

Weight: 38000 kg

The Scania 124L 4x2 has a six-cylinder 12 liters engine with an in-line injection system. The transmission is manually shifted and the truck always has a trailer connected to it.

2.2 The CAN Bus

The CAN[1]-bus is a serial two wire bus for vehicles developed by Bosch GmbH [3]. It is used for communication between the different control units in vehicles called *nodes* of the CAN-bus. The communication is based on different CAN-messages and to identify these they all contain a CAN-identifier. A CAN-message can e.g. be current engine temperature or the speed of the right front wheel.

[1] Controller Area Network

3

Truck Modeling

The basic idea for weight estimations is to treat the truck as one rigid body and apply Newton's second law or Newton's generalized second law [14]. When using Newton's second law the truck is treated as a mass and the engine output as a longitudinal force causing a longitudinal acceleration. An equivalent situation, which is used in this chapter, is to treat the truck as a moment of inertia and the engine output as a torque. A schematic picture of the truck as a moment of inertia, J, is seen in Figure 3.1.

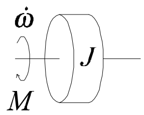

Figure 3.1 *Physical model of the truck.*

If the torque, M, and angular acceleration, $\dot{\omega}$, are measured and compared it is possible to estimate the moment of inertia, J. Different parts of the truck contribute to the moment of inertia of the rigid body in different ways, and the topic of this chapter is finding the expressions for calculating the mass from the estimated J.

Modeling the driveline can be done in many different ways and with different order of the model [12]. The model should have enough complexity to be able to reproduce the aimed physical phenomena, but choosing a higher complexity also includes more parameters. If these extra parameters are unknown, they have to be estimated in some way and that introduces uncertainty.

The physical model in Figure 3.1 represents a first order model. This assumes a stiff driveline without any flexibility or possibilities to model driveline oscillations. It is assumed that this model is sufficient for weight estimations, since the problem with driveline oscillations can be avoided or filtered out over time.

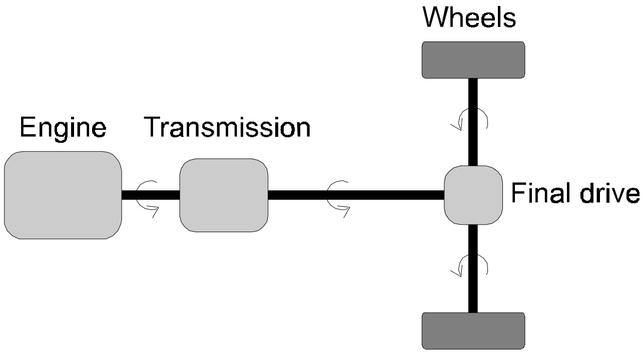

__Figure 3.2__ The driveline of the truck. The engine torque is scaled in the transmission and the final drive, and results in a motive force at the wheels.

The driveline is modeled as several rotation moments of inertia and two gears. Figure 3.3 shows the stiff physical model of the driveline.

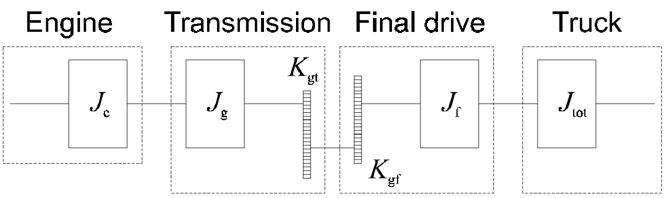

__Figure 3.3__ Physical model of the driveline. The last part represents the rest of the truck which can be seen as a big moment of inertia.

The inertia of the truck and the moment of inertia of the wheels are replaced by an equivalent mass moment of inertia, J_{tot}.

3.1 Driveline Equations

Engine Equations

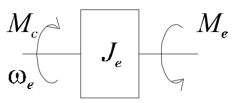

***Figure 3.4** Engine model.*

Newton's second law applied to the engine gives the following equation

$$\dot{\omega}_e J_e = M_c - M_e \tag{3.1}$$

where M_c is the torque delivered from the combustion compensated by internal engine friction, and M_e is the torque output from the engine when the engine's mass moment of inertia, J_e, is taken into consideration. The engine speed is represented by ω_e.

Direct measure of the torque is not possible, which means that the torque has to be estimated in some way. A simple approximation of the diesel engine torque is a linear function of injected fuel amount and engine speed. One drawback with this model is that it is a static function and no dynamically behavior of the torque is considered, but the approximation is assumed to be satisfactory.

A model of the engine friction varies with speed and temperature of the engine and is measured in a test bench.

Transmission Equations

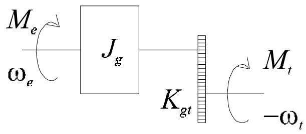

Figure 3.5 *Transmission model.*

The transmission is described by

$$\omega_e = K_{gt}\omega_t \tag{3.2}$$

$$\dot{\omega}_e J_g = M_e - \frac{M_t}{K_{gt}} \tag{3.3}$$

where K_{gt} is the gear ratio and J_g the mass moment of inertia in the transmission. Speed and torque at the output shaft are ω_t and M_t, respectively.

