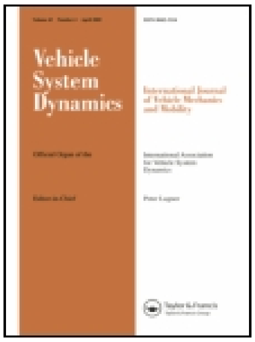

Vehicle System Dynamics

International Journal of Vehicle Mechanics and Mobility

ISSN: 0042-3114 (Print) 1744-5159 (Online) Journal homepage: http://www.tandfonline.com/loi/nvsd20

Road Slope and Vehicle Mass Estimation Using Kalman Filtering

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Vehicle System Dynamics Supplement 37 (2002), pp. 12-23

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SUMMARY

Kalman filtering is used as a powerful method to obtain accurate estimation of vehicle mass and road slope. First the problem of estimating the slope when the vehicle mass is known is studied using two different sensor configurations. One where speed is measured and one where both speed and specific-force is measured. A filter design principle is derived guaranteeing the estimation error under a worst case situation (when assuming first order dynamics). The simultaneous estimation problem required an Extended Kalman Filter (EKF) design when measuring speed only whereas the additional specific force case yielded a simple filter structure with a time-variant measurement equation. Additionally the filter needs present propulsion force which in our case is calculated form the engine speed and amount of fuel injected. When the vehicle uses the foundation brakes the estimates are frozen since varying friction properties makes the braking force unknown. Both sensor configurations are concluded to be robust and accurate by simulation and experimental field trials.

1. INTRODUCTION

The major parameters in the energy balance of moving vehicles, setting the requirements on the propulsion and retardation systems in the actual driving situation, are current values of vehicle speed, road slope and vehicle mass. In an effort to improve the control of longitudinal vehicle motion it is thus essential to have access to accurate on-line estimates of these parameters.

When it comes to simultaneous estimation of road slope and vehicle mass mainly one approach is seen in the literature. The basic idea is to calculate the vehicle acceleration at two successively points that are relatively close to each other in time (no more than 0.5s) so that gravity, rolling- and air-resistance forces can be considered constant. By stating Newton's second law at the two measurement points the only unknown is the mass of the vehicle. Since the acceleration is calculated from a rather noisy vehicle speed signal (usually the passive ABS wheel speed sensor is used) a clever choice of measurement point has to be made in order to predict the mass successfully. By making one measurement just before a gearshift and the following one during the shift (zero propulsion force) a large difference in acceleration is obtained and hence increasing the accuracy of the mass prediction.

There are some obvious problems with this approach. First of all this method requires measurements to be made under very difficult circumstances. Oscillations arise both from the flexible driveline and from the play between truck and trailer. Both these are induced by the discontinuous propulsion force when changing gear. Furthermore the method can not be used for vehicles equipped with automatic gearshift (powershift) simply because these vehicles don't separate the driveline during a gearshift. Vehicles equipped with automatically shifted manual transmissions are increasing their market shares. This type of vehicle separates the driveline during a gearshift enabling for the above estimation method to work. It is though a fact that manufactures are trying to minimise the time of no propulsion and thereby decreasing the time left to calculate the vehicle acceleration consequently leading to a low accuracy mass estimate. Another typical situation where the algorithm fails to estimate vehicle mass is when a truck drives up on a relatively flat highway after for example a short refuel. Large uncertainties in the estimate arise simply because the vehicle manages to accelerate with only a few up-shifts.

This paper investigates the possibility of achieving slope and mass estimates using available information on propulsion and brake system characteristics, a vehicle speed measurement and the possible improvement through the addition of a longitudinal accelerometer. Estimation theory (Kalman Filtering) is used to obtain appropriate computation algorithms and make assessments of resulting estimator performance. With this approach a crucial part is the formulation of stochastic models of different force mechanisms entering the vehicle. Disturbances originating from road elevation profile, wind speed, road and tire condition, discrepancy between engine and brake maps and resulting true traction force, measurement errors etc. all have to be modelled.

Some earlier attempts to slope and mass computation, without explicit dynamic error modelling, was done by P.Frank [1], H.Ohnishi et.al [2] and E.Fritzen [3]. In A.G Stefanopoulou et.al. [4] a Model Reference Adaptive System is designed to control vehicle brakes, including and on-line estimator of vehicle mass and road slope utilising a Lyapunov based method.

