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Observer design and model augmentation for bias compensation with a truck engine application

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ABSTRACT

A systematic design method for reducing bias in observers is developed. The method utilizes an observable default model of the system together with measurement data from the real system and estimates a model augmentation. The augmented model is then used to design an observer which reduces the estimation bias compared to an observer based on the default model. Three main results are a characterization of possible augmentations from observability perspectives, a parameterization of the augmentations from the method, and a robustness analysis of the proposed augmentation estimation method. The method is applied to a truck engine where the resulting augmented observer reduces the estimation bias by 50% in a European transient cycle.

1. Introduction

In many application areas there are quantities that are important for control and diagnostics but that are not measured due to for example difficulties with the measurement methods or high costs of the sensors. This has made estimation an important and active research area, which is especially true in the automotive area where cost is important, see Lino, Maione, and Amorese (2008), García-Nieto, Martínez, Blasco, and Sanchis (2008), and Andersson and Eriksson (2004) for some examples.

In all model-based control or diagnosis systems, the performance of the system is directly dependent on the accuracy of the model. In addition, modeling is time consuming and, even if much time is spent on physical modeling, there will always be errors in the model. This is especially true if there are constraints on the model complexity, as is the case in most real time systems. Another scenario is that a model developed for some purpose, e.g. control, exists but needs improvements before it can be used for other purposes, for example diagnosis.

In many applications, like for example engine control and engine diagnosis, it is crucial to have unbiased estimates. In model based diagnosis, the true system is often monitored by comparing measured signals to estimated signals. If the magnitude of the difference, the residual, is above a certain limit a decision that something is wrong is made. In engine control, one objective is to maximize torque output while keeping the emissions below legislated levels and the fuel consumption as low as possible. For diesel engines this is especially hard since the control system does normally not have any feedback information from a λ- or NO_x-sensor and have to rely on estimated signals instead (Wang, 2008). In both cases, biased estimates impairs the performance.

The objective of this work is to develop a systematic method for reducing estimation bias in observers without involving further modeling efforts. This work is an extension of preliminary results in Höckerdal, Frisk, and Eriksson (2008) and the main extensions are a theoretical characterization of all solutions and additional method evaluations, including a robustness analysis with respect to measurement noise and model uncertainty.

The method utilizes an observable model and measurement data from the true system. The given model, referred to as the default model, and the measured inputs and outputs from the true system are used to estimate a suitable model augmentation. Then, the augmented model is used to design an observer that is shown to give estimates with reduced bias compared to an observer based on the default model. Three approaches for estimating a bias compensating augmentation are developed and evaluated with respect to measurement noise and model errors. Key results are a theoretical characterization of all possible augmentations from observability perspectives and a parametrization of the estimated augmentations. Finally the method is evaluated on a non-linear diesel engine model with experimental data from an engine test cell.

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2. Problem formulation

Previous experience at Scania CV AB of state estimation based on an existing state-space model of a truck engine reveals that the model captures dynamic behavior reasonably well but suffers from stationary errors (Höckerdal, Eriksson, & Frisk, 2008). Designing an observer based on this model results in biased estimates. How to reduce the bias in a systematic manner is the topic of this paper.

The starting point is an existing model, referred to as the default model, that is provided in state-space form

$$\dot{x} = f(x, u), \tag{1a}$$

$$y = h(x), \tag{1b}$$

where x is the state-vector, u the known control inputs, y the measurement vector, and f and h are non-linear functions.

The objective is to find a systematic way to design an observer that gives an unbiased estimate of either the complete state x or a function of the state $z = g(x)$. This should be done even though the default model is subject to significant bias errors. A direct approach to compensate for constant, or slowly varying, biases is to augment the default model with bias variables q as

$$\dot{x} = \tilde{f}(x, u, q), \tag{2a}$$

$$\dot{q} = 0, \tag{2b}$$

$$y = \tilde{h}(x, q), \tag{2c}$$

and design the observer using this augmented model. If the augmentation captures the true modeling errors and the augmented system is observable, the observer estimates is made unbiased. An obvious question is then how to introduce the bias variable q in the model equations. One way could be through process knowledge, which have been successfully applied in Andersson and Eriksson (2004) and Tseng and Cheng (1999). However, in this paper an estimation procedure based on available measurement data is proposed.