Final Drive Equations

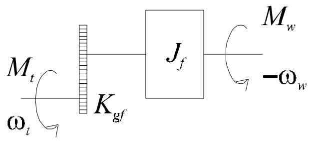

Figure 3.6 *Final drive model.*

The model in Figure 3.6 leads to the following equations

$$\omega_w K_{gf} = \omega_t \tag{3.4}$$

$$\dot{\omega}_w J_f = M_t K_{gf} - M_w \tag{3.5}$$

where K_{gf} is the gear ratio and J_f is the moment of inertia of the final drive. The speed and torque of the wheels are ω_w and M_w.

Longitudinal Equations

The longitudinal forces acting on the truck are shown in Figure 3.7, where the wheel radius is r_w and m_t' is the weight of the truck without the wheels.

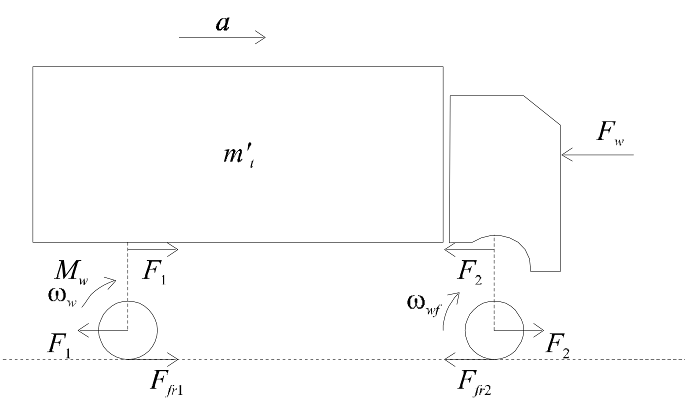

Figure 3.7 *Longitudinal forces acting on the truck.*

F_w is the resulting force of all longitudinal forces acting from the outside on the truck and a is the acceleration of the truck. The rotational speed of the front wheel is ω_{wf}.

At the rear wheel the following equations apply.

$$M_w - F_{fr1} r_w = \dot{\omega}_w J_{wr} = \frac{a}{r_w} J_{wr} \tag{3.6}$$

$$m_{wr} a = F_{fr1} - F_1 \tag{3.7}$$

Where J_{wr} is moment of inertia and m_{wr} is the weight of the rear wheels.

The equations at the front wheel are

$$F_{fr2} r_w = \dot{\omega}_{wf} J_{wf} = \frac{a}{r_w} J_{wf} \tag{3.8}$$

$$F_2 - F_{fr2} = m_{wf} a \tag{3.9}$$

The right lane in (3.6) and (3.8) is made under the assumption that no slip exists between the tire and the road.

The longitudinal forces on the truck are described by

$$F_1 - F_2 - F_w = m_t' a \tag{3.10}$$

Combining (3.6) - (3.10) yields the following expression

$$\begin{aligned} M_w &= \left[J_{wr} + J_{wf} + (m_t' + m_{wr} + m_{wf}) r_w^2 \right] \dot{\omega}_w \\ &= \left[J_w + m_t r_w^2 \right] \dot{\omega}_w \end{aligned} \tag{3.11}$$

which makes it possible to derive the truck’s weight from the total moment of inertia.

Inserting (3.3) into (3.5) gives

$$\dot{\omega}_w J_f = (-\dot{\omega}_e J_g + M_e) K_g - M_w \tag{3.12}$$

where $K_g = K_{gt}K_{gf}$. With (3.1) the expression becomes

$$\dot{\omega}_w J_f = (-\omega_e(J_g + J_e) + M_c)K_g - M_w \tag{3.13}$$

and insertion of (3.2) and (3.4) into (3.13) yields

$$\dot{\omega}_w J_f = -K_g^2 \dot{\omega}_w (J_g + J_e) + M_c K_g - M_w \tag{3.14}$$

Finally, (3.11) and (3.14) gives the desired model

$$\dot{\omega}_w \left[J_f + J_w + m_t r_w^2 + K_g^2 (J_g + J_e) \right] = M_c K_g - F_w r_w \tag{3.15}$$

3.2 Modeling External Forces

When estimating the road gradient the force F_w has to be divided into its components: air drag, rolling resistance and resistance from the slope of the road.

$$F_w = F_{air} + F_{roll} + F_{slope} \tag{3.16}$$

Modeling Aerodynamic Drag

At speed v and headwind speed v_0 the air drag is [4]

$$F_{air} = \frac{1}{2} \rho \cdot c_w A (v + v_0)^2 \tag{3.17}$$

where ρ is the air density, c_w the drag coefficient and A the frontal area of the vehicle. Here some difficulties with the unknown headwind speed occur.

Modeling Rolling Resistance

The rolling resistance occurs when the tire deforms in contact with the road. An approximation of the resistance is [5]

$$F_{roll} = m_t(c_{r1} + c_{r2}v) \tag{3.18}$$

where c_{r1} and c_{r2} are parameters depending on e.g. type of tires and road pavement.

Modeling Climbing Resistance

Climbing resistance is a product of the gravitational force and the slope of the road. It is calculated by

$$F_{slope} = m_t g \sin\chi \tag{3.19}$$

where χ is the slope of the road.