2. KALMAN FILTERING

A Kalman filter is an estimation method for linear systems in state space form. It is an observer that considers the statistic behaviour of process and measurement disturbances. The system is mathematically formulated on state space form

$$\dot{x} = Ax + Bu + v\,; \quad y = Cx + Du + w \tag{1}$$

where x is the state vector, y is the measurement vector, u is the known system input and v and w being the process and measurement disturbance vectors (white noise). The Kalman filter generating the state vector estimate $\hat{x}$ minimising the (variance of) the estimation error $x-\hat{x}$ is obtained as:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu + K(y(t) - C\hat{x}(t)) \tag{2}$$

The optimal stationary filter coefficient vector is given by

$$K = PC^T R_2^{-1} \tag{3}$$

where P is the stationary estimation error variance (covariance matrix in the vector case) as given by the Riccati equation [1,2]

$$AP + PA^T - PC^T R_2^{-1} CP + R_1 = 0 \tag{4}$$

Parameters R_1 and R_2 are the process disturbance and measurement noise intensities.

3. SLOPE ESTIMATION WITH SPEED MEASUREMENT ONLY

In this section we formulate and investigate different filter formulations for road slope estimation when the vehicle mass is known. We begin by stating the motion equation of the vehicle in the longitudinal direction.

$$m\dot{v} = mg\sin(\alpha) + f_p - f_r \tag{5}$$

where α, f_p, f_r are road slope, propulsion force and retardation force respectively. The propulsion force is the positive engine torque filtered via the transmission of the vehicle and the retardation force consists of forces generated by wheel, auxiliary brakes and deterministic parts of rolling resistance and air drag ($\sim v^2$). Both these forces are considered as known filter input $u(t) = f_p(t) - f_r(t) = f(t)$. Choosing vehicle speed and road slope as states we chose the following simple state space equations

$$\begin{aligned} x_1 &= v \Rightarrow \dot{x}_1 = g x_2 + \frac{1}{m} f(t) + \upsilon_1 \\ x_2 &= \alpha \Rightarrow \dot{x}_2 = \dot{\alpha} = \upsilon_2 \\ y &= x_1 + w \end{aligned} \tag{6}$$

Slope variations are modelled as integrated white noise (random walk) whereas force (acceleration) errors and measurement disturbances are approximated as white noise processes. The intensities of v_1, v_2 and w are a, b and c respectively. The simplicity enables us to find an explicit solution to the stationary Riccati equation:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} \sqrt{ca + 2cg\sqrt{bc}} & \sqrt{bc} \\ \sqrt{bc} & 1/g\sqrt{ab + 2gb\sqrt{bc}} \end{bmatrix} \tag{7}$$

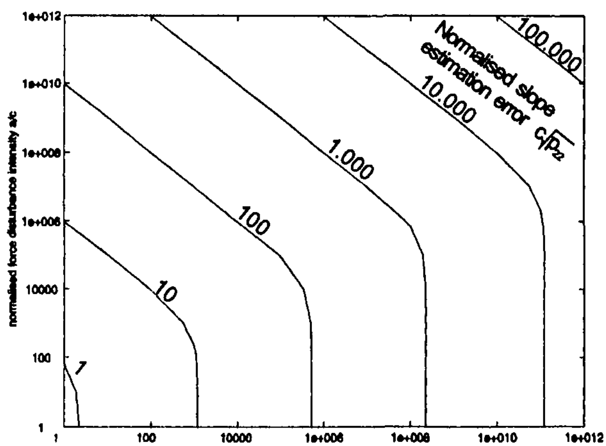


Fig. 1. Normalised slope estimation filter performance (standard deviation; simple models)

A parametric study can be done to see how estimation error (filter performance) is affected by process and measurement disturbances, *Fig.*1. Everything is normalised with the intensity of the measurement noise c. The knees in Fig 1 clearly show areas where improvements in the force estimation does not affect the slope estimation.

3.1. Improved modelling of road slope

Figure 2 shows the power spectral density (PSD) of slope variations in a typical west-swedish road section is, the standard deviation being 0.028 rad. The integrated white noise model of the previous paragraph would correspond to a straight line with negative unit slope. For the figure case it is clear that a first order model with a cutoff frequency of f_c=0.002 cyc/m (spatial frequencies!) and a noise intensity of

0.8 $(rad)^2/(cyc/m)$ is a good representation of road slope, e.g. giving the same standard deviation as the experimental curve (dashed line segments in Fig 2).

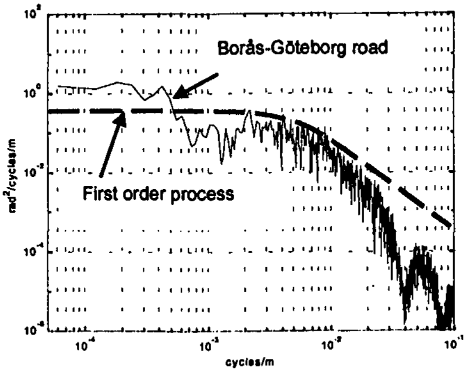


Fig 2. PSD for road section Borås-Göteborg (65 km). The dashed line is first order low pass filtered white noise which is the approximation used here fore the road slope process.

