Institutionen för systemteknik
Department of Electrical Engineering

Examensarbete

On Estimation of Momentary Average Engine Speed and Acceleration

Examensarbete utfört i Fordonssystem
vid Tekniska högskolan vid Linköpings universitet
av

Per Boström

LiTH-ISY-EX--13/4667--SE

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Linköpings universitet
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Skattning av momentant medelvarvtal och medelacceleration

On Estimation of Momentary Average Engine Speed and Acceleration

Författare
Author

Per Boström

Sammanfattning
Abstract

The engine speed is one of the most important signals in the engine management system of a combustion engine. The signal is used to control the fuel injection, estimate the engine torque, and to generate reference values. Combustions in the cylinders result in the engine speed oscillating around a momentary average, and many applications are depending on stable estimates of this average engine speed and the average acceleration. This thesis provides a signal model based method to estimate the momentary average engine speed and acceleration.

The estimation of momentary average engine speed and acceleration is complicated by imperfections in the process of measuring the engine speed. Limited accuracy in the measurements causes quantization distortion in the engine speed signal. The effects of these errors are investigated and quantified.

A signal model representing the engine speed is developed and used to estimate the momentary average and acceleration using a Kalman filter. The regular Kalman filter cannot provide estimates with low noise levels at steady state and at the same time be fast enough to track the signal during transient behavior. This problem is overcome by extending the Kalman filter with a change detection algorithm. While this signal model based method gives a satisfying result, it is computationally complex. To evaluate its performance, it is compared to a moving average FIR filter, which is computationally less expensive but does not succeed as well as the signal model based method in filtering out all oscillations.

Nyckelord
Keywords

Engine speed, engine acceleration, quantization, signal model, Kalman filter, change detection

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The engine speed is one of the most important signals in the engine management system of a combustion engine. The signal is used to control the fuel injection, estimate the engine torque, and to generate reference values. Combustions in the cylinders result in the engine speed oscillating around a momentary average, and many applications are depending on stable estimates of this average engine speed and the average acceleration. This thesis provides a signal model based method to estimate the momentary average engine speed and acceleration.

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Sammanfattning

Motorvarvtalet är en av de viktigaste signalerna för motorstyrsystemet hos en förbränningsmotor. Signalen används bland annat för att styra bränsleinsprutning, uppskatta genererat vridmoment från motorn och för börvärdesgenerering. Förbränningar i motorns cylindrar leder till att motorvarvtalet oscillerar kring ett momentant medelvärde. Många applikationer är beroende av stabila skattningar av detta medelvarvtal. I rapporten presenteras en signalmodellbaserad metod för att skatta medelvarvtal och medelacceleration.

Skattningen av momentant medelvarvtal och medelacceleration kompliceras av brister i processen för att mäta motorvarvtalet. Begränsad noggrannhet i mätningarna leder till att varvtalssignalen lider av viss kvantiseringsdistorsion. Effekterna av dessa fel utreds och kvantifieras.

En signalmodell som representerar motorvarvtalet utvecklas och används för att uppskatta momentant medelvarvtal och medelacceleration med hjälp av ett Kalmanfilter. Ett vanligt Kalmanfilter klarar inte av att framgångsrikt undertrycka brus vid långsamma förändringar i varvtal samtidigt som det är tillräckligt snabbt för att följa signalen under transienter. Detta problem kringgås genom att utvidga Kalmanfiltret med en algoritm för detektion av förändringar i signalen. Den signalmodellbaserade metoden ger ett bra resultat, men är beräkningsmässigt komplex. För att utvärdera dess prestanda jämförs resultaten med skattningar från ett glidande medelvärdesfilter, ett FIR-filter, som är beräkningsmässigt billigare men inte lyckas lika väl i att filtrera ut alla oscillationer.

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Per Boström
Linköping, May 2013

Contents

Nomenclature

Acronyms

Acronym	Meaning
EMS	Engine Management System
CAD	Crank Angle Degree
SNR	Signal-to-Noise Ratio
DFT	Discrete Fourier Transform
FIR	Finite Impulse Response
CASMA	Crank Angle Synchronous Moving Average
CUSUM	Cumulative Sum
BD	Backwards Difference
LP	Low Pass

Chapter 1

Introduction

This is the report for a Master thesis in Electrical Engineering. The thesis is examined at the Division of Vehicular Systems at Linköping University and performed at Scania CV AB in Södertälje. The purpose of this report is to describe the work and results of the thesis. This chapter gives an introduction to the thesis work, which includes background and the aims and objectives of the project.

1.1 Background

The engine speed is one of the most important signals in the Scania Engine Management System (EMS). The signal is used among other things to control the fuel injection and for on-line diagnosis of the fuel injection system. There are also functionality in the EMS whose parameters change with the engine speed. It is thus important to extract as much information as possible from the signal.

The engine speed ω, or more precisely the rotational speed of the engine flywheel, is not constant over a full combustion cycle. Essentially, combustions in the cylinders increase the rotational speed while compressions and load decrease it. As a consequence, the instantaneous engine speed oscillates around a momentary average. This means that the engine speed signal can be approximated as the superposition of a slowly changing component $\bar{\omega}$ and a periodic component $\tilde{\omega}$:

$$\omega = \bar{\omega} + \tilde{\omega}. \tag{1.1}$$

A number of applications are dependent on the momentary average $\bar{\omega}$ rather than the actual engine speed, i.e. estimates of the engine speed where the oscillations have been filtered out. Also the engine acceleration is an important signal, used to control the engine speed. As the engine speed oscillations, the fluctuations in acceleration are undesirable in many applications. Hence, the derivative of the momentary average engine speed with respect to time, $\dot{\bar{\omega}}$, is the most interesting part of the engine acceleration in this work. Since the EMS has limited memory and processing power, an important aspect of the methods is their computational complexity.

The engine speed is measured by counting the time it takes for the flywheel to rotate a fixed amount of crank angle degrees CAD. The time is measured with an internal counter that has a limited clock frequency, which leads to quantization errors in the measurements. The effects of these errors are analyzed in this work.

Figure 1.1 shows an example of the engine speed signal, which is the central subject of this thesis. The signal suffers from quantization distortion, caused by the limited accuracy in the measurement process. The oscillations of the continuous signal resembles a sine wave, which is filtered out to estimate the momentary average engine speed. The ideal output from a filter estimating the momentary average engine speed for use in the EMS is a straight line for this signal. Estimating this signal is difficult in practice, since the EMS has limitations in memory and processing power. One approach is to use a moving average filter, but as the figure shows, this method does not suppress all of the noise in the signal.

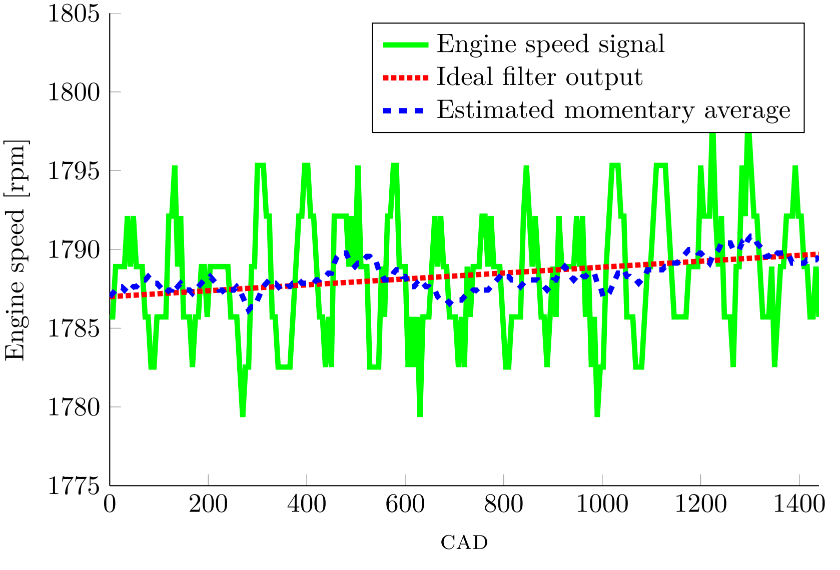


Figure 1.1. The engine speed during two combustion cycles.

1.2 Aims and Objectives

The main objectives of this thesis are to analyze the quantization distortion and to develop a new method to estimate momentary average engine speed and acceleration. These objectives can be summarized as:

Estimation of the momentary average engine speed: By the use of signal models and different filters, extract the momentary average from an oscillating engine speed signal. The methods will be evaluated from their noise suppressing ability and computational complexity.

Estimation of the mean engine acceleration: Develop a method to estimate the mean engine acceleration, i.e. the derivative of the momentary average engine speed with respect to time.

Quantization effects in the engine speed signal: Conduct a theoretical study on how the limitations in the process of measuring the engine speed distorts the measurements with quantization errors.

1.3 Related Research

The engine speed signal is widely used in research areas such as torque estimation and misfire detection. In [1] a Kalman filter is used to monitor the engine speed and torque in order to detect misfires. Unlike in this work, the method used in [1] makes use of a physical model of the engine. The idea of estimating the average speed by attenuating the oscillations caused by combustions by means of a moving average filter in the crank angle domain is treated in [2]. By comparing the properties and performance of this with the signal model based method developed in this thesis, the method is used for evaluation in this work. The method is also further analyzed and combined with an algorithm to estimate the engine acceleration in [3]. Other papers that cover the acceleration estimation are [4] and [5].

The basic functionality of a rotational speed sensor and discussions regarding the computations needed to convert from the angular domain to the time domain are found in [6], and [7] covers problems in event based engine control. In the process of measuring the instantaneous engine speed, the time between each sample is measured and uniformly quantized, which leads to distortion in the engine speed signal. The effects of uniform quantization can often be modeled by an additive noise that is uniformly distributed, uncorrelated with the input signal, and has a white spectrum. This model is analyzed in [8] and also investigated in this work.

1.4 Outline

The first chapter of this report presents the background and gives a short introduction to the thesis. The following chapters can be divided into two parts, where the first part covers the quantization distortion related to the measurement process. The second part describes the method derived to estimate the momentary average engine speed and acceleration, and then a comparison between the new method and a standard method for the purpose. A more detailed outline, with all chapters is described is:

Chapter 1: Gives a short introduction to the thesis and describes its aims and objectives.

Chapter 2: Describes the process of measuring the engine speed and discusses problems related to the procedure.

Chapter 3: Describes the dynamics of the flywheel and presents a signal model of the engine speed.

Chapter 4: Describes the methods used to estimate the momentary average engine speed.

Chapter 5: Describes the methods used to estimate the engine acceleration.

Chapter 6: Presents the results of the thesis.

Chapter 7: Presents the conclusions and suggests improvements and future work.

Chapter 2

Engine Speed Measurements

This chapter describes the process of measuring the engine speed and discusses problems related to the procedure.

2.1 Event and Time Based Sampling

To describe a continuous signal from the real world in a computer, the first thing to do is to obtain signal measurements from the continuous signal at several time instances. This process is called sampling and results in a discrete sequence of numbers that represent the continuous signal. The time interval between the samples is denoted T_s and it is either constant or time-varying, depending on which sampling technique that is used. In this section two different techniques are compared: time based sampling and event based sampling.

Using the time based sampling technique, the amplitude of a continuous signal $y(k)$ is sampled at equidistant time instances with intervals T_s.

$$y_k = y(kT_s), \quad k = 1, 2, \dots \tag{2.1}$$

Even though time based sampling may be the traditional way of sampling a continuous signal, there are other alternatives. One option is to sample the signal every time the amplitude passes certain levels. This technique is called event based sampling, of which the theory is presented in [9]. With event based sampling, the discrete signal is described as:

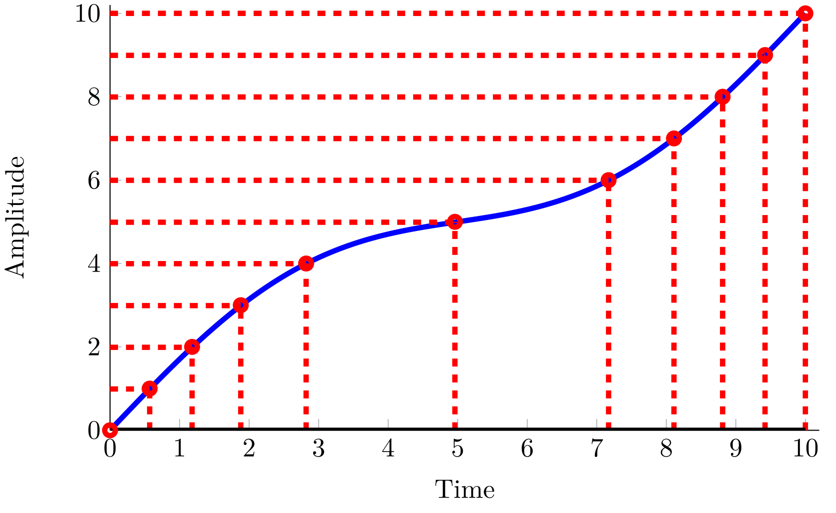
$$y(t_k) = y_k, \quad k = 1, 2, \dots, \tag{2.2}$$

where y_k is the pre-defined amplitude sampled at time instance t_k. If the time continuous signal is not monotonously increasing or decreasing the formulation in (2.2) leads to problems, since the signal $y(t_i)$ may be equal to y_k for several time instances t_i. However, for applications with monotonous time continuous signals and uniformly distributed levels, (2.2) can be formulated as

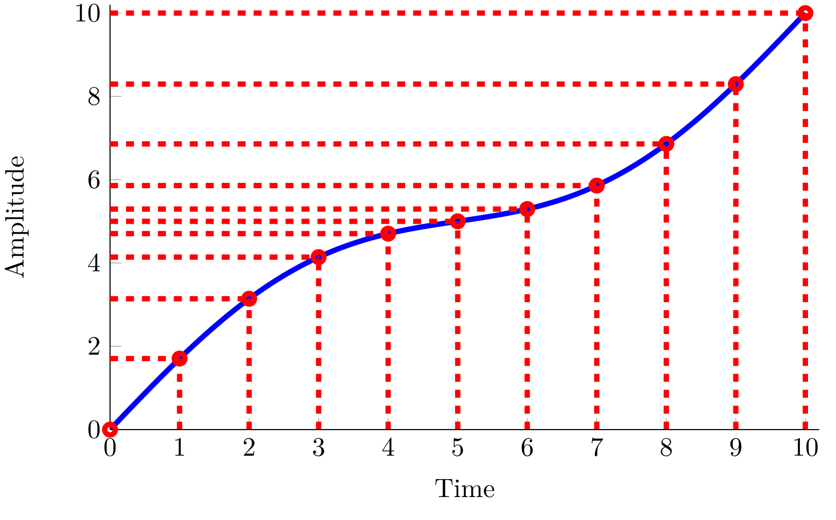
$$y(t_k) = kY_s, \quad k = 1, 2, \dots, \tag{2.3}$$

where Y_s is the amplitude sample period.

One way to relate event based sampling to the time based sampling technique is to consider the event domain signal as a time domain signal with varying sampling period. Figure 2.1 illustrates the principles and differences between event based sampling and time based sampling.



(a) Event based sampling. The continuous signal, solid line in the figure, is sampled at every instant when the signal amplitude passes an integer (dashed lines).



(b) Time based sampling. The continuous signal, solid line in the figure, is sampled at every integer time instant (dashed lines).

Figure 2.1. Illustration of the principles of event based sampling and time based sampling.

2.1.1 The Sampling Theorem

The sampling theorem [10] states the necessary conditions under which a continuous time signal can be uniformly sampled and reconstructed perfectly. It is also called Shannon's rule or the Nyquist theorem. The sampling theorem states that if the bandwidth, f_0, of the continuous time signal is less than a half of the sampling frequency, $f_s = 1/T_s$, the signal can be reconstructed perfectly. Hence, the critical frequency in sampling is half the sampling frequency, which is also called the Nyquist frequency:

$$f_N = \frac{f_s}{2}, \tag{2.4}$$

and perfect reconstruction is possible if

$$f_0 < f_N. \tag{2.5}$$

When the condition of the sampling theorem is fulfilled, it is guaranteed that the frequency spectrum of the reconstructed signal, if reconstructed ideally, will be equal to the spectrum of the original continuous time signal. If the sampling theorem is not fulfilled, i.e. a too low sampling rate is used, frequency content above the Nyquist frequency will be folded into the interval $f \in [-f_N, f_N]$. This effect is called aliasing and causes high frequencies to appear as lower frequencies.

2.1.2 Orders

When it comes to rotational speed of shafts, dealing with frequencies are not very common but rather dealing with orders. The orders, or harmonics, are multiples and sub multiples of the basic frequency, which is exactly equal to the shaft rotational speed. If the shaft is rotating at R rpm, then the second order is simply $2R$ rpm and the mth order is equal to mR rpm. The corresponding frequency of the orders for a given rotational speed of R rpm is:

$$f_m = \frac{mR}{60}, \tag{2.6}$$

or if the rotational speed is given as ω radians per second

$$f_m = \frac{m\omega}{2\pi}, \tag{2.7}$$

where f_m is the frequency of the mth order.

The advantage of using orders instead of frequencies is that they are independent of the current rotational speed. The first order is always the shaft speed, the second order is always twice the shaft speed and so on. By using the rotation itself as a basis and use event based sampling, i.e. collect data at equal increments of the rotational angle rather than at equidistant time instances, a signal that is synchronized with the shaft rotational speed is obtained.

The recorded data is sampled in units of a fraction of a revolution rather than as a fraction of a second. By applying a Fourier transform to the signal, the result is an order spectrum rather than a frequency spectrum. The amplitude and phase of the transformed signal are given as a function of orders instead of hertz.

If the data is sampled with N points in each revolution, the sampling rate is N samples/revolution. Completely analogous to time based sampling, the sampling theorem states that there will be alias effects if there is power above $N/2$ orders.

2.2 Rotational Speed Sensors

This section discusses the basic functionality of rotational speed sensors and presents some examples of common sensors used in motor vehicles.

In situations where it is desired to measure the angular velocity of rotating shafts, a common approach is to use so called rotational speed sensors. An illustration of a rotational speed sensor is shown in Figure 2.2 and its basic functionality is described below. For further information on rotational speed sensors, please refer to [6].

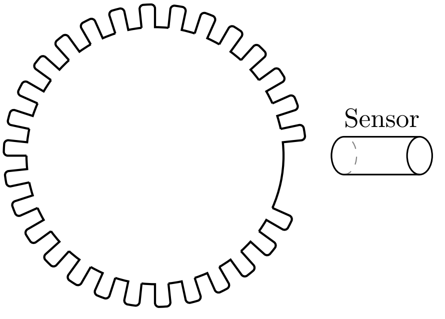


Figure 2.2. Rotational speed sensor used to measure the angular velocity of the rotating crank shaft. The flywheel has two missing cogs that are used to detect a reference position.