3.3 Final Driveline Model

Combining (3.15)-(3.19) yields the resulting model

$$\begin{aligned}&\dot{\omega}_w\left[J_f + J_w + m_t r_w^2 + K_g^2(J_g + J_e)\right] = \\ &M_c K_g - \frac{1}{2}\rho \cdot c_w A(v+v_0)^2 r_w - m_t(c_{r1} + c_{r2}v)r_w - m_t g \cdot r_w \sin\chi\end{aligned} \tag{3.20}$$

If v_0 is neglected everything except m_t and χ can be measured or calculated. These two can to be estimated, and the method of doing this is explained in the next chapter.

4

Method Development

The basic idea with estimating the weight is to compare the acceleration of the vehicle with the torque output from the engine, as discussed in the previous chapter. Figure 4.1 shows an example of the acceleration and the torque from the engine compensated by the current gear ratio to achieve the torque at the wheels.

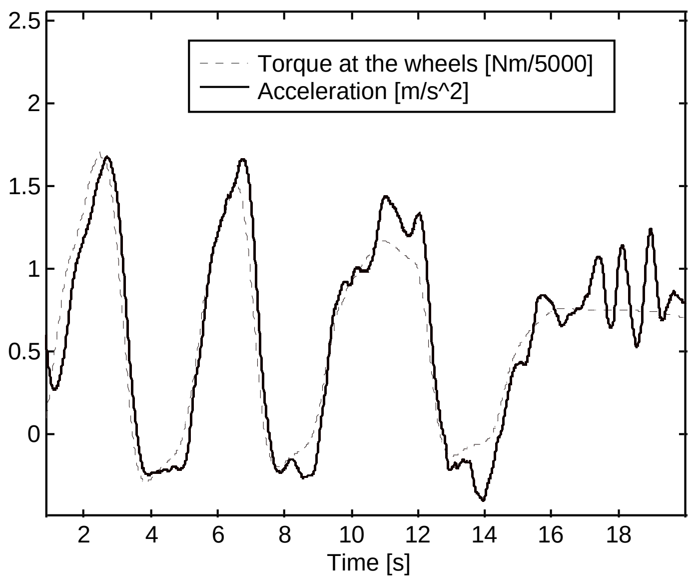

Figure 4.1 *Comparison between the vehicle's acceleration (solid) and the torque at the wheels (dashed). The correlation between these two is strong and the basic idea behind estimating the weight. Note the driveline oscillations at t = 18.*

There is a strong correlation between these two, and finding the dependency between them is the key to estimate the weight. This physical relationship is described by the model (3.20) under certain conditions described below.

When identifying parameters in the model it is important to know when the model is valid and in which situations it is more or less reliable.

Validity of Model

The model is an approximation of the driveline with the engine and three external forces. It does not model braking or driveline oscillation. Braking must be monitored not to disturb the measurements. Avoiding driveline oscillations is more difficult, but by starting measuring a few seconds after the gear is engaged most of the driveline oscillations are strongly reduced and the influence is rather small.

Parameter Estimation

The model is of first order and can thus be interpreted as a straight line. The model (3.20) can be rewritten as

$$f_2(M_c, K_g, v) = \dot{\omega}_w f_1(m_t) + f_3(m_t, \chi) \qquad (4.1)$$

which shows the dependencies of the variables. The dependence of the velocity in the rolling resistance have here been neglected according to the discussion in Section 5.5.

If $\dot{\omega}_w$ and $f_2(M_c, K_g, v)$ are measured, $f_1(m_t)$ is the slope of the line and $f_3(m_t, \chi)$ is the intersection with the y-axis. To estimate this line, at least two points, ($\dot{\omega}_w$, $f_2(M_c, K_g, v)$), are needed.

One important observation is that a longer interval between the measured points makes the estimation of a straight line less dependent on errors in acceleration and torque. Another observation is that a lot of points also make the estimation more robust. But $f_3(m_t, \chi)$ must be regarded as a constant during the estimation, and since the gradient of the road χ varies, the time of collecting the measurable variables must be short enough to consider these to be constant. These circumstances lead to two methods; estimating during acceleration, discussed in Section 4.1, and estimating during gear shifting, discussed in Section 4.2.

The fact that m_t is included in two terms in (4.1) is discussed later in Chapter 5.

4.1 Estimating During Acceleration

This method estimates the two parameters from a short interval of an acceleration. There has to be a tradeoff of the interval length not be too short, which makes the acceleration interval too small, or too long since the external forces must be considered to be constant.

An advantage with this method is that the driveline is transferring torque in the same direction, thus making the influence of drivline oscillation small. But the acceleration is positive and probably from one gear only, making the acceleration interval quite small and therefore the estimation more uncertain.

4.2 Estimating During Gear Shift

By measuring the acceleration and torque just before and when a gear is disengaged, a big difference in acceleration is measured. This forms the base for a good estimation as the errors in acceleration and torque does not affect the estimation too much. The disadvantage is danger with driveline oscillations.

5

Algorithm Development

This chapter covers development of algorithms used when estimating during both acceleration and gear shift. The experimental equipment is used to sample data from real driving with trucks. MATLAB [6] is used for testing and developing the algorithms. The development includes both implementation of the driveline model and handling of numerical problems and sampling effects.

5.1 Sampling CAN-bus Messages

The CAN communication is based on *broadcasts*, i.e. every node sends out each type of message at a certain rate. Depending on type of control system, node and type of message, this rate can vary from 1 Hz to 100 Hz. These rates are selected, depending on the bandwidth of each signal, to avoid aliasing. To prevent additional aliasing, sampling by the algorithms is done at 100 Hz. This means that some of the signals are resampled at a higher rate then they were sampled originally, but with low-pass filtering after resampling, extra distortion is avoided.