The complete state space model (still 2nd order) then turns to

$$\left.\begin{array}{l} x_1 = v \Rightarrow \dot{x}_1 = gx_2 + \frac{1}{m} f(t) + \upsilon_1 \\ x_2 = \alpha \Rightarrow \dot{x}_2 = \dot{\alpha} = -\omega_c x_2 + \upsilon_2 \end{array}\right\} \Rightarrow A = \begin{bmatrix} 0 & g \\ 0 & -\omega_c \end{bmatrix} \quad \upsilon = \begin{bmatrix} \upsilon_1 \\ \upsilon_2 \end{bmatrix} \tag{8}$$

The Riccati equation for (8) is numerically solved and a parameter study can be done. In Fig 3 both relative and absolute slope estimation error is shown as function of normalised process disturbance. The relative estimation error is $\sqrt{p_{22}/2b}$ where b is the intensity of the slope process (temporal frequencies).

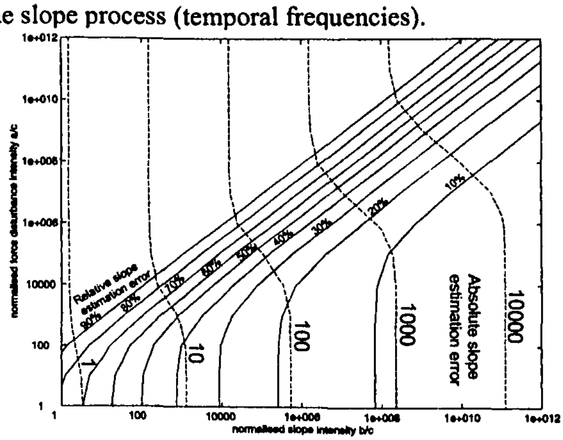


Fig 3. Parameter study of slope estimation error (relative is with respect to slope standard deviation)

In Fig 3 we see that the area where we like to make our estimation is the lower right part where the relative estimation error is low. The curves representing estimation error now have two knees each. For constant slope rate intensity we see that the estimation error now is affected only in an interval by the force disturbance.

3.2. Dynamic modelling of force disturbance

We now want to improve the unrealistic assumption of white noise force disturbance by replacing it with a first order model. The errors in the engine/brake torque estimation, rolling resistance and air resistance are relatively well known in magnitude but much less known in their frequency content. We have to enlarge our state space formulation with one additional state $x_3 = f_{dist}$.

$$A = \begin{bmatrix} 0 & g & 1/m \\ 0 & -\omega_c & 0 \\ 0 & 0 & -\omega_d \end{bmatrix} \quad Bu = \begin{bmatrix} f(t)/m \\ 0 \\ 0 \end{bmatrix} \quad v = \begin{bmatrix} 0 \\ v_2 \\ v_3 \end{bmatrix} \tag{9}$$

where ω_d is the disturbance force cutoff frequency and $v_3(t)$ is the forcing noise (with intensity d giving a disturbance force variance of $p_d = d/(2\omega_d)$).

It is interesting to investigate the nature of the force disturbance that affects the estimation error the most. With a given disturbance variance p_d the cutoff frequency ω_d is varied with a noise intensity $d = 2\omega_d p_d$ (giving the same variance regardless of cutoff frequency). A parameter study of this is shown in Fig. 4. It shows that the cut-off frequency that affects the estimation the most equals approximately the cut-off frequency for the road slope i.e. $\omega_d = \omega_c$. This leads to a non-observable but detectable system, meaning that the non-observable mode is stable and the Kalman theory can still be used (it is difficult for a filter to separate two signals with same assumed frequency content; the system is in reality of 2nd order).

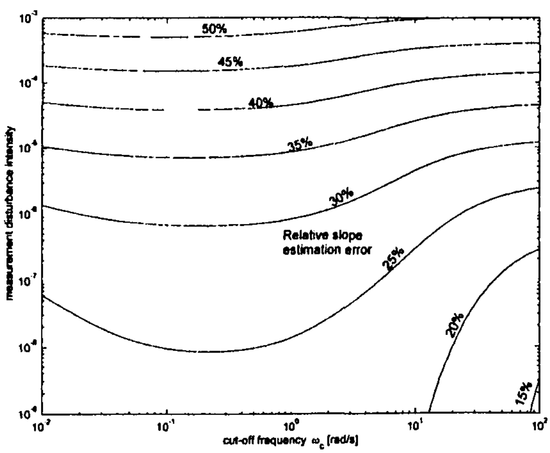


Fig 4 Influence of the force disturbance characteristics on relative estimation error. The cutoff frequency between 10^0 and 10^1 affects the estimation error the most. The road is set to Borås-Göteborg and the vehicle is traveling with constant speed 20 m/s.