A cogwheel with N_{cog} cogs is mounted to the shaft of which the rotational speed is measured. A sensor placed by the cogwheel is used to detect when an edge of a cog passes a certain point. The measurement is made by counting the number of clock cycles of a high frequency clock between two cogs. The angular speed is then calculated as:

$$\omega = \frac{d\theta}{dt} \approx \frac{\Delta\theta}{mT_c}, \tag{2.8}$$

where m is the number of clock cycles of duration T_c that have been counted over last $\Delta\theta$ radians.

To set up a simple equation for approximating the instantaneous angular speed, it is assumed that the cogwheel is ideal. Ideal in this case means that the cogwheel is completely circular and mounted in its center, and also that the angle between each cog is $2\pi/N_{cog}$ radians.

Let the time instance of when cog k is passed be denoted t_k. The corresponding angle, denoted $\theta_k = k\frac{2\pi}{N_{cog}}$, can be described either as an angle or a function of time $\theta(t_k)$. Hence, there are two different domains in this situation: the angular domain and the time domain. This makes the rotational speed sensor a typical example of where event based sampling is used. The sampling procedure can be described just as in (2.3) by:

$$\theta(t_k) = kY_s, \quad k = 1, 2, \ldots, \tag{2.9}$$

where Y_s is replaced by the angular distance $\alpha = \frac{2\pi}{N_{cog}}$.

The sampling period is thus a function of the rotational speed ω and the distance between cogs α:

$$T_\omega(\omega) = \frac{2\pi}{N_{cog} \cdot \omega} = \frac{\alpha}{\omega}. \tag{2.10}$$

If the data samples would had been captured regularly in the time domain, the number of recorded samples for each revolution would depend on the momentary rotational speed. With twice the speed and the same sampling frequency, only half as many samples are recorded for each revolution. Sampling in the angular domain means that it makes no difference how fast the wheel is rotating, there are always the same number of samples, N_{cog}, recorded per revolution.

The basic formula for approximating the angular speed $\omega(t_k)$ at time t_k is:

$$\hat{\omega}_k = \frac{2\pi}{N_{cog}(t_k - t_{k-1})} = \frac{\alpha}{\Delta t_k}, \tag{2.11}$$

which can be seen as the average speed in the interval $t \in [t_{k-1}, t_k]$. It also means that if $\omega(t)$ is constant for $t \in [t_{k-1}, t_k]$, then $\hat{\omega}_k = \omega(t)$ in the interval. The fact that the angular speed is measured in the angular domain causes some problems. The main computational issues are discussed in [6]:

- Sampling time effects
  The signal is sampled using event based sampling. This means that the sampling period of the angular speed is proportional to the current speed. Since most applications of the rotational speed signals are synchronously executed in time and not in the angular domain, approximations are needed to convert from one domain to the other, which may cause distortions such as aliasing.

- Quantization effects
  The time between two samples are counted by an internal clock with a limited clock frequency. The higher frequency, the more correct the time instances can be determined. However, there will always be a quantization error that increases with higher engine speed.

- Non-ideal cogs
  Small manufacturing defects cause the angle between two adjacent cogs to deviate from the ideal $2\pi/N_{cog}$ radians. This leads to minor errors in the computed angular speed signal.

- De-centralized cogwheel
  If the cogwheel is not mounted to the shaft in its center, periodic errors will appear in the computed angular speed signal.

2.2.1 Engine Speed Sensors

In motor vehicles, the most common engine speed sensors are magnetic sensors. They are popular since they allow measuring of the rotational speed without the sensor physically touching the rotating shaft and are relatively cheap. Another option is to use optical sensors, which gives a higher accuracy but also are more expensive. In [11] the principles of a few sensors are presented. Their properties are summarized here.

Inductive sensor

The inductive sensor is a permanent magnet that is surrounded by a coil, mounted at a small distance from the cogwheel. As the cogwheel rotates, the distance between cogwheel and sensor varies, causing a time-varying magnetic flow ϕ_M that induces a sinusoidal voltage U_{ind}, calculated as:

$$U_S = U_{ind} = w\frac{\partial\phi_M}{\partial\theta}\frac{\partial\theta}{\partial t}, \tag{2.12}$$

where w is the number of windings in the coil. The time between the cogs is given by the zeros of the sinusoidal voltage U_S in the sensor.

The advantages of the inductive sensor principle are the low production costs, a wide operating temperature range and that there is no electronic unit to protect. The disadvantages are that at higher engine speeds higher voltages are induced, causing errors to occur. Also, vibrations cause the distance between the cogwheel and sensor to vary which implies additional errors.

Differential Hall sensor

The differential Hall sensor consists just like the inductive sensor of a permanent magnet. At each end of the magnet, a Hall element is placed facing the ferromagnetic cogwheel. As soon as a cog passes the Hall elements, the change in the magnetic field causes a proportional Hall voltage according to the Hall effect:

$$U_S = U_{H,2} - U_{H,2} = R_H I_H \frac{B_2 - B_1}{l_H}, \tag{2.13}$$

where U_S is the voltage in the sensor, $U_{H,1}$ and $U_{H,2}$ are the measured Hall voltages induced by the magnetic fields B_1 and B_2, R_H is the Hall coefficient and I_H the current in the Hall elements with length l_H. The time between two cogs is measured in the same way as for an inductive sensor. An advantage with the differential Hall sensors is that they compensate for the varying distance between sensor and cogwheel. This makes them suitable for engine speed measurements with higher accuracy demands.

Optical sensor

The setup for an optical sensor differs a bit from that of an inductive or a differential Hall sensor. Instead of a ferromagnetic cogwheel, a specially marked disk is used. The disk reflects or lets light from a light source pass to a photo diode. The engine speed can then be measured by the photo diode. The marked disk can be produced with high resolution and hence it is possible to generate more accurate measurements. The optical sensor is however sensitive to dirt that may distort the measurements.

2.3 Quantization Effects

The method used to measure the engine speed has limited accuracy, which leads to quantization effects in the measurements. This section analyzes how the quantization distortion affects the engine speed signal.

2.3.1 Quantization Effects in the Engine Speed Signal

The elapsed time Δt_k between cog $k-1$ and k cannot be determined exactly. Instead, it is approximated by the difference $\hat{t}_k - \hat{t}_{k-1}$, where $\hat{t}_k$ is the estimated time instance when cog k passed the sensor. The time instances t_k is estimated using an internal counter with limited clock frequency, by approximating $t_k \approx \hat{t}_k = m_k T_c$, where m_k is the number of clock cycles counted until cog k and T_c is the duration of a clock cycle. The faster the clock is, the more accurate the time instances will be logged. This means that the measurements suffer from quantization errors:

$$\hat{t}_k = t_k - q_k, \tag{2.14}$$

where t_k is the actual time instant for the event and q_k is the quantization error. As in [8] and [6], it is reasonable to assume that q_k is a sequence of independent stochastic variables uniformly distributed between 0 and T_c, i.e. $q_k \in U(0, T_c)$. The mean and variance of such a variable is:

$$\mathrm{E}\{q_k\} = \frac{T_c}{2}, \tag{2.15}$$

$$\mathrm{Var}\{q_k\} = \frac{T_c^2}{12}. \tag{2.16}$$

Using (2.11) and (2.14), it is possible to analyze the effects of the quantization errors on the calculated engine speed.

$$\hat{\omega}_k = \frac{\alpha}{\hat{t}_k - \hat{t}_{k-1}} = \frac{\alpha}{t_k - q_k - t_{k-1} + q_{k-1}} = \frac{\alpha}{\Delta t_k - q_k + q_{k-1}}, \tag{2.17}$$

where Δt_k is the exact elapsed time between cog $k-1$ and cog k.

The sequence q_k of stochastic variables depends only on the frequency of the clock and are independent of the current speed. As the rotational speed increases, the actual time between two cogs, Δt_k, decreases. This means that when the engine is rotating at a high speed, q_k and q_{k-1} become the dominating components in the denominator in (2.17). Thus, when the rotational speed increases, the impact of the quantization errors increases [6]. The variance of the engine speed estimates is investigated as follows. The difference $\hat{t}_k - \hat{t}_{k-1}$ contains the difference of two equally distributed independent variables, q_k and q_{k-1}, which means that it is an unbiased estimate of $t_k - t_{k-1}$ with twice the variance of q_k:

$$\mathrm{Var}\left\{\hat{t}_k - \hat{t}_{k-1}\right\} = \mathrm{Var}\left\{q_{k-1} - q_k\right\} = 2\mathrm{Var}\left\{q_k\right\} = \frac{T_c^2}{6}. \tag{2.18}$$

By identifying the true angular speed ω_k and then using a first order Taylor expansion, the expression in (2.17) can be approximated as:

$$\hat{\omega}_k = \underbrace{\frac{\alpha}{\Delta t_k}}_{\omega_k} \frac{1}{1 + \frac{q_{k-1} - q_k}{\Delta t_k}} \approx \omega_k \left(1 - \frac{q_{k-1} - q_k}{\Delta t_k}\right) \tag{2.19}$$

The expression given by the first order Taylor expansion indicates that the quantization leads to angular speed errors with zero mean and variance

$$\mathrm{Var}\left\{\hat{\omega}_k\right\} \approx \left(\frac{\omega_k}{\Delta t_k}\right)^2 \frac{T_c^2}{6} = \frac{T_c^2}{6} \frac{\omega_k^4}{\alpha^2}. \tag{2.20}$$

This means that the computed speed is unbiased, but has a variance that is proportional to the actual speed to the power of four and to the square of the clock cycle duration.

By creating a model of the rotational speed of an idling engine and simulating the sampling of the crank shaft at every 6th degree, both the underlying signal and a quantized version is generated. In Figure 2.3, the simulated engine speed signals, where a clock cycle duration of 1 μs has been used, for an engine idling at 700 and 3000 rpm are shown as a function of crank angle degrees. At the lower speed, the quantization errors are small with a signal-to-noise ratio (SNR) of 29 dB. However, for the signal with an average engine speed of 3000 rpm, the quantization effects are much more prominent and the SNR is just 4 dB.

In Figure 2.3, it is apparent that the engine speed affects the impact of quantization errors. Another important parameter for the quantization errors, as seen in (2.20), is the clock frequency or the clock cycle duration $f_c = 1/T_c$. In Figure 2.4, the SNR has been computed and shown for several choices of clock frequencies and engine speeds. SNR levels lower than 0 dB has been set to zero to make the plot more compact. Not surprisingly, with a higher clock frequency the quantization is finer also for high engine speeds.

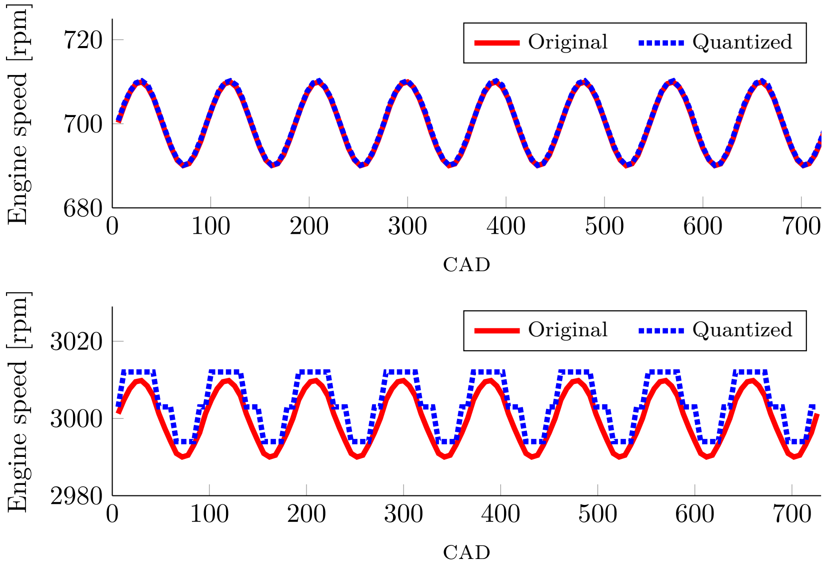


Figure 2.3. At low engine speeds, the quantization is fine and the signal is not distorted by quantization errors. As shown in the lower figure, the quantization is coarser at higher engine speeds.

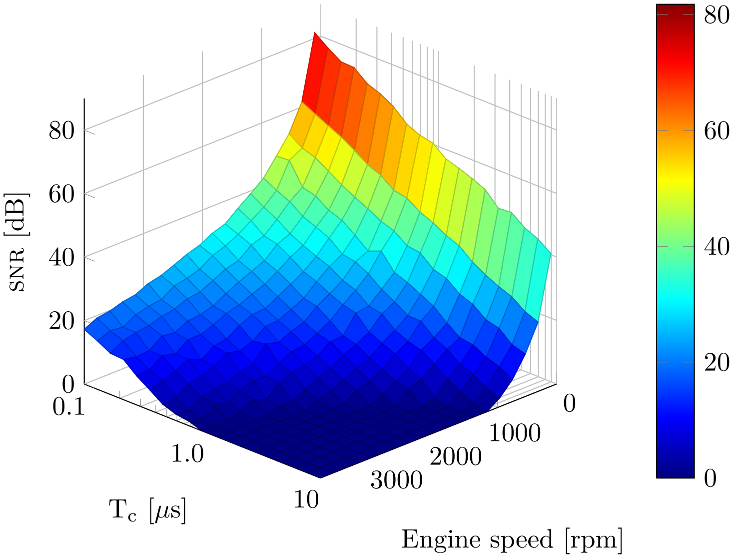


Figure 2.4. The signal-to-noise ratio as a function of clock cycle duration and engine speed. At low engine speeds, a lower clock frequency still gives a satisfactory SNR, but at higher speeds the signal is heavily distorted by the quantization errors.

2.3.2 Maximum Quantization Error

The maximum quantization error is the largest possible difference between the actual engine speed and the measured engine speed, due to limitations in the clock frequency of the internal counter. The maximum error has been calculated earlier in [11], and is presented here.

With a clock frequency f_c, the maximum quantization error is the clock cycle duration T_c:

$$\left|t - \hat{t}\right| = |t - mT_c| \leq T_c, \tag{2.21}$$

where $\hat{t}$ is the estimate of t, the actual time elapsed between two cogs and m is the number of clock cycles between the two cogs. With the true engine speed denoted ω and the measured engine speed $\hat{\omega}$, the relative quantization error is calculated as:

$$\varepsilon_{q,rel} = \frac{|\hat{\omega} - \omega|}{\omega} = \left|\frac{\frac{\alpha}{mT_c} - \frac{\alpha}{t}}{\frac{\alpha}{t}}\right| = \left|\frac{t - mT_c}{mT_c}\right|. \tag{2.22}$$

Combining (2.21) and (2.22), the relative quantization error becomes:

$$\varepsilon_{q,rel} \leq \frac{T_c}{mT_c} = \frac{1}{m} = \frac{\alpha}{\alpha m T_c f_c} = \frac{\hat{\omega}}{\alpha f_c}. \tag{2.23}$$

Equation (2.23) shows that the relative quantization error is larger at high engine speeds than at low. It also shows that a finer quantization as expected reduces the errors. It is also important to note that a higher angular resolution, i.e. a higher number of cogs, comes with the price of increased quantization effects.

The maximum quantization error is obtained by multiplying the maximum relative quantization error by the current engine speed:

$$\varepsilon_{q,max}(\omega) = \varepsilon_{q,rel}\omega = \frac{\omega^2}{\alpha f_c} \quad \text{[rad/s]}. \tag{2.24}$$

So far the engine speed ω has been treated as a value in rad/s. The engine speed is given in revolutions per minute, rpm, which is a scaled version of rad/s:

$$\text{rpm} = \frac{60}{2\pi}\text{rad/s}. \tag{2.25}$$

Using the engine speed in rpm, denoted n_{eng}, to calculate the maximum quantization error the formula is:

$$\varepsilon_{q,max}(n_{eng}) = \frac{n_{eng}^2}{\alpha f_c}\frac{2\pi}{60} \quad \text{[rpm]}. \tag{2.26}$$

Figure 2.5 shows the maximum quantization error for different engine speeds when a clock cycle duration of 1 μs is used.

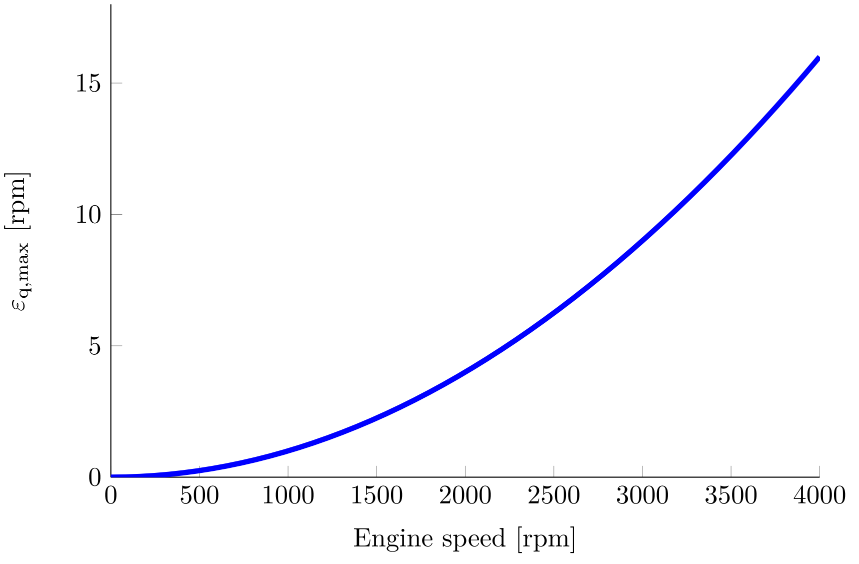
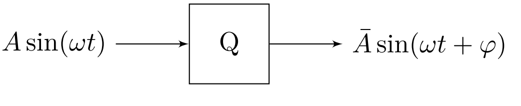


Figure 2.5. The maximum quantization error as a function of engine speed.

2.3.3 Low Order Distortion

The engine speed oscillates in a sinusoidal manner, with one dominating component. The dominating component is the combustion order, which is equal to the number of cylinders that are igniting in each revolution. Figure 2.6 shows the Discrete Fourier Transform (DFT) of a typical engine speed signal from an engine with eight cylinders, where the combustion order, that is $\frac{N}{2} = 4$ for this engine, is the is the most prominent component. The amplitude of the combustion order component, A_{comb}, is between 10-20 rpm. Typical amplitudes of the lower order components are around three rpm. Other factors that contribute to the measured engine speed are low frequency oscillations from the powertrain and high frequency oscillations due to crankshaft torsion. The road that the vehicle is driving also induces vibrations in the vehicle, which act as disturbances on the crankshaft [12].