5.2 Measuring Acceleration

Measuring acceleration is done by taking the derivative of the velocity. Special care has to be taken when numerical differentiation is used. Noise is a big problem and the differentiation have to be combined with filtering. The velocity is available at the front wheels if the truck is equipped with ABS[1], and always available from the output shaft of the transmission. Measuring velocity at the front wheels is a bit better because the propeller shaft is more exposed to driveline oscillating.

Three differentiation algorithms [13] are compared. The first (5.1) is a simple backward differentiation and (5.2) is short non causal symmetrical algorithm that uses values both from the ‘future’ and the past. This means that the input data have to be delayed to make this possible. The third

[1] Antilock Braking System

algorithm (5.3) is also non causal and symmetrical but it spans over a longer interval compared to (5.2).

$$y_a'(t) = \frac{y_a(t) - y_a(t-1)}{h} \tag{5.1}$$

$$y_b'(t) = \frac{-y_b(t+2) + 8y_b(t+1) - 8y_b(t-1) + y_b(t-2)}{12h} \tag{5.2}$$

$$y_c'(t) = \frac{y_c(t+3) - 9y_c(t+2) + 45y_c(t+1) - 45y_c(t-1) + 9y_c(t-2) - y_c(t-3)}{60h} \tag{5.3}$$

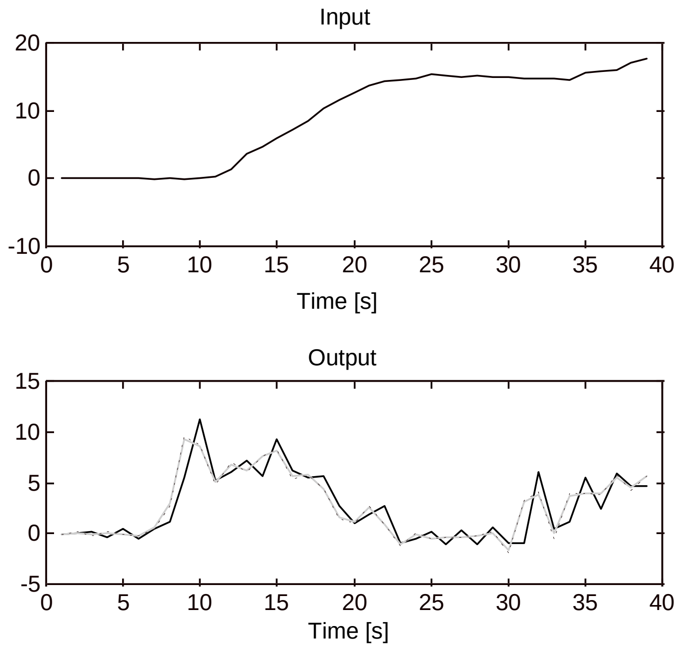

Figure 5.1 *Different outputs of differentiation algorithms. The simple backward difference (solid black) varies more compared with the non causal (5.2) plotted in solid gray. The more complex (5.3) (dotted) nearly follows the more simple (5.2) and gives no significant enhancement.*

As seen in Figure 5.1, the simple backward difference (5.1) varies more compared to the other. By buffering some samples and therefore causing a slight delay, a non causal differentiation can be used. (5.2) is a short algorithm of that type, and as seen in the figure, the characteristic are better. When extending the algorithm to (5.3) no significant gain in accuracy is obtained.

Filtering the differentiation output from (5.2) with an appropriate low-pass filter yields an acceleration which is usable. This is shown in Figure 5.2 where a second order Butterworth filter is used.

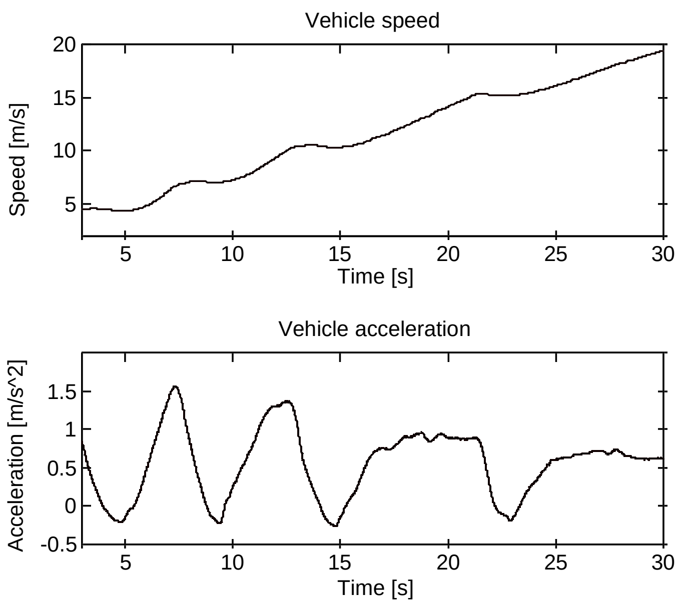

Figure 5.2 *An example of calculating acceleration. The differentiation algorithm (5.2) is used with a second order Butterworth low pass filter.*

5.3 Estimating Engine Torque

The engine torque and friction are estimated in the ECU, as described in Section 3.1, and they depend on engine speed, injected fuel amount and engine temperature. Figure 5.3 shows the torque measured at normal operating temperature in a test bench, and it can be approximated with a linear function of the fuel quantity and the engine speed.