Equal dynamic characteristics in force disturbance as in road slope variations thus represents a worst case for slope estimation. In the absence of knowledge on the real disturbance dynamics it makes sense to design the estimator for this worst case.

3.3. Worst case filter performance

Choose a cut-off frequency for the force disturbance that represents the worst case according to Fig 4 ($\omega_d = \omega_c$) and calculate the corresponding constant Kalman gain matrix K. How well does our observer perform if the real force disturbance has a characteristic (e. g. cutoff frequency) that differs from the one used to calculate K ? The process and observer are described by the following state equations:

$$\dot{x} = Ax + Bu + \upsilon \qquad \text{Process}$$

$$\dot{\hat{x}} = A_o\hat{x} + Bu + K_o(y - C\hat{x}) \qquad \text{Observer}$$

We like to calculate the covariance for $\hat{x} - x$ i.e.

$$E\{(\hat{x}-x)(\hat{x}-x)^T\} = E\{\hat{x}\hat{x}^T\} + E\{xx^T\} - 2E\{x\hat{x}^T\}$$

One way to obtain this is to expand our state vector to include both observer state and process state. Then we can solve the variance matrix equation (a Lyapunov equation) for covariance.

$$\dot{x}^* = \begin{bmatrix} \dot{x} \\ \dot{\hat{x}} \end{bmatrix} = \begin{bmatrix} A & 0 \\ 0 & A_o \end{bmatrix}\begin{bmatrix} x \\ \hat{x} \end{bmatrix} + \begin{bmatrix} B \\ B \end{bmatrix}u + \begin{bmatrix} \upsilon \\ K_0(Cx + w - C\hat{x}) \end{bmatrix} = \begin{bmatrix} A & 0 \\ K_oC & A_o - K_oC \end{bmatrix}\begin{bmatrix} x \\ \hat{x} \end{bmatrix} + \begin{bmatrix} B \\ B \end{bmatrix}u + \begin{bmatrix} \upsilon \\ K_0 w \end{bmatrix} \quad (10)$$

Where A_o, K_o are constant, for a constant cut-off frequency, and w and v are uncorrelated process and measurement noises. To calculate the variance of $\hat{x} - x$ we simply have to solve the stationary Lyapunov equation in Matlab. Fig 5 shows filter performance for 3 different filter design cases, Low Frequency (LF), Worst Case (WC) and High Frequency (HF) (constant disturbance variance in all three cases).

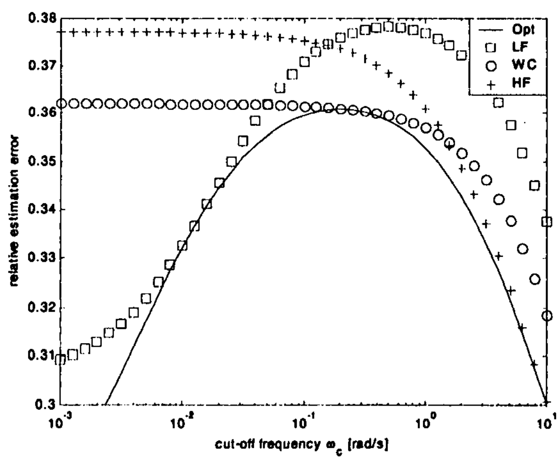


Fig 5 Relative estimation error as function of force disturbance cut-off frequency. The solid line represents optimal filtering i.e. new K is calculated at every ω_d.

In the worst case we see that the observer always keeps the relative estimation error under the maximum error 0.36. Though the performance does not improve for lower frequencies (bias) as for the optimal curve (solid) we always know that the error is equal to or under the maximum error. The HF case shows that designing the filter for higher frequencies deteriorates the observer performance in the low frequency region.

Two fundamental parameters of interest are the variance of the force disturbance (x_3) and the measurement disturbance c. How does the measurement disturbance affect the filter performance in a worst-case situation? In Fig 6 a parameter study is presented.