The low orders of the engine speed signal are used for example in diagnosis of the fuel injection system. An interesting aspect of the quantization is therefore to investigate when the errors caused by quantization become too large for the signal to be useful in the diagnosis. Important errors are the amplitude and phase distortion of low orders, i.e. how A and $\bar{A}$ are related and if there is any phase shift φ after quantization.



The errors are likely depending on the engine speed, the amplitude A and also

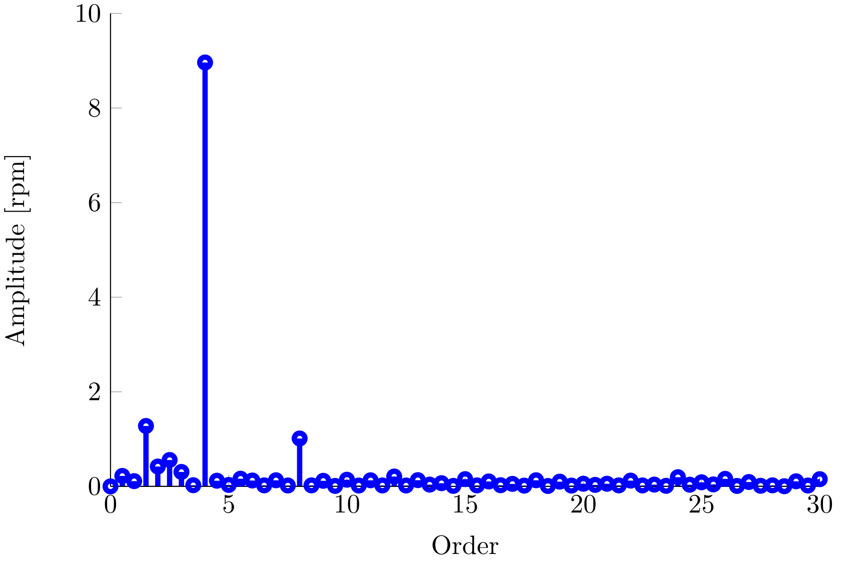


Figure 2.6. DFT of the engine speed signal from an eight cylinder engine. The combustion order (4) is clearly the dominating component and its first harmonic (8) is also significantly larger than the other.

the clock frequency f_c. A larger amplitude A should mean that the quantization effects have smaller impact, i.e. that the ratio $\bar{A}/A$ is closer to 1. As already noted in Section 2.3.2, a higher clock frequency leads to more accurate time stamps and therefore smaller errors, while a higher engine speed increases the errors. A way to investigate this is to compare the DFT of a quantized signal with the DFT of the original signal. The distortion can then be numerically quantified. The amplitude distortion is here defined as

$$D_A = \frac{A - \bar{A}}{A}, \tag{2.27}$$

where A and $\bar{A}$ are the amplitudes of the order component in the original and quantized signal's DFT of which the amplitude distortion is sought. The phase distortion is defined as the absolute value of the difference between phase before and after quantization:

$$D_\varphi = |\varphi| \tag{2.28}$$

To verify the assumptions regarding the quantization distortion, an engine speed signal is simulated and quantized. The simulated signal is constructed so that it resembles a real engine speed signal, with a dominating combustion order component and lower order components with amplitudes at around three rpm. There are also some noise present that in the simulated signal is represented as uniformly distributed between zero and one rpm on each component in the order spectrum of the signal. The DFT of the simulated engine speed signal looks like the one in Figure 2.6. During the simulations, the clock frequency is fixed at 1 MHz while the average engine speed is varied between zero and 2500 rpm.

By fixing the amplitude of the low order oscillations and clock frequency while varying A_{comb}, it is verified that the specific amplitude of the combustion order component does not affect the distortion for the lower orders. Table 2.1 shows the amplitude and phase distortion for the second order component is shown for a number of combustion oscillation amplitudes, A_{comb}. These results indicate that it is sufficient to simulate the signal for only one choice of combustion amplitude when investigating the quantization distortion for low order components.

Table 2.1. Amplitude and phase distortion for oscillations of the second order at different amplitudes of oscillations at the combustion order. Engine speed at 600 rpm and clock frequency at 1 MHz.

A_{comb}	D_A[%]	D_φ[degrees]
10	0.36	0.20
15	0.36	0.21
20	0.37	0.21
100	0.39	0.23

Figure 2.7 and 2.8 show the amplitude distortion D_A and the phase distortion D_φ of the second order component for a simulated and quantized engine speed. They both show a similar behavior consistent with the assumptions: at low engine speed the errors are very small, but at higher engine speeds both errors increase. Also the variance of the distortion is larger at high engine speed.

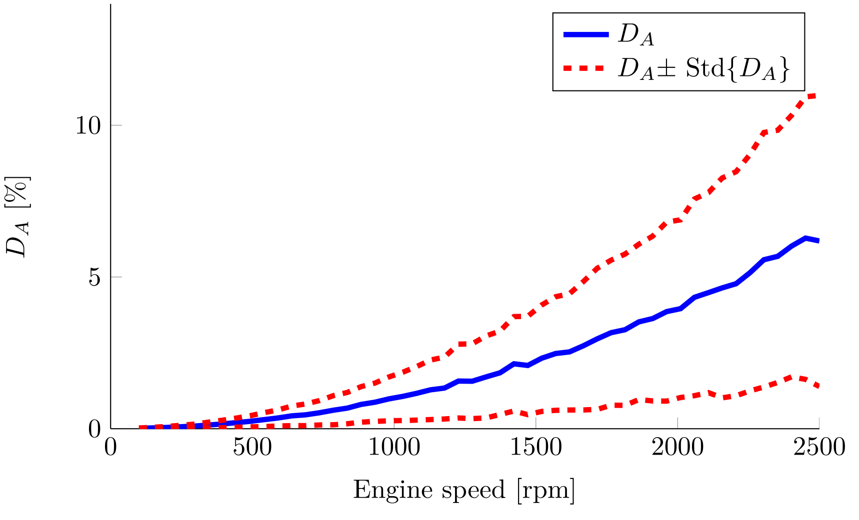


Figure 2.7. Relative amplitude distortion for the second order component due to quantization effects as a function of engine speed, with clock frequency fixed at $f_c = 1$ MHz.

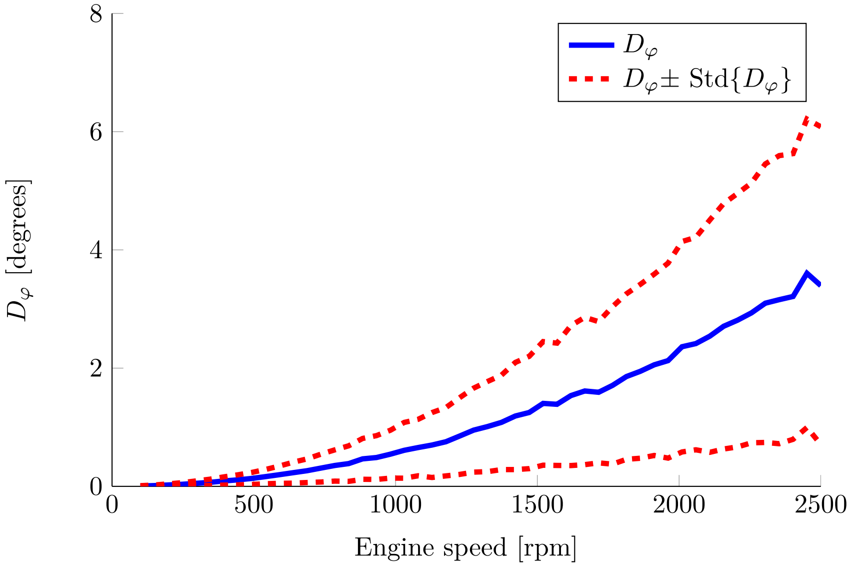


Figure 2.8. Phase distortion for the second order component due to quantization effects as a function of engine speed, with clock frequency fixed at $f_c = 1$ MHz.

Another interesting aspect to investigate is if the errors differ between the orders. If the quantization distorts some of the orders more than the other, it could be that those order components are useless in the diagnosis of the fuel injection system. Quantization is a non-linear operation, which could result in quantization effects differing between the order components or components interfering with each other and thus deteriorate the possibilities to perform the diagnosis. However, as Widrow states in [8], the quantization operation can also be seen as adding a white noise component to the signal. This would mean that the quantization errors depend on the engine speed level rather than the frequency of the oscillations. The simulations in this work verifies this statement. Table 2.2-2.5 show the amplitude and phase distortion for low orders with a fixed clock frequency at 1 MHz. Since all of the oscillation orders fluctuates around the same level and the distortion levels are very similar for all orders, the results support the theory that the quantization distortion depend on the engine speed level rather than the frequency of the oscillations.

Since the diagnosis of the injection system requires accurate measurements of engine speed, it is interesting to investigate whether it might be worth using a higher clock frequency to reduce the quantization errors. Figure 2.9 and Figure 2.10 show how the quantization errors decrease as a higher clock frequency is used. The clock frequency used in the engines in this work is 1 MHz. By increasing it to 10 MHz, the distortion clearly would not be as severe as it is now. However, to give a recommendation on whether to increase the clock frequency or not, one first has to decide on an acceptable distortion level.

All of the quantization investigations above have been done using simulated

Table 2.2. Relative amplitude distortion D_A for low order components due to quantization effects at varying engine speed.

	Engine speed [rpm]				
Order	500	1000	1500	2000	2500
0.5	0.25	0.96	2.28	3.81	6.44
1	0.25	0.98	2.14	4.03	5.96
1.5	0.25	0.95	2.18	3.93	6.27
2	0.26	1.00	2.22	3.80	6.21
2.5	0.25	0.99	2.25	3.84	6.37
3	0.26	0.97	2.27	4.00	6.47
3.5	0.25	1.00	2.24	4.12	6.31

Table 2.3. Standard deviation of the relative amplitude distortion D_A for low order components due to quantization effects at varying engine speed.

	Engine speed [rpm]				
Order	500	1000	1500	2000	2500
0.5	0.19	0.75	1.73	3.02	4.78
1	0.19	0.75	1.62	2.99	4.50
1.5	0.19	0.74	1.73	2.90	4.63
2	0.19	0.75	1.64	2.91	4.68
2.5	0.20	0.76	1.68	3.03	4.70
3	0.20	0.74	1.67	3.17	4.89
3.5	0.19	0.76	1.70	3.11	4.73

Table 2.4. Phase distortion D_φ for low order components due to quantization effects at varying engine speed.

	Engine speed [rpm]				
Order	500	1000	1500	2000	2500
0.5	0.14	0.57	1.27	2.24	3.63
1	0.15	0.59	1.28	2.31	3.66
1.5	0.14	0.58	1.27	2.28	3.68
2	0.14	0.55	1.30	2.28	3.55
2.5	0.14	0.56	1.30	2.26	3.57
3	0.14	0.57	1.27	2.30	3.52
3.5	0.14	0.57	1.29	2.38	3.65

Table 2.5. Standard deviation of the phase distortion D_φ for low order components due to quantization effects at varying engine speed.

	Engine speed [rpm]				
Order	500	1000	1500	2000	2500
0.5	0.10	0.46	0.99	1.62	2.81
1	0.11	0.43	1.00	1.70	2.73
1.5	0.11	0.42	0.95	1.71	2.67
2	0.11	0.43	0.97	1.71	2.72
2.5	0.11	0.44	0.99	1.74	2.73
3	0.11	0.42	0.96	1.71	2.68
3.5	0.11	0.43	0.96	1.73	2.75

data, since this is the only way to be able to numerically compare the signal before quantization with the quantized version of the same. For real engine speed signals, it is difficult to quantify the distortion numerically, but by visual inspection of the signals it is apparent that the quantization distortion is affected by the engine speed. Figure 2.11 shows two measured engine speed signals. One where the engine speed is low, around 500 rpm, and the other one for a high engine speed, just over 2300 rpm. For the low engine speed, the quantization effects are minor, but for the high engine speed, the signal is severely distorted.

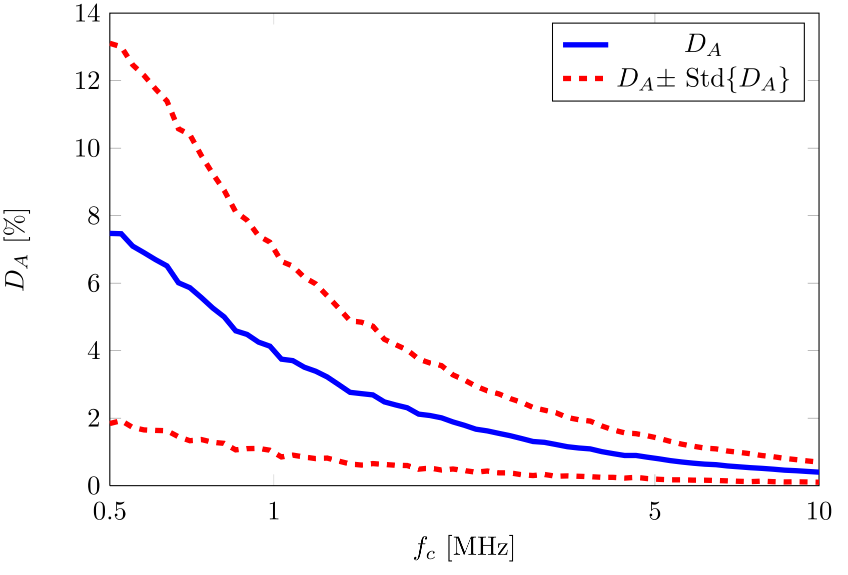


Figure 2.9. Relative amplitude distortion for the second order component due to quantization effects as a function of clock frequency, with engine speed at 2000 rpm.

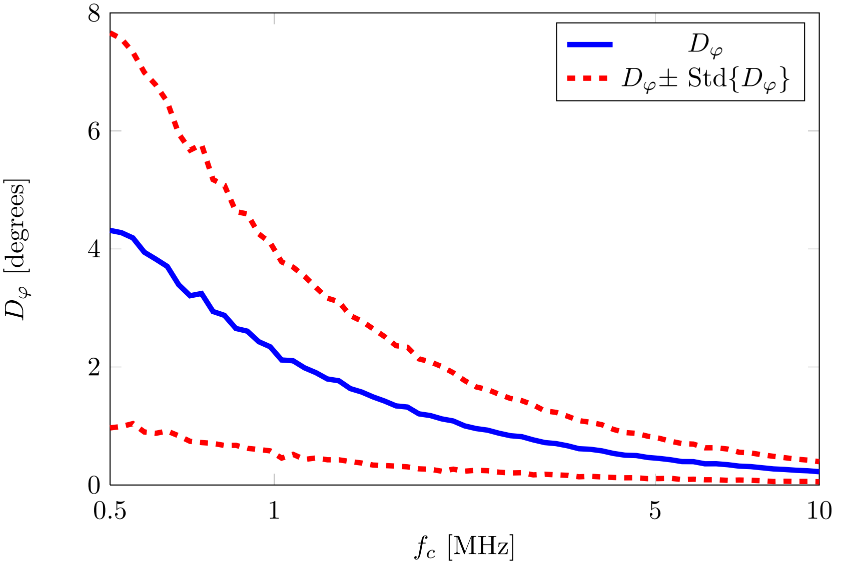
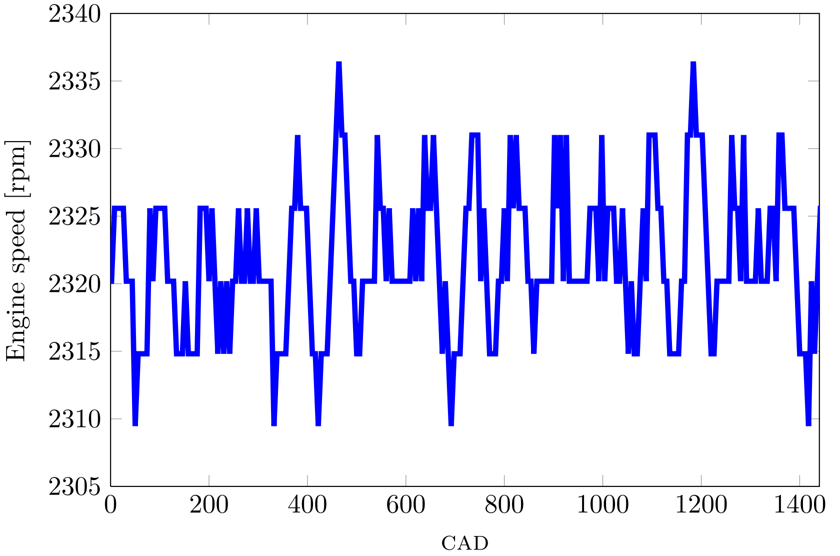
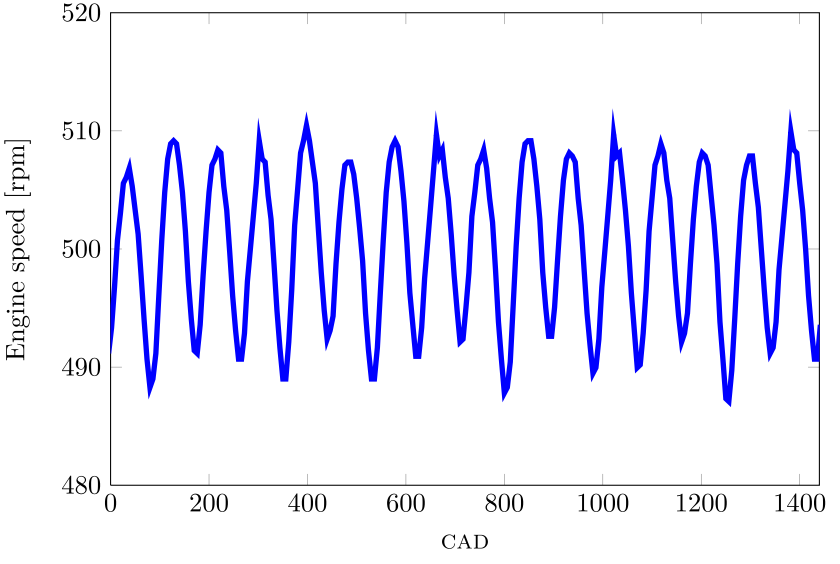


Figure 2.10. Phase distortion for the second order component due to quantization effects as a function of clock frequency, with engine speed at 2000 rpm.



(a) Severe quantization distortion at high engine speed.



(b) Fine quantization at low engine speed.

Figure 2.11. These figures show two real engine speed signals, captured with an internal clock frequency of 1 MHz. It is apparent that the quantization distortion is more severe in the upper figure (a), where the average engine speed is higher than in the lower figure (b).

Chapter 3

Modeling

This chapter gives a short description of the operation of the diesel engine, the generation of engine torque, and how the engine speed dynamics is related to the torque. By separating both the torque and engine speed into a component corresponding to the average value and a periodical component, a signal model of the engine speed is constructed.