Actually, it is the torque that results in a motive force that is wanted. This means that if there are some accessories that consume power from the engine, they will affect the resulting torque at the wheels. This can be e.g. the air compressor, the alternator or the cooling fan. If all accessories operate at the same time this could be as much as 15 % of the maximum produced power by the engine. When using the experimental trucks it is impossible to know when the accessories consume power, therefore subtracting a statistical mean value of the consumed power from the engine's power is assumed to be sufficient.

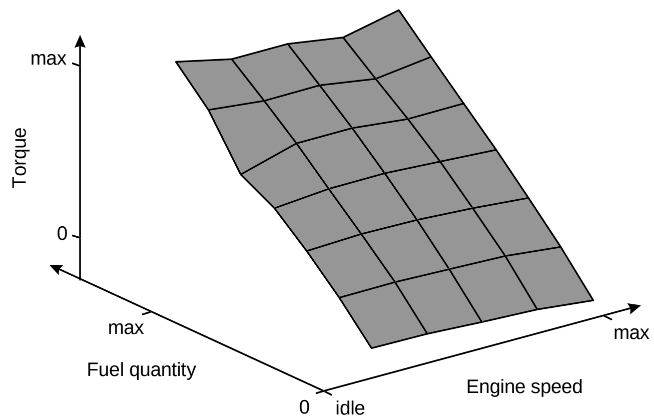

Figure 5.3 *Torque map measured in a test bench. The output torque of the engine can roughly be approximated to a linear function of the fuel quantity and the engine speed.*

5.4 Estimating Gear Ratio and Shift Detecting

Manually operated transmissions have no sensors that indicates which gear is used and because of this an estimation of the current gear ratio has to be made. The gear ratio is defined as speed of the input shaft divided by speed of the output shaft of the transmission. Simply dividing these two rotational speeds is not sufficient since the speed sensors have limited bandwidth. This especially concerns the sensor at the output shaft which is worse than the sensors at the front wheels. It is obvious that the quotient has to be filtered in some way. Ordinary low-pass filtering is not suitable because when a gear is engaged strong filtering of the quotient is desirable. But on the other hand, during gear shift very little filtering is wanted for a quick adaptation to the new gear ratio. An adaptive algorithm supported by a change detector [7] is used to solve the problem, giving fast response to big changes in gear ratio but slow response to small changes. The change detector is also used as a gear shift indicator as shown in Figure 5.4.

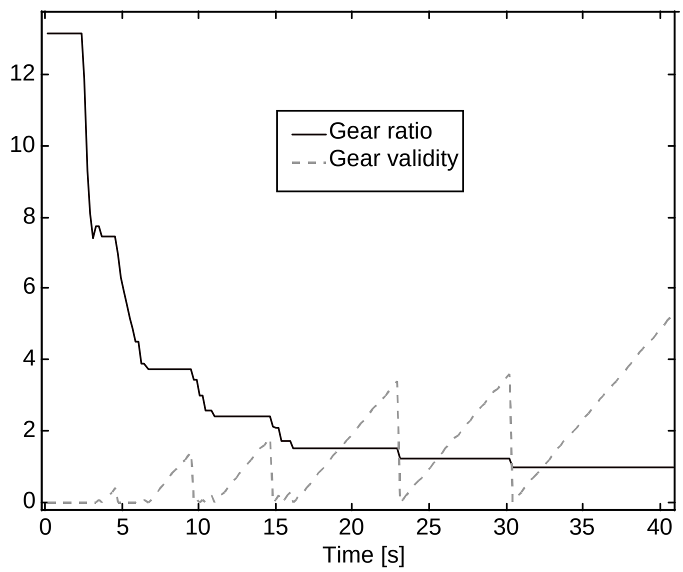

Figure 5.4 *Gear ratio estimation (solid) and gear detection (dashed). The gear validity is a measure of how long time a certain gear is used which can be used to avoid driveline oscillations. The adaptive filtering of the gear ratio makes it constant bit by bit.*

5.5 Weight and Gradient Estimation

When all variables are measured, a straight line approximation gives the truck's weight and the gradient of the road. Equation (5.4) makes a comparison with the straight line equation $y = kx + l$.

$$\underbrace{\begin{matrix} M_c K_g - \dot{\omega}_w\left(J_f + J_w + K_g^2(J_g + J_e)\right) - \\ \frac{1}{2}\rho \cdot c_w A(v+v_0)^2 r_w \end{matrix}}_{y} = \underbrace{m_t r_w^2}_{k}\underbrace{\dot{\omega}_w}_{x} + \underbrace{r_w m_t (g \sin\chi + c_{r1})}_{l} \tag{5.4}$$

As seen in (5.4) the estimation of the weight, m_t, is simply done by dividing the slope of the line with r_w^2. Extracting the gradient, χ, from l can only be done with knowledge of the weight, but this problem is easily solved since the estimation of the weight is independent from χ and therefore can be done in advance. As χ is small, it is a good approximation to use $\sin \chi = \chi$. Since it is not possible to measure the headwind speed, the estimation of the gradient has to be made with the assumption that the influence of headwind speed is negligible. The part of the rolling resistance that depends on the velocity is $c_{r2} r_w m_t v$ and can not be fit into either y or l. Since this part is small compared to the other parts in (5.4), it is a good approximation to ignore it.