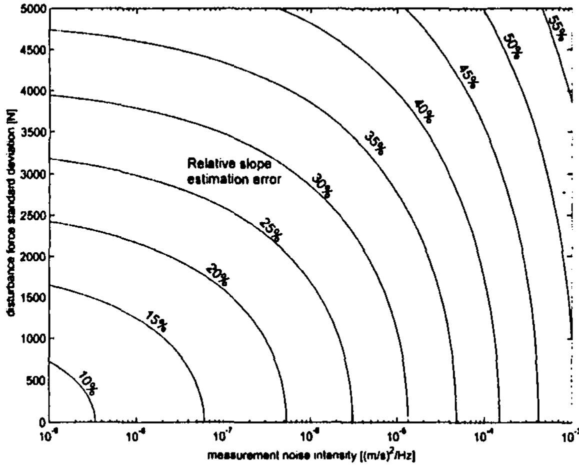


Fig.6 The influence of force disturbance and measurement noise on relative estimation error. Measurement noise as function of force disturbance. Worst-case design.

From the parameter study above we can set a limit for the maximum allowed measurement noise. The relative estimation error is clearly influenced by the measurement noise between 10^{-6} to 10^{-8}. For lower noise levels in the speed measurement the estimation is mainly influenced by the force disturbance. As noted earlier the WC design gave a detectable model and we can therefore reduce our observer by setting $x_{2tot} = x_2 + x_3$. Our system is redefined and the relation between

$$\left.\begin{matrix} x_2 \to gx_2 \\ x_3 \to x_3/m \end{matrix}\right\} \Rightarrow A = \begin{bmatrix} 0 & 1 & 1 \\ 0 & -\omega_c & 0 \\ 0 & 0 & -\omega_d \end{bmatrix}, \upsilon = \begin{bmatrix} 0 \\ gv_2 \\ v_3/m \end{bmatrix}$$

$\hat{x}_{2tot}$ and $\hat{x}_2$ is proportional to the ratio of the second element of the full sized observer and the second element of the reduced observer.
By setting $x_{2tot} = x_2 + x_3$ we get

$$A_r = \begin{bmatrix} 0 & 1 \\ 0 & -\omega_c \end{bmatrix} \upsilon = \begin{bmatrix} 0 \\ gv_2 + v_3/m \end{bmatrix} \quad \text{and} \quad \hat{x}_2 = \frac{K_2}{K_{2tot}} \hat{x}_{2tot}$$

4. ESTIMATION OF SLOPE AND MASS WITH SPEED MEASUREMENT ONLY

To be able to simultaneously estimate vehicle mass and road slope we have to enlarge our state space model (section 3.2) with at least one additional state for the vehicle mass. This gives us the following equations

$$\dot{v} = g\alpha + \frac{f(t)}{m} + \frac{f_{dist}}{m} \qquad \begin{aligned} \dot{v} &= \dot{x}_1 = gx_2 + \frac{f(t)}{x_3} + \frac{x_4}{x_3} \\ \dot{\alpha} &= \dot{x}_2 = -\omega_c x_2 + \upsilon_2 \\ \dot{m} &= \dot{x}_3 = \upsilon_3 \\ \dot{f}_{dist} &= \dot{x}_4 = -\omega_d x_4 + \upsilon_4 \end{aligned} \tag{11}$$

This is a non-linear state-space equation system and we can no longer use standard linear Kalman filtering. Instead Extended Kalman Filtering (EKF) is used [5].

Linear/non-linear equations $\begin{aligned} \dot{x} &= f(x,t) + \upsilon \\ y &= g(x,t) + w \end{aligned}$

In our case $f(x,t)$ is a non-linear function and $g(x,t)$ is linear. The basic idea with EKF is to linearise the model around $\hat{x}$ and then use the time variant linear Kalman filtering equations for filter coefficient K and estimation error covariance P.

It is preferable to work with difference equations instead of differential equations in real-time applications. The state-space formulation is therefore discretisized with an Euler approximation ($\dot{x} = (x(t+1) - x(t))/h$, h being the time increment):

$$\begin{aligned} x_1(t+1) &= x_1 + hgx_2 + \frac{hf(t)}{x_3} + \frac{hx_4}{x_3} = f_1 \\ x_2(t+1) &= (1 - h\omega_c)x_2 + hv_2 = f_2 + hv_2 \\ x_3(t+1) &= x_3 + hv_3 = f_3 + hv_3 \\ x_4(t+1) &= (1 - h\omega_d)x_4 + hv_4 = f_4 + hv_4 \end{aligned} \tag{12}$$

As mentioned the next step in deriving a filter is to linearise the non-linear equations around the estimated state vector $\hat{x}$.