3.1 Four Stroke Cycle Diesel Engine

The engine is the power producing component in the powertrain of a vehicle. Power is produced by fuel combustion in the cylinder, creating a force on the piston that is converted into torque acting on the crankshaft. For a common diesel engine, a full combustion cycle lasts for two crankshaft revolutions, where the cylinders in the engine ignites evenly distributed over the 720 crank angle degrees.

The resulting torque acting on the crankshaft generated by a cylinder during a full combustion cycle has a distinct maximum at the combustion event. With several cylinders connected to the crankshaft, the sum of the torque contributions from all cylinders is reminiscent of a sine wave. This is utilized in the model of the engine speed that is derived in this chapter.

3.2 Modeling Engine Dynamics

Under the assumption that the crankshaft is infinitely stiff, a dynamic model of the rotating flywheel under the action of net engine torque T_e and load T_l is obtained from the torque balancing equation [13]:

$$J\ddot{\theta} = T_e - T_l, \tag{3.1}$$

where J is the effective moment of inertia of the flywheel. The net engine torque is the sum of the torque contributions from all cylinders, of which each consists of three main parts: indicated torque, reciprocating torque and friction torque [14]. The indicated torque is generated as a consequence of gas pressure forces in a cylinder. The reciprocating torque is generated due to the reciprocating motion of the piston inside the cylinder. It does not contribute any net energy to the system, but can cause significant fluctuations at the combustion frequency. The friction torque represents energy loss due to friction in the engine. There are also other torques that contribute to the total torque acting on the crankshaft [12], but the effects of these are insignificant compared to the first three and therefore neglected here.

As the geometry of the engine under the assumption that the crankshaft is infinitely stiff causes a periodicity with respect to the crank angle, denoted θ, it is suitable to create a model based on the crank angle instead of time [15]. With the notation $\dot{\theta} = \omega$ and the derivative chain rule, $\ddot{\theta}$ can be transformed to the crank angle domain:

$$\ddot{\theta} = \frac{\mathrm{d}^2\theta}{\mathrm{d}t^2} = \frac{\mathrm{d}\omega}{\mathrm{d}t} = \frac{\mathrm{d}\omega}{\mathrm{d}\theta}\frac{\mathrm{d}\theta}{\mathrm{d}t} = \frac{\mathrm{d}\omega}{\mathrm{d}\theta}\omega. \tag{3.2}$$

It is thus possible to rewrite (3.1) as:

$$J\omega\frac{\mathrm{d}\omega}{\mathrm{d}\theta} = T_e(\theta) - T_l(\theta) \tag{3.3}$$

The assumptions of inertia and stiffness imply that the engine is treated with rigid body motion [13]. A more accurate engine model would include the elasticity and damping of the crankshaft. While this would increase modeling accuracy, it would also increase model complexity significantly. Hence, the motor is modeled by a single lumped inertia.

The periodical nature of the net engine torque $T_e(\theta)$ is the main reason for the engine speed oscillations and has complex nonlinear dynamics. By letting each torque contribution consist of a slowly varying component $\bar{T}(\theta)$, that is constant at idling and represents the momentary average of the engine torque, and a time-varying component $\tau(\theta)$, the net engine torque can be written as:

$$T_e(\theta) = \bar{T}_e(\theta) + \tau_e(\theta). \tag{3.4}$$

The time-varying component $\tau_e(\theta)$ can be characterized as a periodic function in the angular domain. This makes Fourier series expansion a practical tool for analyzing the signal. Utilizing the hypothesis that all engine processes are band limited [14], $\tau_e(\theta)$ can be expressed in terms of a truncated Fourier series expansion:

$$\tau_e(\theta) = a_0 + \sum_{n=1}^{M} a_n \cos\left(n\frac{N}{2}\theta\right) + b_n \sin\left(n\frac{N}{2}\theta\right) + \varepsilon_M, \tag{3.5}$$

$$\lim_{M\to\infty} \varepsilon_M = 0, \tag{3.6}$$

where M is the number of harmonics and N is the number of cylinders in the engine. By noting that the mean value of τ_e during a full combustion cycle is zero, it is realized that $a_0 = 0$. The principle of the spectrum of τ_e is shown in Figure 3.1. The distinct peaks at multiples of the combustion order $N/2$, where N is the number of cylinders in the engine, is the result of torque variations from cylinder combustions.

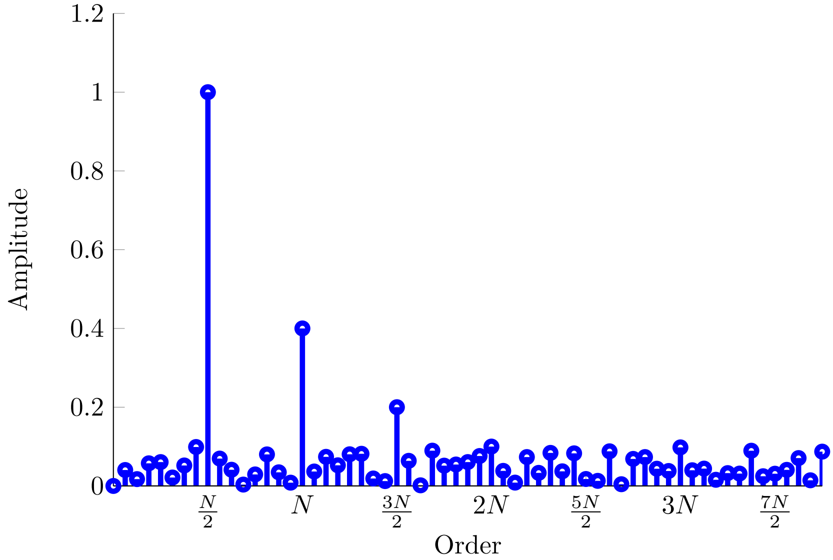


Figure 3.1. Principle of the spectrum of the time-varying component $\tau_e(\theta)$ of the torque acting on the crankshaft. The distinct peaks at multiples of the combustion order $N/2$, where N is the number of cylinders in the engine, is the result of torque variations from cylinder combustions.

The net engine torque $T_e(\theta)$ causes the flywheel to rotate at an angular speed $\omega(\theta)$. In the same manner as the torque, the resulting engine speed can be split into an average, or a slowly varying, angular speed $\bar{\omega}(\theta)$ and an oscillating speed variation $\tilde{\omega}(\theta)$ around $\bar{\omega}(\theta)$:

$$\begin{aligned} \omega(\theta) &= \bar{\omega}(\theta) + \tilde{\omega}(\theta), \\ \bar{\omega}(\theta) &= \text{momentary average engine speed}, \\ \tilde{\omega}(\theta) &= \text{oscillating engine speed}. \end{aligned} \tag{3.7}$$

The momentary average engine speed is affected mainly by the slowly varying torque component $\bar{T}(\theta)$, while the time-varying torque $\tau(\theta)$ influences the oscillating engine speed $\tilde{\omega}(\theta)$. This idea, in combination with (3.3), means that the derivative of $\tilde{\omega}$ with respect to θ is strongly connected to time-varying torque, which explains its periodical nature.

It is $\bar{\omega}(\theta)$, the slowly varying component or the momentary average engine speed, that is sought in this work. Figure 3.2 shows the principle of the engine speed signal, with the two components forming the total, and measured, engine speed.

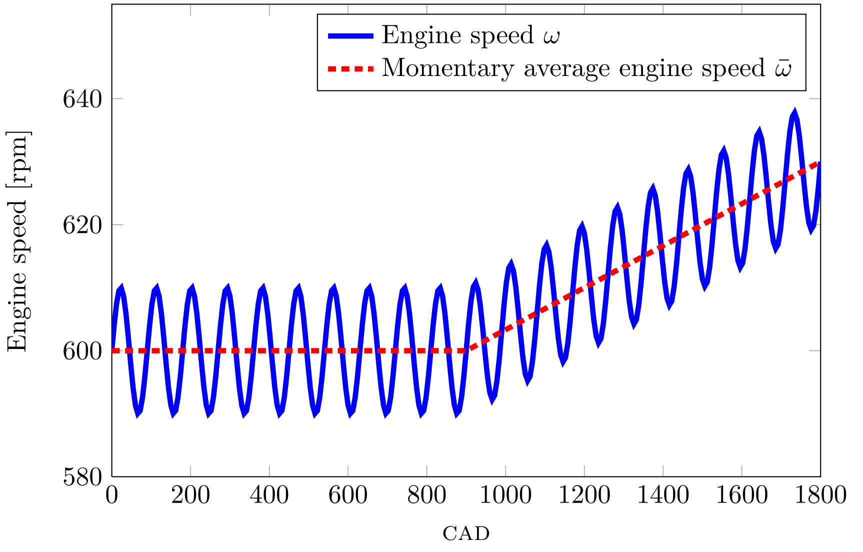


Figure 3.2. This figure explains the composition of the engine speed, consisting of a momentary average $\bar{\omega}$ and an oscillating component $\tilde{\omega}$. The superposition of the two components form the total engine speed ω.

3.3 State Space Representation

In this section a state space representation of the engine speed signal is presented. The state space model utilizes the fact that, as stated in the previous sections of this chapter, the torque acting on the crankshaft and thus the engine speed can be seen as the superposition of a momentary average and an oscillating component. First, a simple model of the momentary average engine speed is presented. Then, the oscillations are modeled as noise and the two separate parts are combined into a full state space model that is used for estimation of the momentary average engine speed.

3.3.1 Average Speed Model

The purpose of the average speed model is to describe the dynamics of the slowly varying component of the engine speed. The momentary average is constant during idling, and at accelerations or gear shifts it has a rather constant derivative. Using a second order model with two states, the momentary average engine speed $\bar{\omega}$ and its derivative with respect to the crank angle $\frac{\mathrm{d}\bar{\omega}}{\mathrm{d}\theta}$, the basic model in continuous time is described by

$$\frac{\mathrm{d}^2\bar{\omega}}{\mathrm{d}\theta^2} = u, \tag{3.8}$$

and the corresponding state space model is:

$$\begin{aligned}
\bar{x} &= \begin{bmatrix} \bar{\omega} & \frac{\mathrm{d}\bar{\omega}}{\mathrm{d}\theta} \end{bmatrix}^T, \\
\frac{\mathrm{d}}{\mathrm{d}\theta}\bar{x} &= \underbrace{\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}}_{A_c} \bar{x} + \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_{B_c} u, \\
y &= \begin{bmatrix} 1 & 0 \end{bmatrix} \bar{x}.
\end{aligned} \tag{3.9}$$

The output vector y corresponds to measuring the momentary average engine speed if there where no oscillations, i.e. $\tilde{\omega}(\theta) = 0,\ \forall\theta$. For the purpose of discrete time filtering, the state space model needs to be discretized. By assuming that the acceleration u is piecewise constant between the sampling instants, which is reasonable since $\bar{\omega}$ is the slowly varying component of the engine speed, the model can be discretized using the zero-order hold method [10]. The differential equation is then integrated from $\theta = \theta_0$ to the next sampling instance $\theta = \theta_0 + \alpha$, with the solution

$$\bar{x}(\theta_0 + \alpha) = A_{\bar{\omega}}\bar{x}(\theta_0) + B_{\bar{\omega}}u(\theta_0), \tag{3.10}$$

where

$$\begin{aligned}
A_{\bar{\omega}} &= e^{A_c\alpha} \approx I + A_c\alpha + A_c^2\alpha^2/2! + A_c^3\alpha^3/3! + \ldots, \\
B_{\bar{\omega}} &= \int_0^\alpha e^{A_c s} B_c \,\mathrm{d}s.
\end{aligned} \tag{3.11}$$

By noting that

$$A_c^2 = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \tag{3.12}$$

it is realized that

$$A_{\bar{\omega}} = e^{A_c\alpha} = I + A_c\alpha = \begin{bmatrix} 1 & \alpha \\ 0 & 1 \end{bmatrix}. \tag{3.13}$$

Further,

$$\begin{aligned}
B_{\bar{\omega}} &= \int_0^\alpha e^{A_c s} B_c \,\mathrm{d}s = \int_0^\alpha \begin{bmatrix} 1 & s \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} \mathrm{d}s \\
&= \int_0^\alpha \begin{bmatrix} s \\ 1 \end{bmatrix} \mathrm{d}s = \begin{bmatrix} \alpha^2/2 \\ \alpha \end{bmatrix}.
\end{aligned} \tag{3.14}$$

The deterministic parts of the continuous state space model are then fully discretized. To get a stochastic model the acceleration u is modeled as Gaussian white noise w_{1k} with covariance σ_1^2. The resulting model is

$$\begin{aligned}
\bar{x}_{k+1} &= \begin{bmatrix} 1 & \alpha \\ 0 & 1 \end{bmatrix} \bar{x}_k + \begin{bmatrix} \alpha^2/2 \\ \alpha \end{bmatrix} w_{1k}, \\
y_k &= \begin{bmatrix} 1 & 0 \end{bmatrix} \bar{x}_k, \\
w_1 &\sim N\left(0, \sigma_1^2\right).
\end{aligned} \tag{3.15}$$

3.3.2 Noise Model

The momentary average engine speed $\bar{\omega}$ is not possible to measure directly, since it is not the real engine speed. As seen in Figure 3.2, the actual engine speed consists of the momentary average plus oscillations that are seen as disturbances in this model:

$$\omega = \bar{\omega} + \tilde{\omega}. \tag{3.16}$$

One solution is to model the disturbances as white noise. In this case, it is known that the disturbances have an apparent oscillating behavior. It is thus not natural to describe them as white noise but rather as a signal with one or several distinct peaks in its spectrum, see [16]. From the periodical nature of the engine speed signal it is understood that the disturbance spectrum, i.e. the spectrum of the oscillations, have a peak at the combustion order $\lambda_c = \frac{N}{2}$. This is also seen in the spectrum of the engine speed signal in Figure 2.6.

To model the noise as a process with distinct peaks in its spectrum is also motivated by the fact the time-varying torque τ_e, which in (3.5) and Figure 3.1 is characterized as a signal with distinct peaks in its spectrum, affects the derivative of $\tilde{\omega}$ with respect to the crank angle θ. The more peaks in the spectrum, the more complex the noise model is. Hence, only the combustion order and none of its harmonics is taken into account in the model. The desired spectrum is generated by letting $\tilde{\omega}$ be represented as the output from a second order time continuous system with poles close to $\pm i\lambda_c$, with the real component $-\xi$ that places the poles in the left half plane, excited by white noise w_2.

$$\tilde{\omega} = H(s)\, w_2 = \frac{1}{(s - \xi - i\lambda_c)(s - \xi + i\lambda_c)} w_2. \tag{3.17}$$

For the noise model to be useful in the full state space representation, it needs to be discretized and transformed to state space form. The discretization is done using the Tustin approximation [10] and the transformation to state space form is done by rewriting the model on controllable canonical form [10]. The two poles of the transfer function $H(s)$ means that the state space representation will have two states.

$$\begin{aligned} \tilde{x}_{k+1} &= A_{\tilde{\omega}} \tilde{x}_k + B_{\tilde{\omega}} w_{2k}, \\ w_2 &\sim N\left(0, \sigma_2^2\right) \\ \tilde{\omega}_k &= C_{\tilde{\omega}} \tilde{x}_k, \end{aligned} \tag{3.18}$$

where

$$\begin{aligned} A_{\tilde{\omega}} &= \begin{bmatrix} a_1 & a_2 \\ 1 & 0 \end{bmatrix}, \\ B_{\tilde{\omega}} &= \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \\ C_{\tilde{\omega}} &= \begin{bmatrix} 0 & 1 \end{bmatrix}. \end{aligned} \tag{3.19}$$

The final noise model consists of two states, of which the second corresponds to $\tilde{\omega}$, the engine speed oscillations.

3.3.3 Full Signal Model of the Engine Speed

Putting the two state space models (3.15) and (3.18) together gives a system with four states:

$$x = \begin{bmatrix} \bar{x} & \tilde{x} \end{bmatrix}^T = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix}^T, \tag{3.20}$$

where x_1 and x_2 represent the average engine speed and x_3 and x_4 represent the noise model. Assuming that the two components of the process noise w_1 and w_2 are mutually independent, the covariance matrix is defined as

$$\Sigma = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} \tag{3.21}$$

The full state space representation of the engine speed can be summed up as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bw_k, \\ y_k &= Cx_k + e_k, \end{aligned} \tag{3.22}$$

where e_k is the measurement noise, modeled as Gaussian white noise with covariance R, and:

$$\begin{aligned} A &= \begin{bmatrix} A_{\bar{\omega}} & 0 \\ 0 & A_{\tilde{\omega}} \end{bmatrix} = \begin{bmatrix} 1 & \alpha & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & a_1 & a_2 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \\ B &= \begin{bmatrix} B_{\bar{\omega}} & 0 \\ 0 & B_{\tilde{\omega}} \end{bmatrix} = \begin{bmatrix} \alpha^2/2 & 0 \\ \alpha & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \\ C &= \begin{bmatrix} 1 & 0 & 0 & 1 \end{bmatrix}, \\ w &= \begin{bmatrix} w_1 & w_2 \end{bmatrix}^T \sim N(0, \Sigma), \\ e &\sim N(0, R). \end{aligned} \tag{3.23}$$

This model is a signal model of the engine speed describing the momentary average and the oscillations at the combustion order.

Chapter 4

Filtering

This chapter discusses methods to retrieve estimates of the momentary average engine speed $\bar{\omega}$ by trying to filter out the periodic term $\tilde{\omega}$ from the engine speed measurements ω. The signal model from last chapter is used in a signal model based method and the results are compared to estimates from a frequency selective filter. Also discussed in the chapter is how a change detection framework can be used to increase the performance of a filter by changing parameter values at appropriate times.

4.1 Estimation of the Average Engine Speed

When estimating the momentary average engine speed from the engine speed signal, the oscillating component $\tilde{\omega}$ needs to be canceled out. There are many types of filtering algorithms to extract desired parts or reject noise in signals. Frequency selective filters is a class of filters that attempts to pass some bands of frequencies and reject others. The theory behind this class of filters is covered in [17]. In this work, one of the methods used to filter out the oscillations in the engine speed is a frequency selective filter with finite impulse response. A different approach to extract certain parts of a signal is to create a signal model and use a state estimating filter. A classic state estimating filter is the Kalman filter, which in this work is used to estimate the momentary average engine speed.

4.1.1 FIR Filters

A finite impulse response (FIR) filter is a linear filter whose impulse response is of finite duration. The duration of the impulse response corresponds to the filter order, i.e. the number of poles in the transfer function of the filter. An Lth order FIR filter has an impulse response that lasts for $L + 1$ samples. The output y_k of a FIR filter is, as for all linear time invariant systems, given by the convolution between the input signal x_k and the system's impulse response h_k:

$$y_k = \sum_{l=0}^{L} h_l x_{k-l} \tag{4.1}$$

The main advantages of the FIR filters are that they are inherently stable and simple to implement. For more reading on the theory of frequency selective filters, please refer to [17].