In the case with estimating during acceleration, estimating the line can be done with LMS[1] [8] or a similar algorithm.

Filtering the Estimations

A truck's weight is rather constant during driving and therefore strong filtering of the weight estimations is possible. On the other hand, the weight can decrease during driving if the truck is e.g. a gravel truck, thus the filtering must not be too strong. The estimations are influenced by two type of disturbances; an influence by measurement errors, mainly in acceleration measurement, causing a 'white' noise, and a disturbance caused by e.g. vehicle shuffle on a bumpy road. The latter will make some estimations differ a lot from the mean value compared to other estimations, therefore a filter that discards the extreme values before normal filtering is used.

---

[1] Least Mean Square

6

Experiments

The experiments are made with a PC notebook connected to the truck's CAN-bus. Either data can be recorded with the PC and later processed with MATLAB or the algorithms can be implemented in the PC and estimations made in real time.

6.1 Experimental Platform

Connecting the PC to the CAN-bus is accomplished by using an adapter connected to the parallel port which is called PPCan from Mecel [9]. Connected to the CAN-bus, it is possible to listen to the different CAN-messages and thus be able to sample the desired variables. The algorithms can be implemented in the PC and the result displayed directly on screen in real time.

The software on the PC is a real time operating system [10] based on the real time kernel RTKernel [11] together with the PPCan drivers [9]. Including the algorithms everything is written in C which makes the experimental software very flexible and portable.

As seen in Figure 6.2 several variables are displayed simultaneously including both the recent estimation and the filtered weight and gradient.

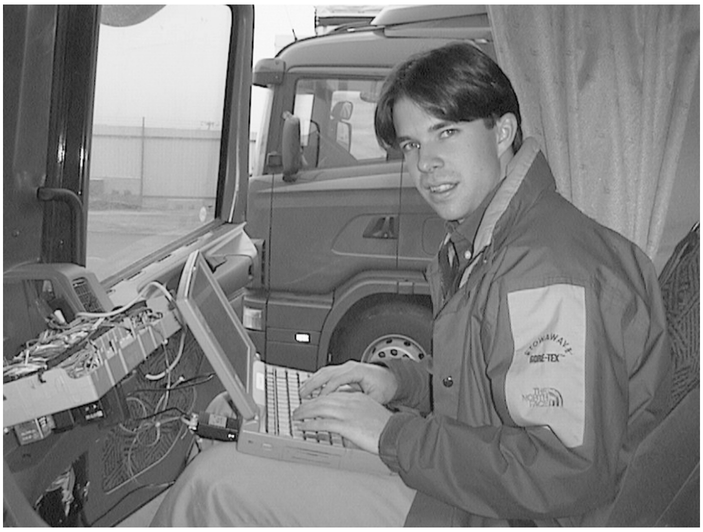

Figure 6.1 *Experimental situation. PC connected via a CAN-adapter to the truck's CAN-bus.*

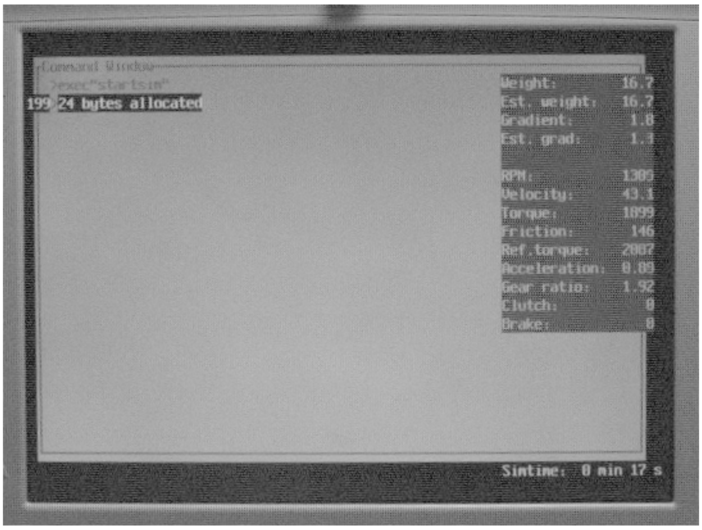

Figure 6.2 *Screen picture of the PC. To the left commands are executed, and to the right variables and estimated parameters are shown in real time.*

6.2 Experiments with the Acceleration Method

The method with estimation during acceleration is only implemented in MATLAB and experiments are done off-line with recorded data. Figure 6.3 shows an estimation based on data during a full throttle acceleration at different gears. This data is collected during several gears in a full throttle acceleration and to make an estimation possible the truck is driven on a flat road as the gradient of the road has to be constant during the time of collecting the data.