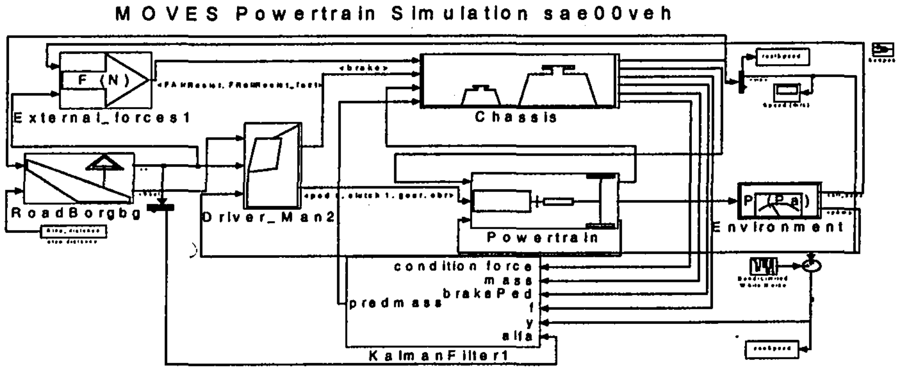
Linearization $\begin{aligned} \delta x &= F\delta x + \upsilon \\ y &= g(x,t) + w \end{aligned}$ where $F = \frac{\partial f(x,t)}{\partial x}$ at $\hat{x}$ yielding:

$$\begin{bmatrix} \delta x_{1_{t+1}} \\ \delta x_{2_{t+1}} \\ \delta x_{3_{t+1}} \\ \delta x_{4_{t+1}} \end{bmatrix} = \begin{bmatrix} 1 & hg & -\frac{h(f(t) - \hat{x}_{4_t})}{\hat{x}_{3_t}^2} & \frac{h}{\hat{x}_{3_t}} \\ 0 & 1 - h\omega_c & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 - h\omega_d \end{bmatrix} \begin{bmatrix} \delta x_{1_t} \\ \delta x_{2_t} \\ \delta x_{3_t} \\ \delta x_{4_t} \end{bmatrix} + \begin{bmatrix} 0 \\ h\upsilon_2 \\ h\upsilon_3 \\ h\upsilon_4 \end{bmatrix}, [y] = [C] \begin{bmatrix} \delta x_{1_t} \\ \delta x_{2_t} \\ \delta x_{3_t} \\ \delta x_{4_t} \end{bmatrix} + [w] \tag{13}$$

4.1. Simulation results for slope and mass estimation

Initial to practical field-tests the filter has been tested in a software environment. The model used here is a complete vehicle model built in Matlab/Simulink, Fig.7. In the simulation the vehicle travels on the measured Borås-Göteborg road profile.

Results from one simulation are shown below. When the driver engages the foundation brakes the estimation process is temporarily frozen (uncertain friction between pad and disc; not the case for auxiliary brakes). The simulations indicate that the road slope and vehicle mass estimation algorithm using Kalman filtering gives reasonable performance (cf. also practical field results presented in section 7).



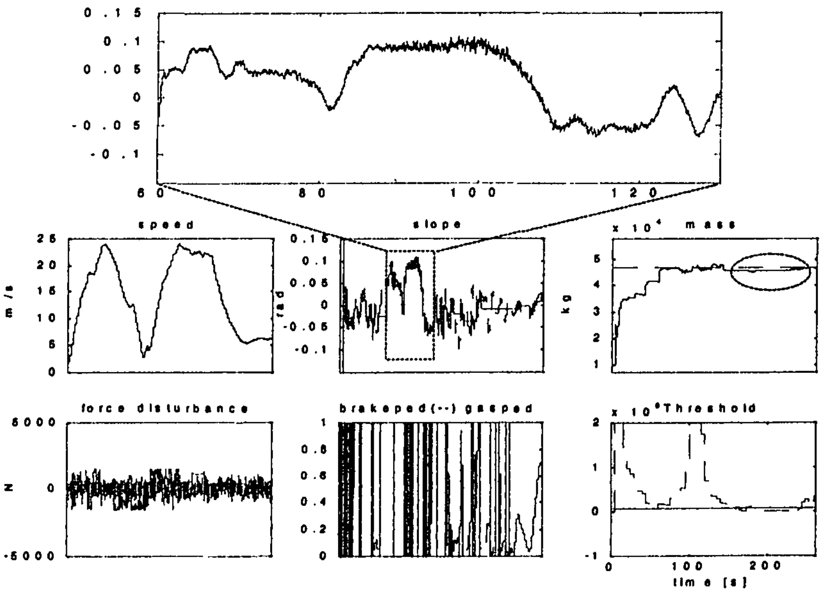


Fig 7 and 8. 7, Overview of simulation model in Simulink. 8, Simulation of estimator performance. Dashed lines are showing real parameter values and there estimates are marked in solid. In the marked area we have poor excitation of the system and the mass estimate would drift without thresholding. Thresholding simply turn the estimator on and off depending on excitation conditions (to avoid covariance drift). Note that the slope can still be estimated in a parallel filter where the mass is set (9).