As stated in Chapter 3, the engine speed can be described as the superposition of a slowly changing term $\bar{\omega}$ and a periodic term $\tilde{\omega}$ that are depending on the combustions. The period of $\tilde{\omega}$ is equal to the angle between the cylinder combustion events. Since all N cylinders ignites in 720 crank angle degrees, there is a combustion event every $\frac{720}{N}$th degree. For the task of suppressing the periodic term, a Crank Angle Synchronous Moving Average (CASMA) filter, described in [2], can be used. The CASMA filter is a regular moving average FIR filter that is applied in the crank angle domain, with a filter length chosen to fit the angular period duration. Since the sampling interval α for the signal in this work is fixed at 6 crank angle degrees, the filter length is chosen as:

$$M = \frac{720}{N\alpha}, \tag{4.2}$$

and the filtered engine speed signal is calculated as

$$\hat{\bar{\omega}}_k = \frac{1}{M} \sum_{l=0}^{M-1} \omega_{k-l}. \tag{4.3}$$

For this choice of filter length, all multiples of the combustion order in the engine speed signal are attenuated. The order response of such a filter, designed for an engine with N cylinders, is illustrated in Figure 4.1.

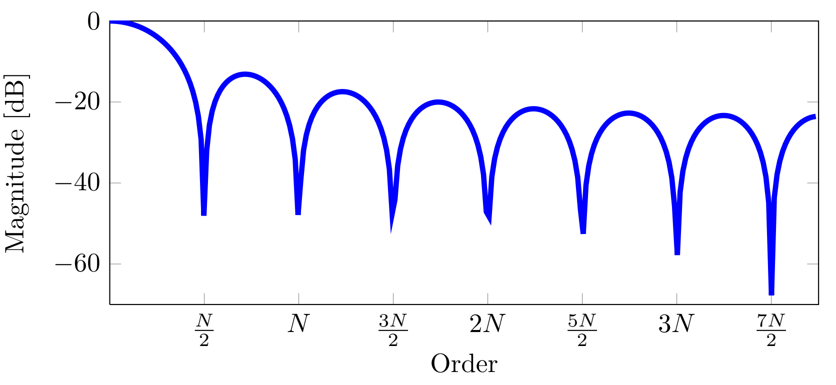


Figure 4.1. Order response of a moving average FIR filter, designed to suppress the combustion order and its multiples in an engine with N cylinders. This is achieved by averaging over the last $\frac{720}{N}$ crank angle degrees. Since the angle between each sample is six degrees, this means that the filter returns the average value of the last $\frac{720}{6N} = \frac{120}{N}$ samples: $\hat{\bar{\omega}}(k) = \frac{N}{120} \sum_{l=0}^{\frac{120}{N}} \omega(k-l)$.

The main advantage of the moving average filter is that it uses only earlier samples of the input signal and no samples from the output signal as input to the filter. This means that not all the samples have to be filtered, but only the ones representing the last combustion period when the EMS needs a new estimated value of the momentary average engine speed. This makes it possible to get a crank angle synchronous estimate of the average engine speed without filtering every single sample and thus keep the number of operations down. Each update requires $M-1$ additions and one division, no matter what the engine speed is. Here, M is the number of samples during one combustion period.

The filter suppresses all oscillations at the combustion order, but lower frequencies pass through. This causes the estimated momentary average engine speed to vary with small fluctuations in the engine speed, see Figure 4.2.

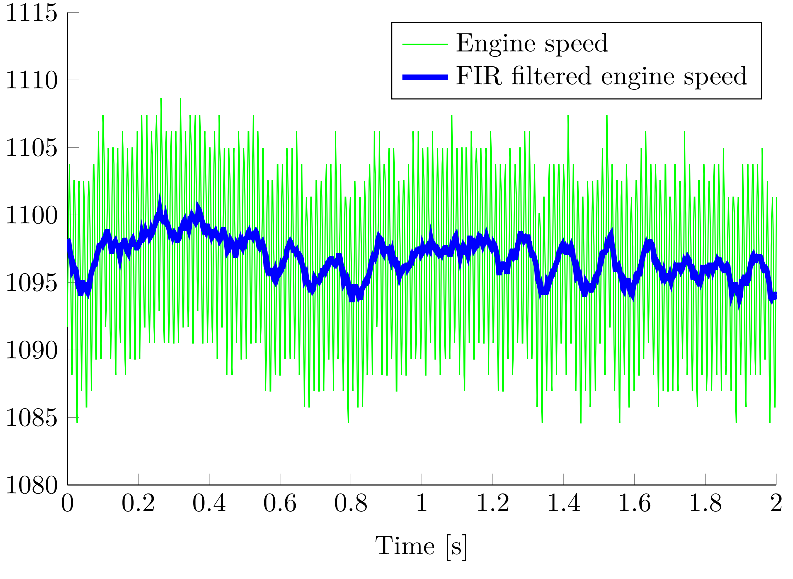


Figure 4.2. Estimated momentary average engine speed of an eight cylinder engine using a moving average FIR filter.

4.1.2 Kalman Filter

The Kalman filter, presented in [18], estimates the states in a state space model described by

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + w_k, \\ y_k &= Cx_k + e_k, \\ x_0 &= \bar{x}_0, \\ Q &= \mathrm{Cov}\{w\}, \\ R &= \mathrm{Cov}\{e\}. \end{aligned} \tag{4.4}$$

In the state space model, A, B and C are known matrices, x_k an unknown state vector, and y_k measured signals. The process noise is described by w_k and e_k is the measurement noise. Independently of the distributions of the process and measurement noise, the Kalman filter is the best linear filter in the sense that it minimizes the estimated error covariance [10]. Figure 4.3 summarizes the signal flow for the signal model and the Kalman filter. Along with the state estimates $\hat{x}$, the filter also provides a covariance matrix P of the estimates.

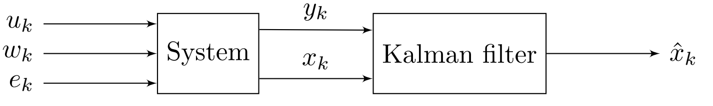


Figure 4.3. Definition of signals for the signal model and Kalman filter.

The operation of the Kalman filter algorithm can be divided into two update steps: the time update and the measurement update. The time update is the prediction part, where the algorithm makes use of the dynamic equation in order to predict the state to the next time step. In the measurement update step, the information available in the new measurement is incorporated into the state estimate. The two steps are then iterated, which makes it possible to illustrate the algorithm as in Figure 4.4. The equations for the two steps are as follows:

Time update

$$\hat{x}_{k+1|k} = A\hat{x}_{k|k}, \tag{4.5}$$
$$P_{k+1|k} = AP_{k|k}A^T + Q, \tag{4.6}$$

Measurement update

$$K_k = P_{k|k-1}C^T \left(CP_{k|k-1}C^T + R\right)^{-1}, \tag{4.7}$$
$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - C\hat{x}_{k|k-1}\right), \tag{4.8}$$
$$P_{k|k} = P_{k|k-1} - K_kCP_{k|k-1}. \tag{4.9}$$

It is possible to save computations in the measurement update by introducing some dummy variables:

$$L_k = P_{k|k-1}C^T, \tag{4.10}$$
$$S_k = CL_k + R. \tag{4.11}$$

The update is then computed as:

$$K_k = L_kS_k^{-1}, \tag{4.12}$$
$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - C\hat{x}_{k|k-1}\right), \tag{4.13}$$
$$P_{k|k} = P_{k|k-1} - K_kL_k^T. \tag{4.14}$$

The matrix K_k is referred to as the Kalman gain. It is a function of the relative certainty of the measurements and the current state estimate. With a high gain, the filter puts more weight on the measurements, and thus follows them more closely. With a low gain, the filter follows the model predictions more closely, smoothing out noise but decreasing the responsiveness.

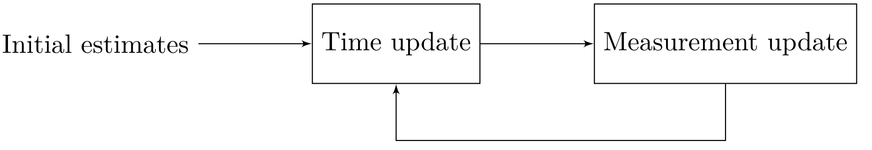


Figure 4.4. Description of the Kalman filter algorithm.

The covariance matrices of the process noise and measurement noise, Q and R, are the design parameters of the Kalman filter. The relation between the matrices determine how much the process and measurement equations are trusted. If the measurements are scalar, so is R, and the relation between the design parameters can be described as follows. With a small R/Q relation, the measurements are trusted more and the filter has a large Kalman gain. If R/Q instead tends to infinity, the Kalman gain tends to zero and the model dynamics are trusted instead of the measurements.

Estimation of Average Engine Speed Using Kalman Filter

The signal model (3.22) presented in Chapter 3, has two mutually independent process noise components. The standard state space model defined for the Kalman filter in (4.4) has a single process noise. By defining

$$w = B \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}, \tag{4.15}$$

$$B = \begin{bmatrix} B_{\bar{\omega}} & 0 \\ 0 & B_{\tilde{\omega}} \end{bmatrix} = \begin{bmatrix} \alpha^2/2 & 0 \\ \alpha & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}, \tag{4.16}$$

the state space model of the signal is back on standard form, with a process noise covariance matrix

$$\bar{\Sigma} = B \Sigma B^T = \begin{bmatrix} \alpha^4\sigma_1/4 & \alpha^3\sigma_1/2 & 0 & 0 \\ \alpha^3\sigma_1/2 & \alpha^2\sigma_1 & 0 & 0 \\ 0 & 0 & \sigma_2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \tag{4.17}$$

where Σ is the covariance of the process noise (3.22), and can be summed up as:

$$\begin{aligned} x_{k+1} &= A x_k + w_k, \\ y_k &= C x_k + e_k, \end{aligned} \tag{4.18}$$

where

$$A = \begin{bmatrix} A_{\bar{\omega}} & 0 \\ 0 & A_{\tilde{\omega}} \end{bmatrix} = \begin{bmatrix} 1 & \alpha & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & a_1 & a_2 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$
$$C = \begin{bmatrix} 1 & 0 & 0 & 1 \end{bmatrix},$$
$$w \sim N\left(0, \bar{\Sigma}\right),$$
$$e \sim N\left(0, R\right). \tag{4.19}$$

Since R is scalar, the $R/\bar{\Sigma}$ relation determines how much the process and measurement equations are trusted. For the purpose of estimating the momentary average engine speed, the filter needs to suppress the oscillations effectively, which requires a large $R/\bar{\Sigma}$. The problem is that makes the filter too slow to track the signal during quick changes in engine speed, which would require a small $R/\bar{\Sigma}$ relation. This problem is illustrated with a gear shift in Figure 4.5. The fast filter tracks the signal well during the gear shift, but gives rather noisy estimates during the normal driving prior to the shift. The slow filter gives a stable signal during the normal driving, but cannot follow the signal during the gear shift. A solution to this would be to use different parameters during different parts of the signal.

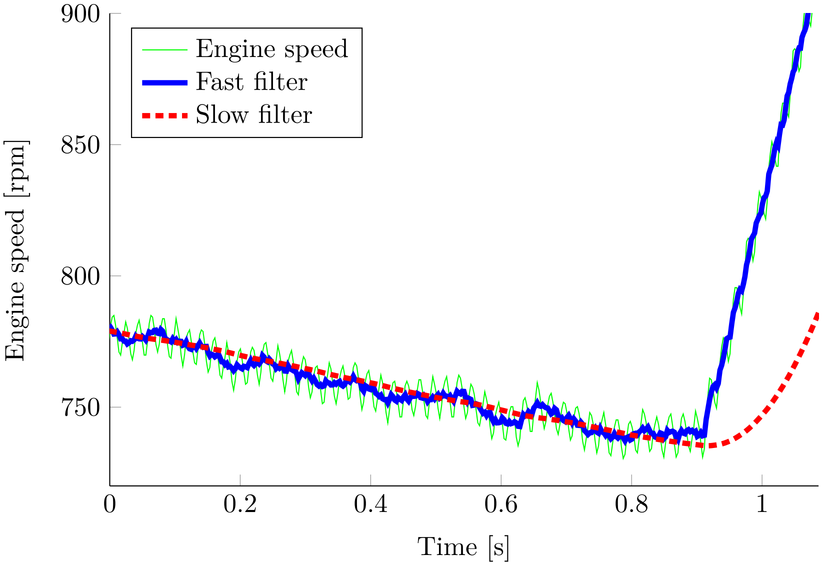


Figure 4.5. Illustration of the difficulty to tune the Kalman filter to provide stable estimates of the momentary average engine without noise, but still follow the signal during quick changes.

Number of Operations

Since the EMS has limited computational power, it is interesting to examine how many computations are needed in each iteration when using the Kalman filter. Let the number of states in the state space model be denoted n and the dimension of the measurement vector be m. The maximum number of computations needed in each equation can then be calculated as the sum of the operations in a multiplication between matrices of the appropriate dimensions. The total number of operations in the time update is then $4n^3 + n^2 - n$, including additions and multiplications in the two equations, see Table 4.1.

Table 4.1. The maximum number of operations needed in the time update step of the Kalman filter for a system with n states and m measurements.

Equation	Mult	Add
(4.5)	n^2	$n^2 - n$
(4.6)	$2n^3$	$2n^3 - n^2$
Total	$2n^3 + n^2$	$2n^3 - n$

For the measurement update, the number of operations are calculated for the computation saving method. The total number of operations are $4mn^2 + 4m^2n + 2mn$ plus the operations needed to compute the matrix inverse in (4.12) and in Table 4.2 the number of operations for the separate equations are presented.

Table 4.2. The maximum number of operations needed in the measurement update step of the Kalman filter for a system with n states and m measurements.

Equation	Mult	Add	Sub	Other
(4.10)	mn^2	$m\left(n^2 - n\right)$		
(4.11)	m^2n	m^2n		
(4.12)	m^2n	$\left(m^2 - m\right)n$		inv
(4.13)	$2mn$	$m\,(2n - 1)$	m	
(4.14)	mn^2	$(m - 1)\,n^2$	n^2	
Total	$2mn\,(m + n + 1)$	$2mn\,(m + n) - n^2 - m$	$n^2 + m$	inv

The number of operations presented above are calculated for the worst case scenario, where every element in the matrices are nonzero. By utilizing the structure of the system, for example by noting that the state transition matrix is a sparse matrix, it is possible to decrease the number of operations.

Given the model (4.18), there are $n = 4$ states and the measurements are scalar values, hence $m = 1$. With $m = 1$, the matrix S_k that is inverted in the measurement update is just a scalar. Thus, the inverse operation and n multiplications can be replaced by n divisions. This means that using a model of the same dimensions as (4.18), for the worst case scenario, the measurement update step takes 44 multiplications, 40 additions, 17 subtractions and 4 divisions. The time update step takes 144 multiplications and 124 additions. One full filter iteration takes a total of 373 operations. The actual number of operations per iteration, after some optimizing of the computations, are presented in Chapter 6.

4.2 Change Detection

As noted in Section 4.1.2, it is difficult to find parameters for the Kalman filter that provides stable estimates of the momentary average engine speed without losing track of the signal during transients. A solution is to detect when the signal changes too fast for the filter and momentarily change the parameters. This section introduces the change detection framework, which considers methods for detection and identification of changes in systems or signals.

4.2.1 Introduction to Change Detection

Many estimation and monitoring problems can be stated as estimating the values of the parameters in a dynamic stochastic system. The change detection framework is an approach to detecting and identifying abrupt changes in the these systems [19]. The changes may come from deviations, failures or malfunctions, but are in all cases reflected by a change in the parameters of the models of the systems. Statistical decision tools for detecting and estimating abrupt changes in the properties of dynamical systems are of great interest and useful for several different purposes:

- Gain updating in adaptive filtering algorithms for improving their tracking ability.
- Monitoring complex structures and industrial processes for fault detection.

As an illustration, Figure 4.6 shows a signal with two abrupt changes in the mean detected by a change detection algorithm. For more theory and applications, please refer to [19].

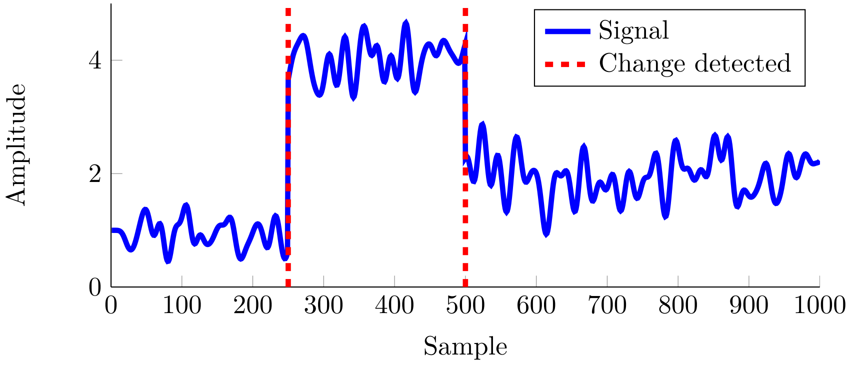
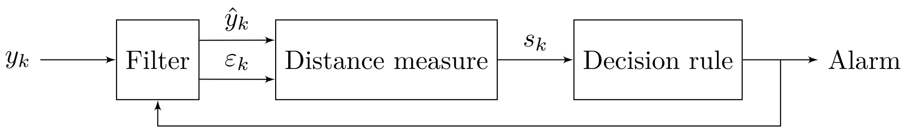


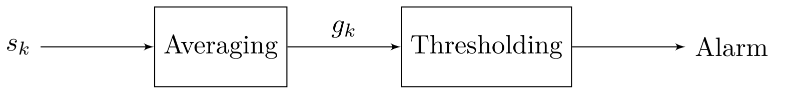
Figure 4.6. Example of how a change detection algorithm can be used to detect abrupt changes in the signal. After 250 and 500 samples, there are steps in the signal and the change detector sends out alarms.

The change detection problem can according to [19] be split into two steps: generation of residuals and residual evaluation. The residuals are ideally zero under no-fault conditions and non-zero after a change. As long as there is no change in the system and the correct model is used, the residuals act like white noise, that is a sequence of independent stochastic variables with zero mean and known variance. The residuals are then mapped to a distance measure, which can vary for different purposes.

The residual evaluation step aims to make a decision if a change has occurred based on these distance measures. The design of a decision rule in the residual evaluation is a compromise between detecting true changes and avoiding false alarms. If the threshold for alarm is too low, the alarm will be triggered easily, leading to a lot of false alarms. A threshold that is too high will instead fail to detect real changes. Figure 4.7 shows the basic structure of the change detection framework.