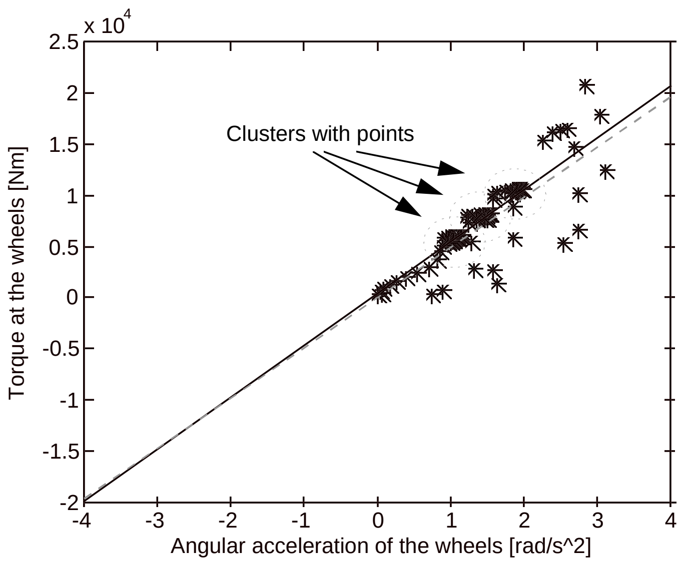

Figure 6.3 *Estimating the weight and road gradient during acceleration. This data comes from a full throttle acceleration and it is possible to see the acceleration at different gears as clusters with points with different acceleration. The slope of the straight line (in solid), made by LMS estimation, gives a weight of 18600 kg which is close to the real weight 18000 kg (dashed) of the Scania 124L 6x2.*

As seen in Figure 6.3 the estimation is quite accurate, except for some points that differ, possibly due to driveline oscillations. This depends on that the data covers an full throttle acceleration at several gears which makes the range of acceleration big. But this does not work in a real situation when the slope and headwind changes during the collection of data. Consider a short time interval when the external forces (3.16) can be treated as constant, say two seconds. Two seconds cover only a part of the time that a gear is normally used, which means an estimation has to be made with a part of the points in one cluster in Figure 6.3. These points will have very little difference in acceleration and torque making a straight line estimation inaccurate. This will not work satisfactorily and that is a reason for investigating the other method more close.

6.3 Experiments with the Gear Shift Method

This method with estimating during gear shifting is implemented in the PC notebook and tested on the three trucks described in Chapter 2. Figure 6.4 shows the results of weight estimations with the Scania 144L 6x2.

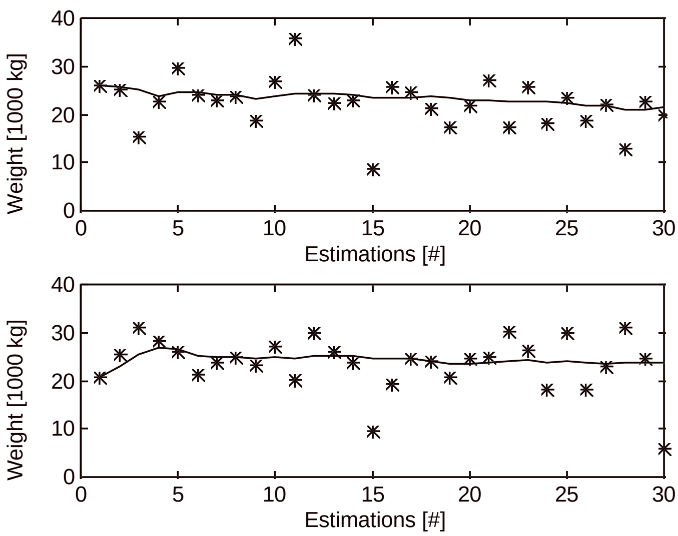

Figure 6.4 *Weight estimations with the Scania 144L 6x2 without a trailer. The real weight is 24400 kg. The dots are the estimations and the solid line the filtered weight. The upper figure is based on velocity sensors from the front wheels, and the lower on a sensor at the output shaft of the transmission.*

The filter used in all estimations works with 15 estimations at a time. The maximum and minimum values are discarded and a mean value of the rest is presented. As shown in the figure above the estimations vary a lot, but the filtered values behave smoother. In the upper figure, the filtered values have a mean value of 22800 kg with a standard deviation of 1.1, and the lower figure have a mean value of 24400 kg and standard deviation of 1.0.

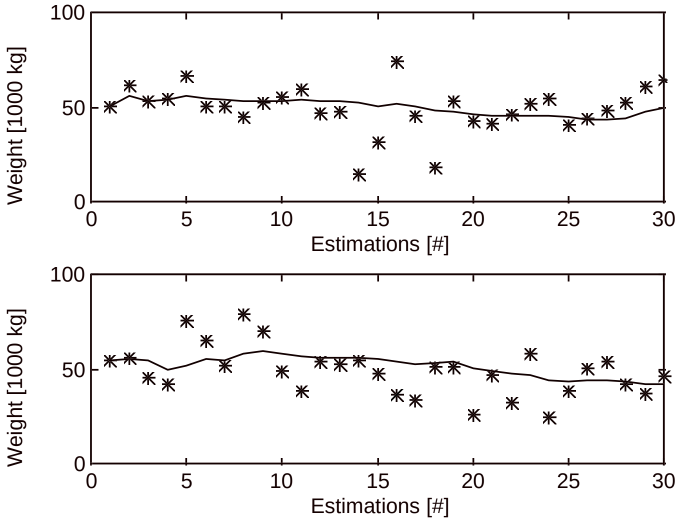

Figure 6.5 *Similar estimation as in Figure 6.4 made with the same truck but with a trailer connected. Total weight is 56400 kg. The variance of the estimations is bigger compared to experiments without the trailer.*

In Figure 6.4 the Scania 144L 6x2 is driven without a trailer and in Figure 6.5 with a trailer. In the last case the estimations vary more compared to estimations without a trailer. Results in the upper part are a mean value of 51200 kg and a standard deviation of 3.8, and in the lower a mean value of 50900 kg and a standard deviation of 5.6.