5. SLOPE ESTIMATION WITH SPECIFIC FORCE MEASUREMENT

In the near past accelerometers using the latest MEMS technology have gained interest in the automotive industry. Low cost and functionality improvement of various automotive systems makes accelerometers interesting sensors. One system that uses this kind of sensor is the ESP system (Electronic Stability Program) in heavy-duty vehicles. The focus in ESP systems is on the lateral and angular acceleration whereas here we are interested in the longitudinal acceleration or more correctly the longitudinal specific-force.

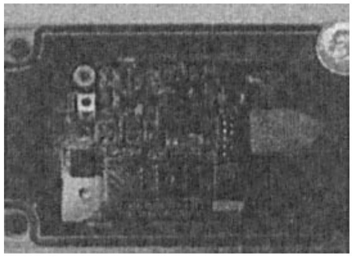


Fig.9. Accelerometer ADXL202EB-232-A mounted in a water tight case.

In the longitudinal direction the accelerometer measures the specific force with a dynamic error that will be regarded as a state variable $x_3(t)$, modelled by a first order process with cutoff frequency ω_d):

$$a(t) = g\sin(\alpha) - \dot{v} \approx g\alpha - \dot{v} + x_3 \tag{14}$$

The complete state model bears strong resemblance to the model of section 3.2:

$$\left.\begin{array}{l} x_1 = v \Rightarrow \dot{x}_1 = g x_2 - a(t) + x_3 \\ x_2 = \alpha \Rightarrow \dot{x}_2 = -x_2\omega_c + \upsilon_2 \\ x_3 = a_d \Rightarrow \dot{x}_3 = -x_3\omega_d + \upsilon_3 \end{array}\right\} \Rightarrow A = \begin{bmatrix} 0 & g & 1 \\ 0 & -\omega_c & 0 \\ 0 & 0 & -\omega_d \end{bmatrix} \quad \upsilon = \begin{bmatrix} 0 \\ \upsilon_2 \\ \upsilon_3 \end{bmatrix} \quad Bu = \begin{bmatrix} -a(t) \\ 0 \\ 0 \end{bmatrix} \quad C = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}^T \tag{15}$$

the only difference being that the control force measurement divided with vehicle mass is here replaced with an accelerometer measurement.

Since the control force error can be expected to be considerably larger than the accelerometer error it is reasonable to believe that the slope estimation accuracy increases when using an accelerometer (lower values on the y-axis in Fig.3).

6. MASS AND SLOPE ESTIMATION WITH SPECIFIC FORCE MEASUREMENT

Using the accelerometer signal $a(t)$, the slope estimation is done without any coupling to vehicle mass, as shown in the previous section. Vehicle mass can then be estimated separately using calculated values of the control force (cf. section 3) $f(t)$ from the simple relation $a(t) = -f(t)/m$. This means that when utilising an accelerometer measurement we can clearly separate the simultaneous estimation problem into two different filters, one "kinematic filter" (no equations of motion involved) for the road slope and one "dynamic filter" for the mass. The formulation of the dynamic filter used to estimate the vehicle mass is shown below:

$$\left.\begin{array}{l} x_1 = m \Rightarrow \dot{x}_1 = \upsilon_1 \\ y = f(t) = \left(a(t) - \hat{x}_3\right)x_1 + w \end{array}\right\} \Rightarrow \quad A = 0 \quad Bu = [0] \quad C = \left[\left(a(t) - \hat{x}_3\right)\right] \quad \upsilon = [\upsilon_1]$$

where $\hat{x}_3$ is the estimated accelerometer error calculated in the kinematic filter.