(a) Structure of a change detection algorithm



(b) Structure of the decision rule

Figure 4.7. The steps in change detection based on hypothesis tests. The stopping rule can be seen as an averaging filter and a thresholding decision device.

Performance Measures

A change detector needs to detect all abrupt changes in the system but should not cause any false alarms. The performance of a change detection algorithm is evaluated by looking at the following measures:

- False alarm rate
  How often a false alarm is generated.

- Time to detection
  How many samples there are between a change and the corresponding alarm.

CUSUM algorithm

The cumulative sum (CUSUM) algorithm [20] is a non-linear decision rule commonly used in change detection. It has two design parameters, ν and h, and the equations used to detect a change in the mean are given by

$$\begin{aligned} s_k &= \varepsilon_k = \hat{y} - y \\ g_k &= \max\left\{g_{k-1} + s_k - \nu, 0\right\}, \\ g_k &= 0, \text{ and alarm if } g_k > h > 0. \end{aligned} \tag{4.20}$$

The idea is to sum up the distance measures s_k and alarm when the sum exceeds a predefined threshold h. At an alarm the sum is reset to zero and the process starts over again. In order to prevent positive drifts of the test statistic g_k, a small term ν is subtracted from each distance measure. To avoid negative drifts that would increase the detection time after a change, g_k is reset to zero each time it becomes negative.

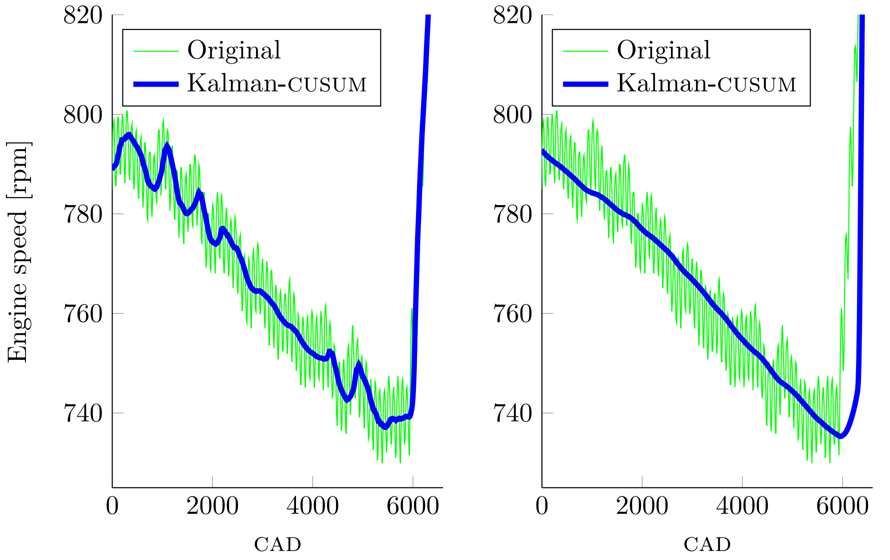
4.2.2 Change Detection for Adaptive Filtering

The performance of a state estimating filter is often evaluated from its tracking ability and the variance error of the estimates. The two measures obstruct one another in the sense that an increased tracking ability often comes at the price of increased noise sensitivity. The tuning of the filter parameters is hence a compromise between the two measures. For the purpose of estimating the momentary average engine speed, it is desirable to get estimates with low error variance. However, during gear shifts or accelerations the derivative of the engine speed may be very large, causing quick changes in the engine speed. A state estimator tuned to give estimates with low variance will be too slow and cause a delay in the estimate. In this case, a filter tuned to have a good tracking ability would perform better than the low variance filter.

The use of change detection makes it possible to select different filters at different signal cases. During steady state operation, a slow filter that dampens all oscillations and giving low error variance can be used. When the signal changes too fast for the slow filter, an alarm from the change detection algorithm triggers the fast filter with focus on tracking ability. The design of the change detector determines how often the fast filter is used. An improper design results in either many false alarms or too few alarms, i.e. the fast filter is used too often or not sufficiently often. Examples are shown in Figure 4.8.

4.2.3 Kalman-CUSUM Filter

In order to improve the tracking ability of the Kalman filter, it is extended by a change detection algorithm that runs in parallel with the filter. The chosen change detection algorithm is the CUSUM algorithm described above. In case of an alarm, a significant change of the momentary average engine speed has occurred and the slow the Kalman filter has caused the estimate to be delayed. To increase the tracking ability of the filter, the Kalman gain needs to be increased. This makes the algorithm trust the measurements more than the model, which allows a quick convergence of the estimated average towards the actual average. Figure 4.9 shows the difference between the response of a conventional Kalman filter and one where the filter is extended with a change detection algorithm.



(a) Too many alarms (b) Too few alarms

Figure 4.8. Examples of consequences of improper design of the change detection algorithm. Figure (a) shows the result of a very low alarm threshold, causing many false alarms. In (b), the threshold is set too high and the delay until the gear shift is detected is too large.

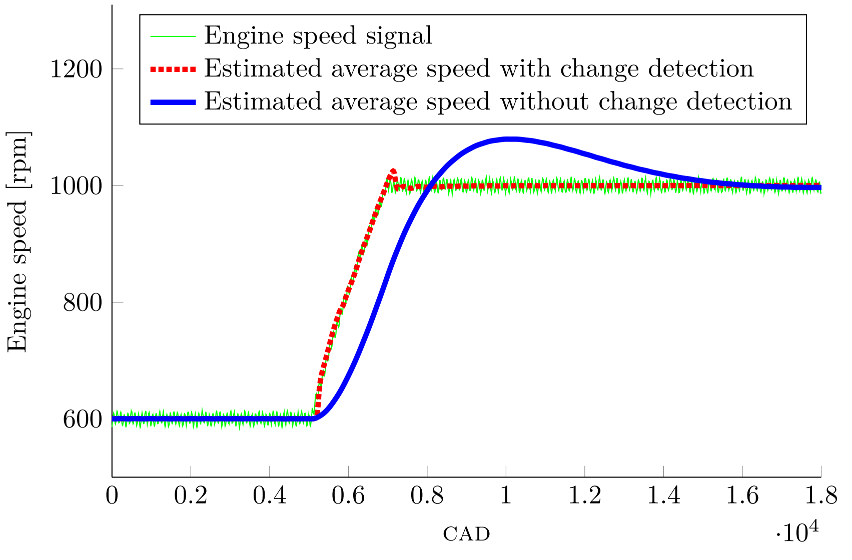
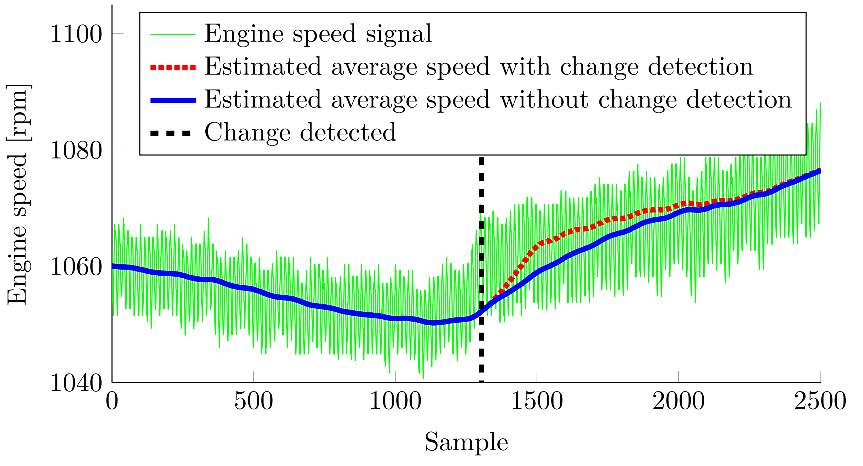


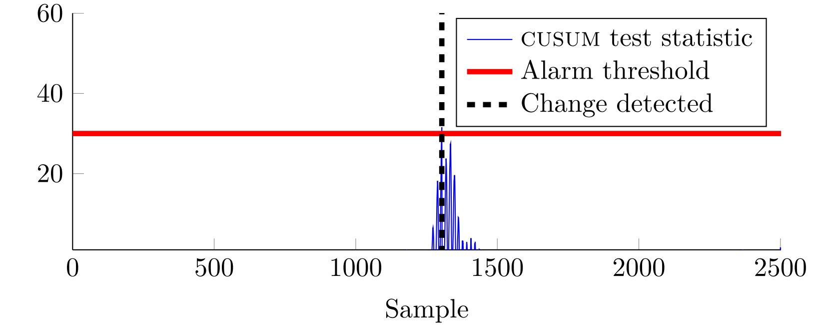
Figure 4.9. Comparative responses of Kalman filter with and without a change detection algorithm when estimating the average engine speed during a simulated gear shift.

The Kalman gain is a matrix, where each element corresponds to one of the states. In this work there are four states and the Kalman gain is thus a 4x1 matrix. The first two elements correspond to the average engine speed and its derivative while the two other elements correspond to the oscillations. The Kalman gain is affected by the covariance matrix P of the state estimates which in its turn is affected by the values of the process noise covariance $\bar{\Sigma}$. When the CUSUM algorithm indicates that the average engine speed has changed, the elements in $\bar{\Sigma}$ corresponding to the process noise for the average engine speed state are momentarily increased to a large value. This is done by increasing the parameter σ_1 in (4.17). The process noise covariance is only increased during one sample, but the change is propagated into the P matrix through (4.6), causing the first two elements in the Kalman gain matrix to stay large for more than one sample. The same behavior could be achieved by resetting the Kalman filter, e.g. by directly setting all the elements in the covariance matrix P to large values, but since that strategy would require more tuning parameters it is convenient to momentarily increase σ_1. Figure 4.10 shows the engine speed signal during an acceleration, where the conventional Kalman filter is too slow to track the actual average engine speed. As the estimated average falls from the actual, the test statistic g in the CUSUM algorithm starts increasing. As it exceeds the alarm threshold, the change detector generates an alarm. At this event, the process noise σ_1 is increased, leading to an increase in the Kalman gain. With a higher Kalman gain, the tracking ability of the filter is improved leading to a quicker convergence and a more accurate estimate of the average engine speed.

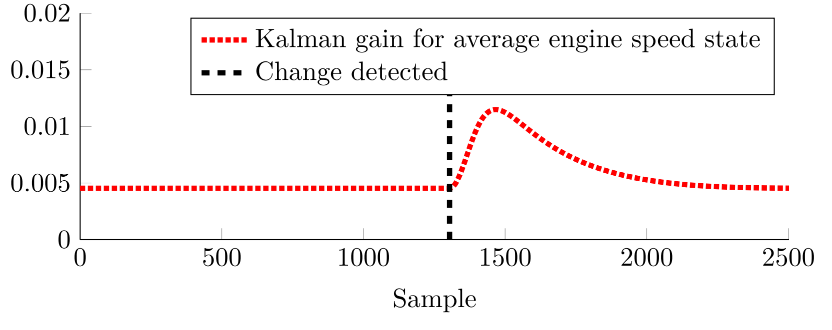
The extension of the Kalman filter by using CUSUM comes at a price of extra operations in every iteration: two subtractions, one addition, one max operation and one comparison.



(a) Engine speed



(b) CUSUM test statistics



(c) Kalman gain

Figure 4.10. Figure (a) shows the comparative responses of Kalman filter with and without a change detection algorithm when estimating the average engine speed during an acceleration. After the change has been detected in (b), the Kalman gain for both the speed and acceleration states are increased. Figure (c) shows the alarm response of the engine speed state's Kalman gain.

Chapter 5

Acceleration Estimation

The mean engine acceleration $\dot{\bar{\omega}}$, i.e. the time derivative of the momentary average engine speed, is used to calculate the torque generated by the engine and is also important in the engine speed control systems. This chapter presents two approaches to estimating the mean engine acceleration.

5.1 Backwards Difference

A standard ad hoc solution to estimate the derivative of a discrete time signal is to simply take the difference between the two last estimates scaled by the sampling period or the time T between the samples:

$$\dot{\bar{\omega}}_k \approx \frac{\bar{\omega}_k - \bar{\omega}_{k-1}}{T}. \tag{5.1}$$

This method is called the backwards difference (BD) [21] and is in this work used in combination with a FIR filter to estimate the mean engine acceleration. The method is sensitive to noise, and since the FIR filtered average engine speed estimates are noisy, the estimated acceleration is in practice often too noisy to be useful without further processing. Figure 5.1 shows an example of the mean engine acceleration estimated with this method, using $T = 10$ ms between each sample. The noise level of the raw estimated acceleration is very high, but filtering using a low pass (LP) filter decreases the noise significantly. Too much low pass filtering introduces extra delay, and since the acceleration is momentary this makes the estimates worse. This makes the LP filtering a trade off between noise suppression and extra delay.

5.2 Signal Model Based Estimation

Instead of using the BD method, it is possible to utilize the structure of the engine speed model to calculate the mean engine acceleration. Using the chain rule it is possible to rewrite the mean engine acceleration as:

$$\dot{\bar{\omega}} = \frac{\mathrm{d}\bar{\omega}}{\mathrm{d}t} = \frac{\mathrm{d}\bar{\omega}}{\mathrm{d}\theta}\frac{\mathrm{d}\theta}{\mathrm{d}t}. \tag{5.2}$$

Both $\frac{\mathrm{d}\theta}{\mathrm{d}t}$ and $\frac{\mathrm{d}\bar{\omega}}{\mathrm{d}\theta}$ have corresponding states in the signal model (3.22), since the state x_1 corresponds to $\bar{\omega}$ and the state x_2 is the derivative of $\bar{\omega}$ with respect to the crank angle θ. Since the engine speed is measured in rpm, both x_1 and x_2 corresponds to the rotational speed in rpm, which needs to be converted to rad/s in order to get the scaling factor correct. This is done by multiplying with $\frac{2\pi}{60}$, which means that

$$\frac{2\pi}{60}x_1 = \frac{\mathrm{d}\theta}{\mathrm{d}t} \quad \left[\frac{\mathrm{rad}}{\mathrm{s}}\right], \tag{5.3}$$

$$\frac{2\pi}{60}x_2 = \frac{\mathrm{d}\bar{\omega}}{\mathrm{d}\theta} \quad \left[\frac{\mathrm{rad/s}}{\mathrm{rad}}\right]. \tag{5.4}$$

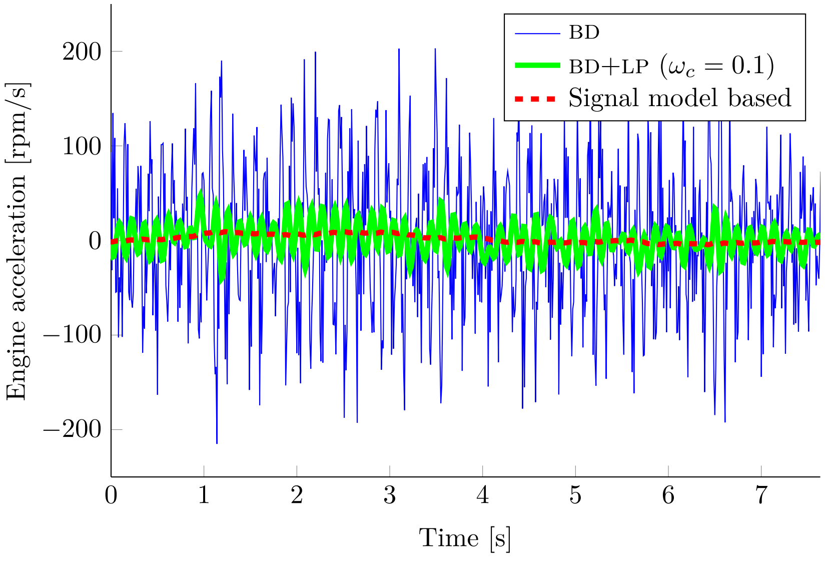
Using equations (5.3) and (5.4) in (5.2), the mean engine acceleration in rad/s^2 can be calculated as

$$\dot{\bar{\omega}} = \left(\frac{2\pi}{60}\right)^2 x_1x_2 \quad \left[\frac{\mathrm{rad}}{\mathrm{s}^2}\right]. \tag{5.5}$$

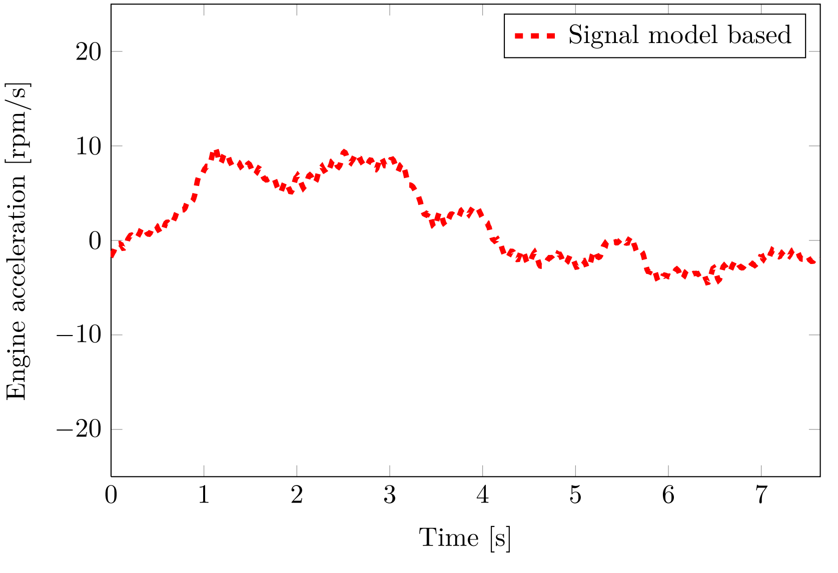
Since the engine speed is measured in rpm in the rest of this work, it is convenient to also express the mean engine acceleration in rpm/s:

$$\dot{\bar{\omega}} = \frac{2\pi}{60}x_1x_2 \quad \left[\frac{\mathrm{rpm}}{\mathrm{s}}\right]. \tag{5.6}$$

Another signal model approach to estimating the mean engine acceleration would be to extend the signal model (3.22) with a state corresponding to $\dot{\bar{\omega}}$. This would lead to an increased number of operations in each iteration of the filter, since there would be five states instead of four. By instead using (5.6), the computational cost is not increased more than necessary. The resulting mean acceleration estimates from the signal model based method is compared to the BD method in Figure 5.1.



(a) Mean engine acceleration



(b) Mean engine acceleration

Figure 5.1. Mean engine acceleration estimated using different methods. The noise level of the BD method is significantly higher than for the estimates from the signal model based method. Figures (a) and (b) show the same signal in different scales.

Chapter 6

Results

In this chapter, the main results of this work is presented. The estimation results from the different methods are compared and discussed.