The difference caused by difference in measuring velocity is not as big as expected according to the discussion in Section 5.2. The problem with propeller shaft oscillations is probably not big enough to make any difference.

Figure 6.6 shows the weight estimations done with the Scania 124L 6x2. In this case a little larger variance in the transmission based estimations is observed.

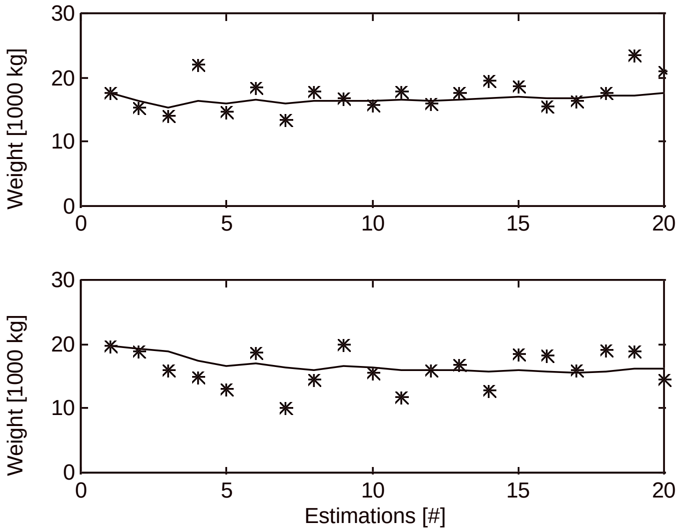

Figure 6.6 *Similar estimations done with the Scania 124L 6x2. The real weight is 18000 kg. The lower figure based on velocity measured at the transmission has bigger variance.*

Results with the Scania 124L 6x2 are with front wheel sensors a mean value of 16800 kg and standard deviation of 1.0. With transmission velocity sensors the result are a mean value of 16600 kg and standard deviation of 1.1.

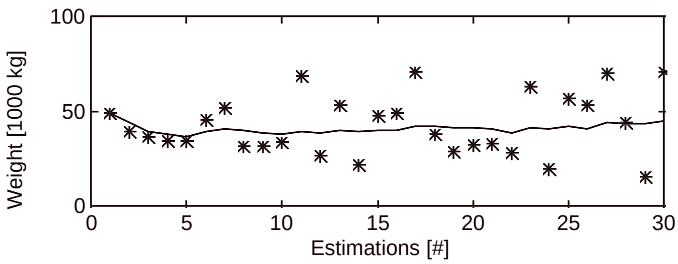

Figure 6.7 *Weight estimations with the Scania 124L 4x2. A trailer is connected and the total weight is 38000 kg. Estimations vary a lot, but the filtered weight is roughly at the right value. The speed sensors at the front wheels are used.*

The mean value of the filtered weight in Figure 6.7 is 41900 kg and the standard deviation is 2.4. In Figure 6.7 and Figure 6.6 the estimations have a big variance compared to the other experiments, this probably depends on the fact that there is a play between the heavy trailer and the truck. This can cause vehicle shuffle when shifting gears which affects the measurement of the velocity.

7

Conclusions

If the weight of a vehicle is used in engine control systems, increased performance of control algorithms can be achieved since the weight affects the dynamic behavior of a vehicle, especially heavy trucks.

A method, based on standard automotive sensors, for estimating the weight by identifying it as a parameter in a model of the truck is developed. The model is based on Newton's second generalized law and it consists of rotating moments of inertia and longitudinal forces acting on the vehicle. The actual estimation is done during gear shifting by measuring acceleration and torque just before and when a gear is disengaged. The model is of first order and assumes a stiff driveline, which means that driveline oscillations are not modeled. By avoiding velocity measurements when oscillations usually occur and by strong filtering of the estimated values, the influence of oscillations is small.

The method is implemented and validated in field trials with three different heavy trucks. The result obtained with trucks without a trailer is a estimated weight that differs ±10 % from the real weight, and with trailers the accuracy is ±20 %. The lighter the trailer is compared to the truck, the better accuracy in the estimation is achieved. The deterioration in accuracy probably depends on play between the truck and the trailer causing vehicle shuffle during the gear shift and thus disturbing the measurements of velocity. A slight improvement in accuracy can be achieved if the velocity sensors at the front wheels are used instead of the sensor at the output shaft of the transmission because of propeller shaft oscillations.

The accuracy is limited mainly due to uncertainties of the actual engine output torque, since problems with knowing how much power is consumed by accessories as air condition and air compressor. The accuracy is however enough to substantially improve control performance.

7.1 Further Work

To improve the estimation of the weight, first of all monitoring of the accessories has to be carried out, which will result in a more accurate engine torque measurement. Additional work can also be done with avoiding certain gear shifts that result in bad measurements. This will decrease the variance of the estimations and therefore improve the accuracy of the filtered weight.

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