7. EXPERIMENTAL RESULTS

The estimation algorithms have been evaluated in field tests. A Volvo FH12 with drawbar trailer and a gear-tronic transmission was used. Required signals where sampled from the CAN SAE J1939 and J1576 bus and transmission ECU. The experiment was not done in real-time mainly to avoid the extra work required to implement software in an ECU and all filters are of course causal. In the below Fig.10 a normal acceleration from standstill is shown. The actual

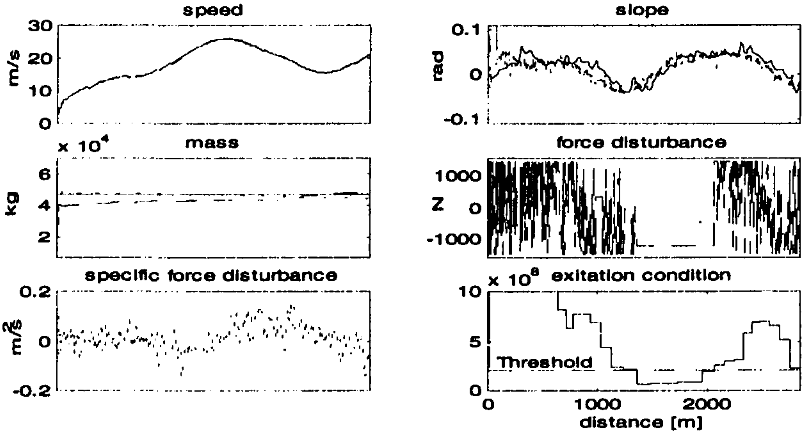


Fig.10. Experimental results for both sensor configurations. Notice that when the threshold work the slope is estimated with the filter derived in section 3 using the mass estimated with the filter in section 4. ——reference ....specific force and — — Speed measurement.

vehicle weight was 47 000 kg and the vehicle passed a ridge after 800 meters which is seen in the slope estimation. Both road slope and vehicle mass approach there correct values respectively. The road slope reference was measured with an atmospheric pressure sensor. Notice that in the speed measurement only case two filters run in parallel to enable slope estimation even when the excitation was considered low.

Varying the process and measurement noise parameters is one way to study the robustness of the filter and this is shown below,Fig.11.

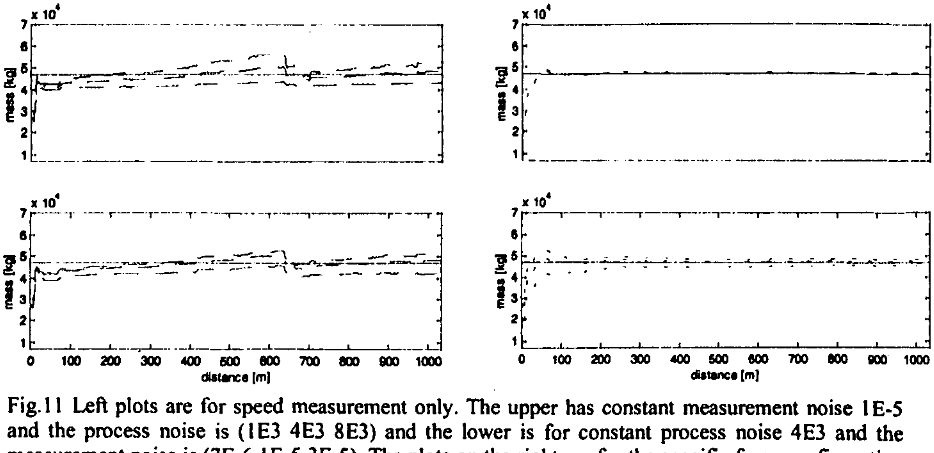


Fig.11 Left plots are for speed measurement only. The upper has constant measurement noise 1E-5 and the process noise is (1E3 4E3 8E3) and the lower is for constant process noise 4E3 and the measurement noise is (7E-6 1E-5 3E-5). The plots on the right are for the specific force configuration and the upper has measurement noise 1E8 and process noise (1E1 1E2 1E3) and the lower has process noise 1E2 and measurement noise (6E7 1E8 2E8).

Both filters perform well for these parameter variations. It is though clear that the additional specific-force measurement improves the somewhat sluggish speed measurement case.

8. FURTHER RESEARCH – ADAPTIVE FEATURES

Several parameters entering the estimation process are depending on varying environmental conditions, e. g. the road profile (the slope characteristics for roads in the alps are substantially different from those in the flatlands!), vehicle conditions (e. g. brakes; cf. section 4.1), etc. One subject for further research will be to investigate system performance under environmentally changing conditions using adaptive schemes for on-line tracking of relevant parameter values, e. g. the magnitude (variance) and time/space behavior (cutoff frequency) of road slope variations.

9. CONCLUSIONS

It has been shown through simulations and practical tests that Kalman filtering is a viable method for on-line estimation of road slope and vehicle mass in heavy duty vehicles. The method is robust and generally applicable and does not have any restrictions concerning different engine, transmission or brake system types, as long as the torque/force balance can be modelled with reasonable accuracy. In case an accelerometer is used as additional (to speed) sensor no torque/force-model is needed for slope estimation.

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