6.1 Average Engine Speed Estimation

This section presents the difference in performance when estimating the momentary average engine speed using the methods from Chapter 4: a moving average FIR filter and a Kalman-CUSUM filter. The most important property of the filtering methods is to provide estimates of the momentary average engine speed that follows the signal during accelerations and retardation with low noise levels. This means that the algorithms should suppress the oscillations at the combustion order and dampen minor fluctuations due to combustion variations.

6.1.1 Normal Driving

The measured engine speed consists of both the momentary average and the oscillating components, which means that the true momentary average engine speed is unknown. It is thus difficult, if not impossible, to numerically evaluate the performance of the methods. Instead of using numerical methods, the performance of the methods is compared by visual inspection of the estimates. The filters should suppress all oscillations but still track the engine speed during accelerations and retardations.

Figure 6.1-6.4 show the engine speed and estimated momentary average during a couple of normal driving scenarios. Both methods suppress the oscillations at the combustion order, but it is apparent that the signal model based Kalman-CUSUM filter gives a more stable estimate of the momentary average. In Figure 6.2, where a quick acceleration occurs after about 2.5 seconds, the disadvantage of the Kalman-CUSUM filter is shown. It is a bit too slow to track the signal during the quick change in engine speed, causing a lag on the estimated momentary average. This property is tunable, but to keep the oscillation suppression effective, it is necessary to let the filter introduce delays in the estimates for a short period after a quick change in engine speed. In the same situation, the FIR filter shows its advantage when it follows the engine speed through the acceleration.

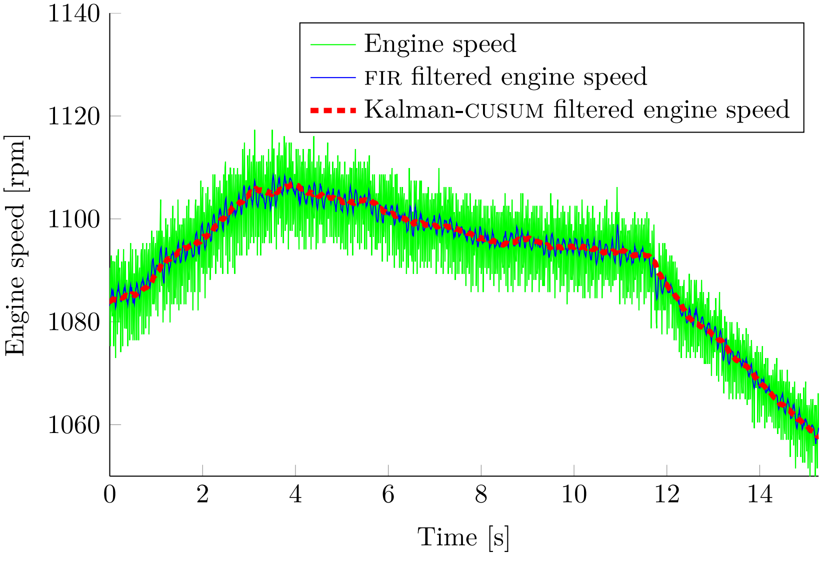


Figure 6.1. Engine speed during normal driving. The noise level for the estimates from the Kalman-CUSUM filter is significantly lower than for the FIR filtered estimates.

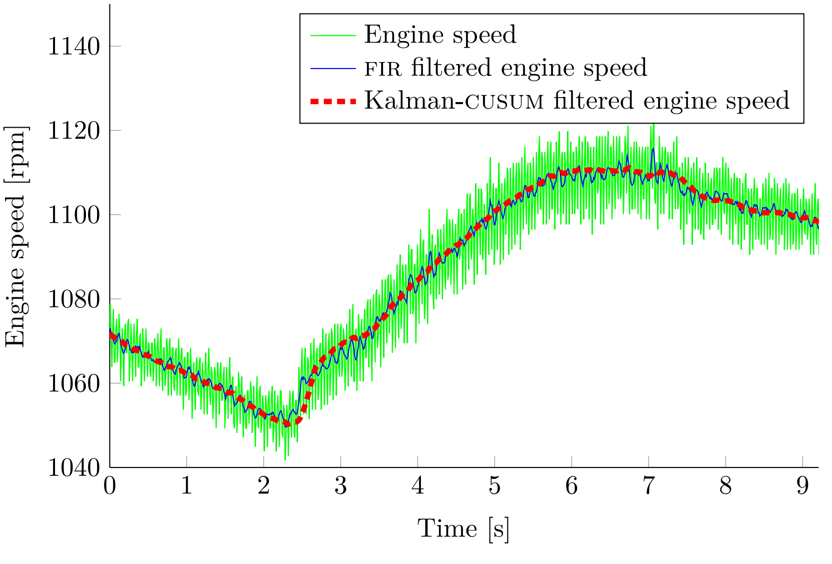


Figure 6.2. Engine speed during normal driving. In the acceleration after about 2.5 seconds, the estimates from the Kalman-CUSUM filter is delayed compared to the ones from the FIR filter.

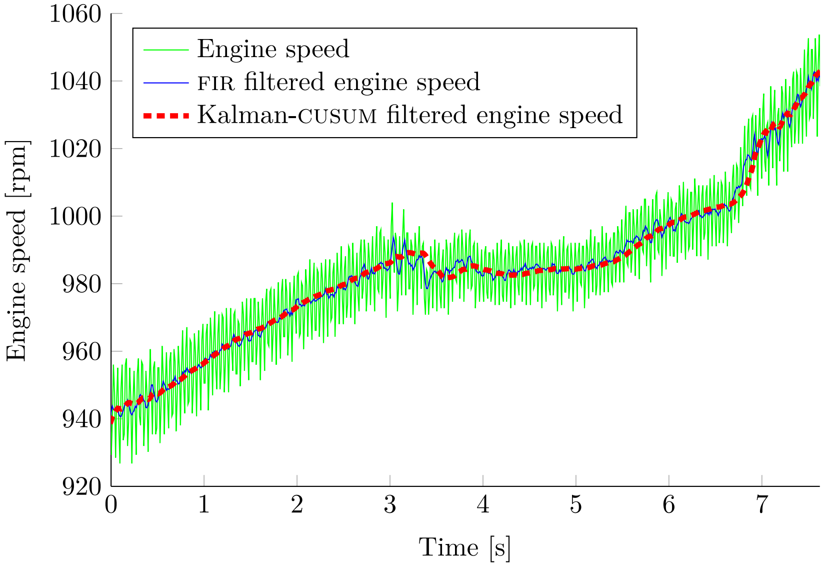


Figure 6.3. Engine speed during normal driving. The noise level for the estimates from the Kalman-CUSUM filter is significantly lower than for the FIR filtered estimates.

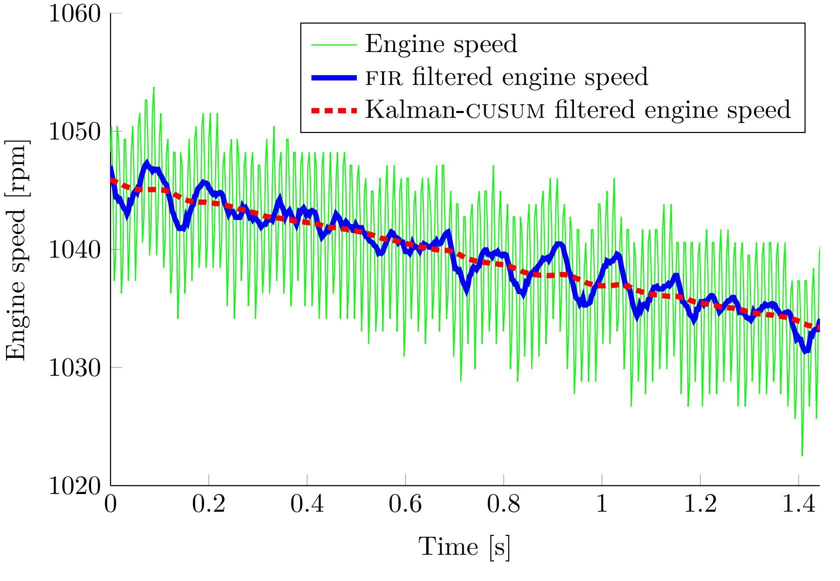


Figure 6.4. Engine speed during normal driving. The noise level for the estimates from the Kalman-CUSUM filter is significantly lower than for the FIR filtered estimates.

6.1.2 Idling

During idling, the actual engine speed oscillates with an amplitude of about 10 rpm and also varies a little from combustion variations. However, the average engine speed is constant and thus the filtering should result in a straight line. Figure 6.5 shows the difference between momentary average engine speed estimates from a moving average FIR filter and a Kalman-CUSUM filter. The FIR filtered signal is not completely constant, but follows the engine speed in its small variations. For the idling engine scenario, the true average engine speed is known. Hence, it is possible to evaluate the methods by computing their standard deviations from the true average. The standard deviation of the FIR filtered signal is 0.8 rpm and the largest deviation from a straight line at the mean of the full signal is 2.5 rpm.

The Kalman-CUSUM filter suppresses the oscillations from the combustions effectively and also dampens the slow oscillations. This makes the filter perform very well in estimating the average engine speed at steady state. The result is almost constant, with a small standard deviation of 0.1 rpm. The largest detected deviation from the mean is 0.4 rpm. The statistics for both methods are presented in Table 6.2.

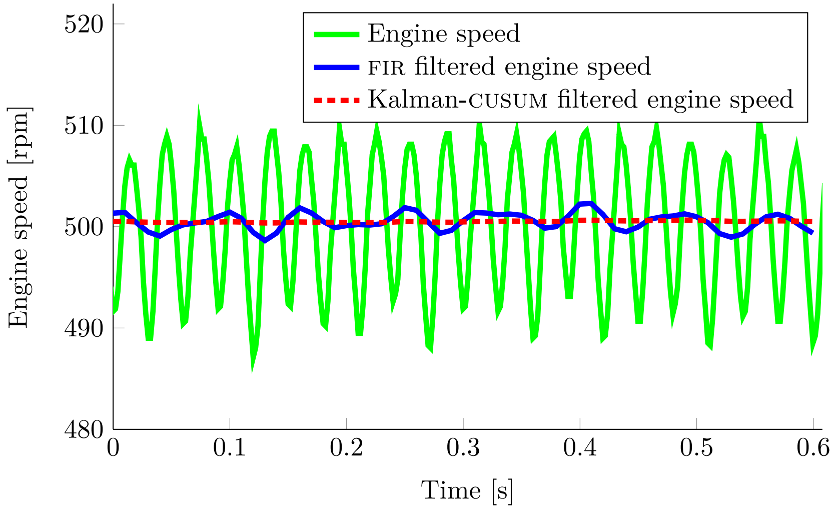


Figure 6.5. Estimated momentary average engine speed for an idling engine. The result using a moving average FIR filter still varies a little, while the Kalman-CUSUM filter provides an almost constant estimate.

Table 6.1. Statistics for average engine speed estimation during idling.

Method	Std dev [rpm]	Max dev [rpm]
Moving average FIR filter	0.8	2.5
Kalman-CUSUM filter	0.1	0.4

6.1.3 Gear Shifts

Gear shifts leads, just like accelerations, to quick changes in the engine speed. For good filtering performance, the filters need to be able the follow the signal in its variations without introducing unnecessary delays.

Since the output from the FIR filter always depend on the same number of measurements, all with the same delay, the phase delay is constant for the average engine speed estimates from the FIR filter. This means that in the ramp of a gear shift, the estimated average speed is slightly delayed for the full ramp. This is shown in Figure 6.6, where the gear shift starts after 0.5 seconds.

Unlike for the FIR filtered estimates, the phase delay of the estimates from the Kalman-CUSUM filter varies. This is due to the change of parameter values in connection to alarms. In case of quick changes in the signal, the slow Kalman filter lags behind, which increases the phase delay. When the CUSUM algorithm detects the change, it sends out an alarm and the filter parameters are changed. After this event, the Kalman-CUSUM filtered engine speed quickly converges to an accurate estimate of the momentary average engine speed and the phase delay decreases.

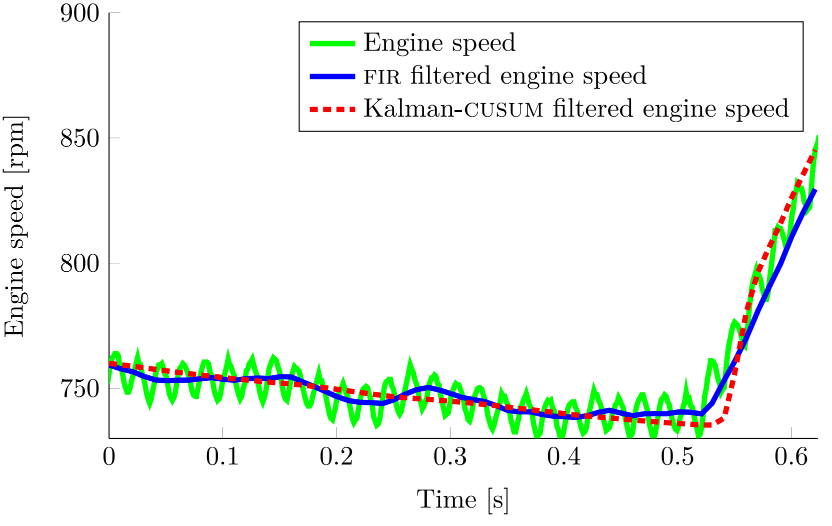


Figure 6.6. Estimated momentary average engine speed for an engine at a gear shift. The FIR filter responds faster to the quick change in engine speed, but the Kalman-CUSUM filter catches up after a few more samples.

Table 6.2. Statistics for average engine speed estimation at gear shift.

Method	Delay [ms]
Moving average FIR filter	< 10
Kalman-CUSUM filter	~ 20

6.2 Acceleration Estimation

This section presents the difference in performance when estimating the mean engine acceleration using the methods from Chapter 5.

6.2.1 Normal Driving

For the BD method, the mean acceleration is calculated from the FIR filter estimates of the momentary engine speed. These estimates contain a significant amount of noise that is propagated into the acceleration estimates. In practice, where the estimated mean acceleration is used to estimate the engine torque, the noise level of these raw estimates make them useless without further processing. As a compromise between delay and stability of the signal, the estimates are filtered using a third order Butterworth LP filter. This reduces the noise without introducing too much delay. The advantage of the BD method is, except for the low computational cost, its fast response at quick accelerations and retardations.

Using the signal model based Kalman-CUSUM filter to estimate the mean engine acceleration, a signal with a lot less noise is obtained. The drawback with the signal model based method to acceleration estimation is, just as for average speed estimation, the delay at quick changes. Depending on the application, the filter can be tuned to provide a more stable estimate at the price of reduced performance during transients. Here, a set of parameters tuned to give a balance between steady state and transient performance is used.

Figure 6.7 and 6.8 show the estimated mean engine acceleration corresponding to the signals in Figure 6.1 and 6.4. The noise level on the estimates from the BD method is a lot higher than for the signal model based estimates, but also gives a faster acceleration estimate at quick changes in the engine speed.

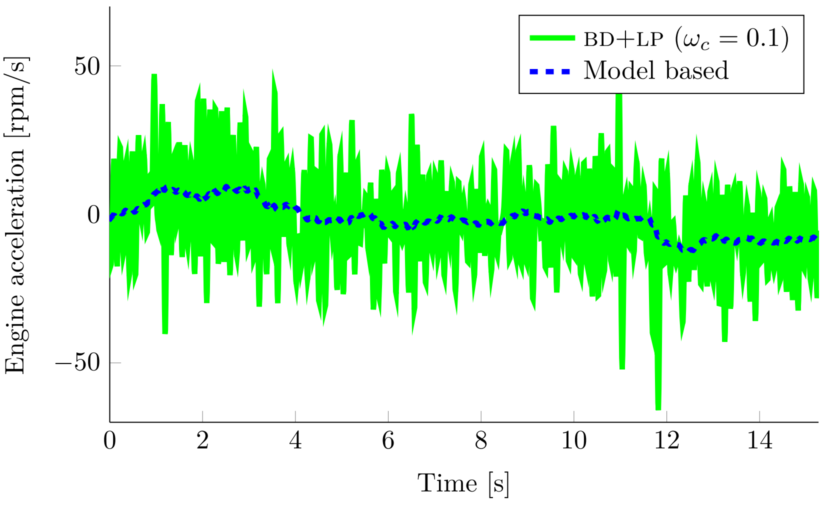


Figure 6.7. Mean engine acceleration during normal driving. The model based estimates have a lower noise level than the estimates from the BD method.

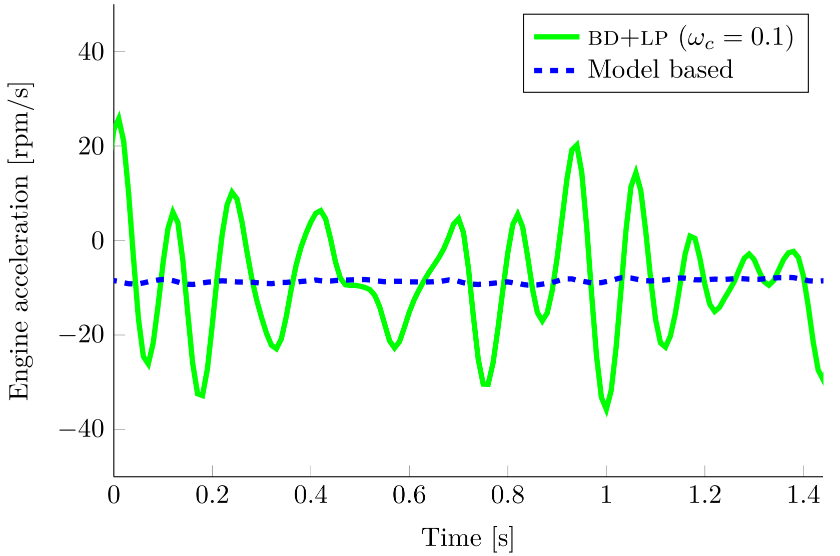


Figure 6.8. Closer view of the acceleration estimates during a section where the engine speed is decreasing.

6.2.2 Gear shifts

During gear shifting, the engine speed changes rapidly and the engine acceleration has a high absolute value. Performance measures for the acceleration estimates during a gear shift are:

- Response time
  How fast the estimates reach and settle at the correct value.

- Overshoot
  An estimated acceleration that is too large is not wanted.

- Noise
  A low noise level is desired.

By simulating a gear shift, the actual engine acceleration, i.e. the ground truth, is known. The advantage of the BD method is that is detects abrupt changes quickly, which means that it performs well during gear shifts. The first sample after the start of the gear shift the acceleration estimate has increased, see Figure 6.9. Just as earlier, the noise of the estimates is very large and some LP filtering is needed. The filtering reduces the noise but also introduces more delay, which makes the filter order and cutoff frequency a compromise between the tracking ability and the tolerated noise level.

The signal model based filter, which is designed to cancel out oscillations, is too slow to track the engine speed signal immediately at a gear shift that leads to a delay also in the acceleration estimates. As the change detection algorithm signals that a change of parameters is needed and the process noise covariance σ_1 increased, the estimated size of the step in engine acceleration gets larger than the actual step size. The overshoot is often as large as 100 % of the actual step size. This is due to the fact that the filter tries to bring back the average engine speed estimate to a correct level as fast as possible, which is not possible without a large acceleration. This is also apparent in Figure 6.6, where the estimated momentary average increases much quicker than the actual engine speed about 0.55 seconds into the plot. As seen in Figure 6.10, the first alarm comes about 20 ms after the start of the gear shift and the second alarm just after the gear shift is finished. Compared to the BD method, which responds just after 10 ms, the signal model based method is a bit slower. However, by tuning the filter a faster response and better acceleration estimation performance can be obtained at the cost of worse oscillation canceling in the average engine speed estimation.

It is not only delay until the alarm that is the problem with the signal model based method. After the overshoot, the time it takes for the acceleration estimate to settle at the correct level is also significant. In Figure 6.10 it takes almost 0.2 seconds from the start of the gear shift until the acceleration estimates reaches the correct level. A similar situation occurs after the shifting when the acceleration quickly switches from a high level to zero. The estimates calculated using the BD method reaches the correct level almost immediately, but the noise level is very high. After LP filtering with a third order Butterworth filter with normalized cutoff frequency 0.1, the settling time is about the same as for the signal model based estimates but without the large overshoot. On the other hand, the noise level is still higher for the LP filtered estimates than for the signal model based ones. Statistics for both methods are presented in Table 6.3.

Summing up, the acceleration estimates calculated with the signal model based method are more accurate than the ones calculated using the BD method at all times except at the events of alarms from the change detection algorithm, i.e. very quick changes in the engine speed. One solution to avoid the overshoot problems at alarms could be to switch to the BD method when the elements of the state covariance matrix P exceeds a certain threshold. After an alarm, the elements of P increase as a consequence of the increase in process noise covariance. To avoid the overshoot problem, a suitable threshold should be found and used.

Table 6.3. Statistics for acceleration estimation during a gear shift.

Method	Settling time [ms]	Overshoot [%]
BD	50	0
Signal model based	200	70
BD+LP ($w_c = 0.2$)	90	20
BD+LP ($w_c = 0.1$)	250	10

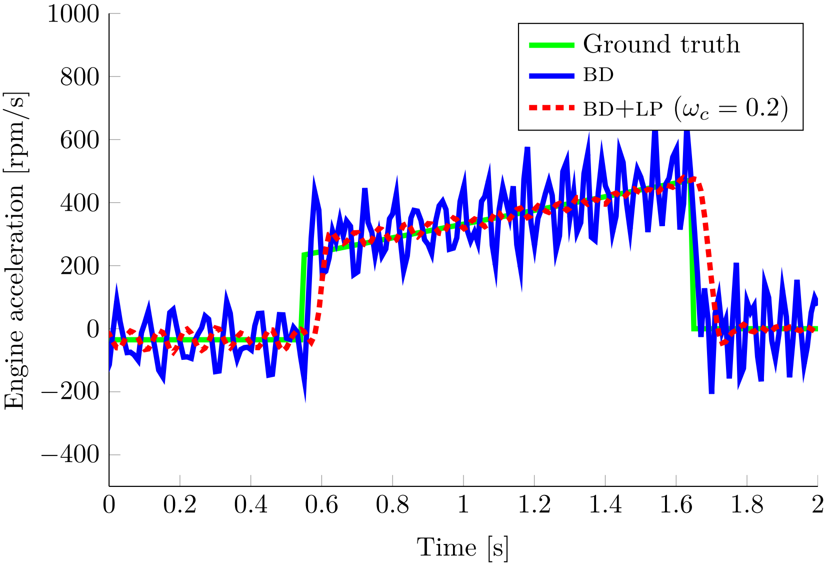


Figure 6.9. Estimated engine acceleration during a simulated gear shift using a FIR filter and the BD method. The raw estimates are very noisy, but by using a LP filter the noise is reduced at the price of slower adaption.

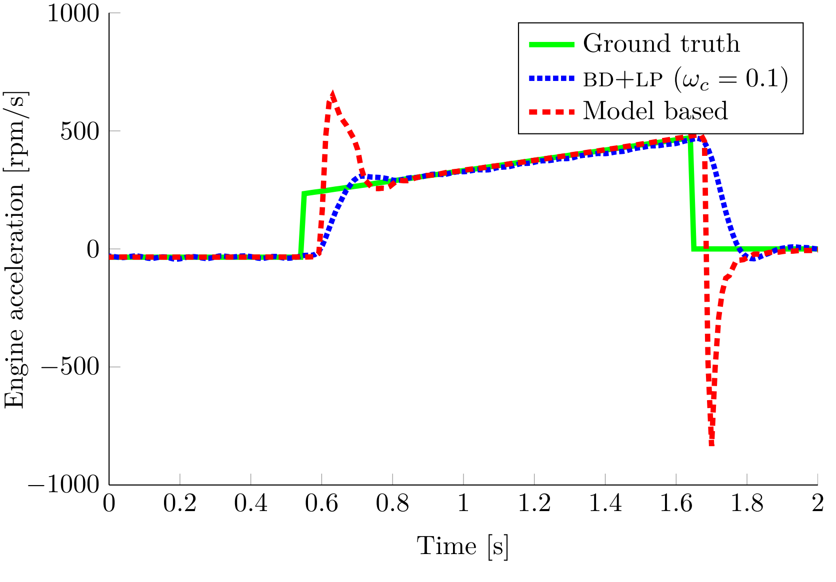


Figure 6.10. During a gear shift the engine acceleration increases abruptly and stays high for a moment. This is a comparison between engine acceleration estimated using a signal model based method and LP filtered BD estimates.

6.3 Computations

The fact that the state transition matrix A in (3.23) is sparse, with only six non-zero elements, of which three are equal to one, makes it possible to save computations. Also, $\bar{\Sigma}$ and C have several elements with the value zero. The actual number of operations in the time and measurement update steps are presented in Table 6.4 and Table 6.5.

Table 6.4. Operations needed in the time update step of the Kalman filter.

Equation	Mult	Add
(4.5)	3	2
(4.6)	24	21
Total	27	23

Table 6.5. Operations needed in the measurement update step of the Kalman filter.

Equation	Mult	Add	Sub	Div
(4.10)		4		
(4.11)		2		
(4.12)				4
(4.13)	4	5	1	
(4.14)	16		16	
Total	20	11	17	4

A total of 50 operations in the time update step and 52 in the measurement update step gives 102 operations in each iteration of the Kalman filter. With the CUSUM check included, the full algorithm takes 107 operations in each iteration. Since the filter is iterated for each sample and the sampling distance α is six crank angle degrees, there are 60 iterations each revolution. With a crank angle based filter, the number of operations per time unit are dependent on the current engine speed. One iteration per second means that the engine turns six degrees per second. With one revolution per second, there are 60 iterations per second, which means that the number of filter iterations per second is equal to the engine speed in revolutions per minute.

$$\text{one rpm} \leftrightarrow \frac{\text{one iteration}}{s}$$

In order to compare the computational complexity of the crank angle based filter with a time synchronous filter, it is interesting to count the number of operations that are needed every second or fraction of a second. Since one iteration for the Kalman-CUSUM filter in this work costs 107 operations, the total number of operations each second is computed as:

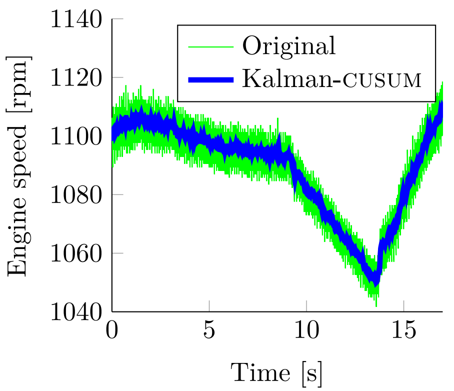
$$107 \cdot \text{rpm} = \frac{\text{operations}}{\text{s}}$$

The FIR filter uses only earlier samples of the input signal and no samples from the output signal as the input to the filter. This means that not all the samples have to be filtered, but only the ones representing the last combustion period when the EMS needs a new estimated value of the momentary average engine speed. Every new update costs 15 operations for an engine with eight cylinders, no matter what the engine speed is.

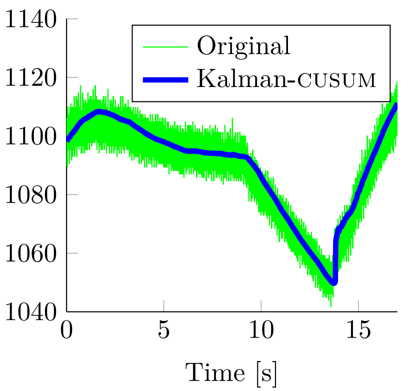
6.3.1 Parameter Tuning

For the signal model based Kalman-CUSUM filter, there are several parameters that can be tuned for different performance. Different applications may have different preferences. For one application, the response at accelerations and gear shifts may be the most important measure, while another application may request a stable signal at steady state. For the Kalman filter part of the method, there are three parameters: the covariances of process noise σ_1 and σ_2 and the measurement noise covariance R. Since the measurements are scalar, only the relations σ_1/R and σ_2/R are important for the filtering properties, so by fixing $R = 1$, there are only two parameters to tune.

The parameter σ_1 is the covariance of the engine speed and acceleration process noise in the signal model (3.22). It determines how fast the two states can adapt to changes in the engine speed signal. This makes σ_1 a parameter that controls the tracking ability of the filter. A low value gives a filter that dampens slow variations in the engine speed well, but adapts slowly during accelerations and gear shifts. A high value results in noisy estimates, but also makes the filter follow the signal better during accelerations. This is illustrated in Figure 6.11.



(a) $\sigma_1 = 10^{-3}$



(b) $\sigma_1 = 10^{-8}$

Figure 6.11. Effects of using a high (a) and a low (b) value of the σ_1 parameter.

The parameter σ_2 is the process noise covariance of the states in (3.22) corresponding to the combustion oscillations. With a very low σ_2 value, the oscillation suppression becomes less effective, causing the estimated momentary average speed to oscillate at the combustion order. A high value causes the filter to focus too much on suppressing the oscillations, leading to slower adaption to the real average and worse tracking ability.

The CUSUM algorithm has two parameters, h and ν. The alarm threshold h controls how fast and often the algorithm sends out alarms. A low threshold results in quick filter response at gear shifts, but may also cause false alarms and thus lead to worse oscillation suppression. The drift parameter ν has similar effects as the threshold. A low ν gives fast detections, but also increases the risk of false alarms. An example of how the ν parameter can be utilized is shown in Figure 6.12. About 0.5 seconds into the plot, a driveline oscillation occur, leading to variations in the engine speed. With a low ν, the filter detects and follows the oscillations, while a high value of ν decreases the effect of the oscillation on the average engine speed estimate. Depending on the application, ν can be tuned either to filter out or let the driveline oscillations be visible in the average engine speed. Functionality that aims to actively suppress the driveline resonances using the engine speed as input naturally do not request the averaging filter to remove the oscillations.

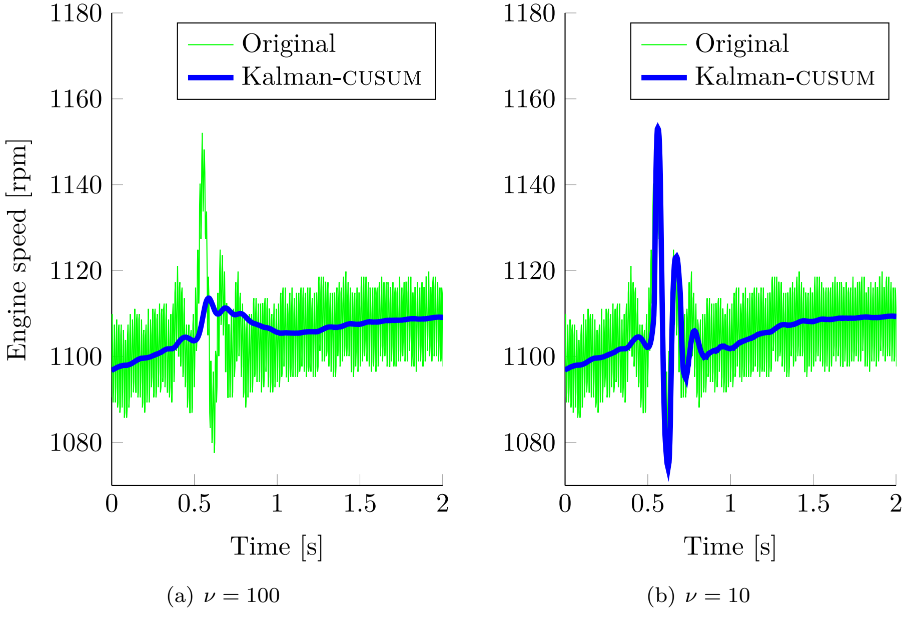


Figure 6.12. Effects of using a high (a) and a low (b) value of the ν parameter.

Chapter 7

Conclusions and Future Work

This chapter presents the most important conclusions of the thesis, along with recommendations for future work on the subject.

7.1 Conclusions

The main contributions of this work, a signal model of the engine speed together with the Kalman-CUSUM filter, provide stable estimates of the momentary average engine speed and mean acceleration with low noise levels. Compared to the FIR filter, the estimation results are improved at an increased computational cost.

7.1.1 Momentary Average Engine Speed

The momentary average engine speed has in this work been estimated using two methods. This section discusses the differences in performance of the both methods.

The strength of the FIR filter is that it follows the engine speed signal during quick changes and suppresses oscillations at the combustion order well. However, its noise suppressing ability is not perfect, which leads to rather noisy estimates of the momentary average engine speed.

The aim when designing the signal model based filter was to find a method to effectively suppress the noise in the engine speed, to get a more stable estimate of the momentary average speed. The filtering properties of the signal model based Kalman-CUSUM filter are controlled by its parameters, which can be tuned for different performance. For a choice of parameter values selected as a compromise between noise cancellation and tracking ability, the filter suppresses oscillations and noise in the engine speed well. This gives a stable estimate of the momentary average with a low noise level. The weakness of the signal model based method compared to the FIR filter is the response time at gear shifts and other quick changes in engine speed. In these situations, the estimates are delayed for a few samples before converging to the actual average. The size of the delay is also controlled by the filter parameters, of which the tuning is a trade off between small delay and effective noise suppression.

The effects of the increased delays at gear shifts are however small compared to the improvements in noise suppression, which make the Kalman-CUSUM filter provide more accurate and stable estimates of the momentary average engine speed than the FIR filter. By only looking at the estimation of momentary average engine speed, the Kalman-CUSUM filter is to prefer over the FIR filter.

7.1.2 Engine Acceleration

To estimate the engine acceleration, i.e. the derivative of the momentary average engine speed with respect to time, two different algorithms has been used. The first algorithm, the BD method uses the FIR filtered engine speed as input, while the signal model based method uses the states estimated by the Kalman-CUSUM filter to compute the acceleration.

Since the mean acceleration estimates from the BD method are computed from FIR filter estimates of the average engine speed, which contain a high level of noise, the acceleration estimates are very noisy. In practice, they need to be LP filtered before being useful. The quick response of the FIR filter at gear shifts and accelerations is immediately propagated into the acceleration estimates, which is the main advantage of the BD method. The other method, the signal model based method, is as input using the states estimated by the Kalman-CUSUM filter, which succeeds to suppress the noise more effectively than the FIR filter. This makes the signal model based method provide more accurate estimates of the mean engine acceleration with low influence of noise.

The estimation of the mean engine acceleration is an important feature of the EMS. By using the signal model based method, the noise level is significantly reduced compared to the BD method in combination with a FIR filter. The reduced noise level is of great value when calculating the engine torque and for control of the engine speed. There is however one situation where the BD method provides more accurate estimates than the signal model based method and that is the moment just after an alarm from the CUSUM algorithm. After an alarm, the estimated momentary average converges rapidly towards a more accurate estimate. This requires a large absolute value of the acceleration and results in overshoots in the acceleration estimates at for example gear shifts. If the Kalman-CUSUM method would to be used in the EMS, this problem needs to be worked around, for example by passing a signal status with the estimates that tells the user when the estimates can be trusted and not. Another solution would be to use the FIR and BD combination as a backup filter, used the moments after CUSUM alarms.

7.1.3 Computational Cost

The computational cost is a critical parameter in the evaluation of the two filtering methods, since there are limitations if the capacity of both the processor and memory in the EMS. The most important difference between the two methods in the aspect of computational complexity is that the FIR filter only uses new measurements as input, while the signal model based method also uses earlier estimates as input. The result of this is that the FIR filtering only needs to be executed when a new estimate of the momentary average engine speed is needed, while the signal model based method has to be iterated for each new sample, no matter of how many samples there are between the needed estimates. This means that the difference in computational cost for the both methods decreases with higher update frequency of the estimates and increases with higher engine speed.

For a system with limited computational power, a low computational cost might be more important than the filtering performance of the algorithms. Even though the Kalman-CUSUM filter results in better estimates of the momentary average engine speed and acceleration, the FIR filter provides estimates with acceptable quality and noise level at a much lower cost. Implementing and using a computationally heavy algorithm such as the Kalman-CUSUM filter in the EMS could lead to a lack of computational power for other functions in the system. For this reason, the FIR filter is a wiser choice of algorithm in the EMS.

7.1.4 Quantization Aspect

The limited clock frequency of the internal counter used when measuring the engine speed results in quantization distortion in the engine speed signal. This work states that the quantization distortion of a certain order component is not affected by other orders. This means that the quantization does not distort the signal in a way that would destroy the diagnosis of the fuel injection system. Also shown is that by increasing the clock frequency, the quantization distortion can be significantly reduced. This would improve and extend the possibilities to perform diagnosis of the fuel injection system.

7.2 Future Work

This section presents some suggestions of future work in area of momentary average engine speed and mean acceleration estimation.

External Triggers

The signal model based method proposed in this thesis make use of the change detection algorithm CUSUM to increase the adaptivity of the Kalman filter. With external triggers signaling when a gear shift or quick acceleration occurs, it should be possible to decrease the delay of the estimates in these situations.

Physical Model

This work uses a random walk model for the momentary average engine speed. A future improvement of the method could include a physical model of the engine and the engine speed.

Computational Saving Method

The reason for computational complexity of the signal model based is that it needs to process all samples to give stable estimates of the average engine speed and mean acceleration. To decrease the number of computations, a method with variable sample distance could be considered.

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