Besides the natural restriction, that the augmented model (2) is observable, it is also desirable not to introduce more extra bias states than necessary. It is therefore desirable to find a bias vector q with as low dimension as possible that manages to reduce the bias. Another reason for finding a low-dimensional bias is that, since the model often is a first-principles physical model, bias in multiple states may be explained by one underlying bias affecting all these states. For example, bias in two pressures can originate from a bias in the mass flow between the two volumes or an incorrect modeling of energy conservation can give rise to bias in several states connected to the energy. However, the bias is necessarily not the same in the entire operating region of the system and may vary between operating points. This is part of the reason for introducing the bias as new states, rather than just a parameter, which allows some tracking ability of the bias.

In model (1) there are two natural ways to introduce biases, in the dynamic equation (1a) or in the measurement equation (1b). In the truck engine application the sensors, intake and exhaust manifold pressures and turbine speed, are considered more reliable than the model and the bias augmentation is therefore introduced in the dynamic equations according to

$$\dot{x} = f(x - A_q q, u), \tag{3a}$$

$$\dot{q} = 0, \tag{3b}$$

$$y = h(x), \tag{3c}$$

where a stationary point of the system is moved by $A_q q$. The matrix A_q is thus a description of how the underlying bias variable q influences the stationary value of the state variable x. The model (3) will be referred to as the augmented model. It is worth mentioning that although the result in this paper focuses on biases in the dynamic equation, it is straightforward to modify the approach to also cover sensor biases.

2.1. Problem and paper outline

Based on the discussion above, the problem studied in the sections to follow can now be stated as: Given an observable default model (1) and available measurement data, find a low order bias augmented model (3) and design an observer that estimates x with reduced bias compared to using the default model. The observer should also be implementable in an engine control unit (ECU).

To solve the problems, some issues need to be addressed. First, which matrices A_q are possible at all? All are not possible since it is required that the augmented system is observable and a characterization of possible augmentations is derived in Section 4. Among these possible bias augmentations, which should be used? Section 5 describes three approaches for how to estimate a, for bias compensation, suitable low order A_q based on measurement data.

Section 6 presents two examples of the proposed estimator design methodology applied to a Scania diesel engine using simulated and real measurement data, respectively.

3. Discretization and linearization

As a first step, the non-linear augmented model (3) is transformed to a linearized time discrete model. A reason for the discretization is the demand on the implementation, which will be done in the ECU as a time discrete system. Here, a simple Euler forward discretization with step size T_s seconds is used. Note that observability does not depend on the choice of discretization method, since as long as T_s is chosen small enough the results are valid also for, e.g. zero-order-hold (Kalman, Ho, & Narendra, 1963).

One objective of the paper is to find a suitable A_q such that (3) is locally observable and to be able to use simple observability conditions, the observability analysis is here performed on a linearization of the non-linear model (3). Of course, non-linear observability is not guaranteed from observability of the linearization. Nevertheless, observability of a linearization in a stationary point is a sufficient condition for local observability of the non-linear system, see Theorem 6.4 in Lee and Markus (1968). Even though observability is not strictly guaranteed, e.g. in transient mode when moving between operating points, the referred result gives theoretical support for using the linearized system in the observability analysis. Thus, when analyzing (3) the following model will be used:

$$\begin{pmatrix} x_{t+1} \\ q_{t+1} \end{pmatrix} = \begin{pmatrix} I + T_s A & -T_s A A_q \\ 0 & I \end{pmatrix} \begin{pmatrix} x_t \\ q_t \end{pmatrix} + \begin{pmatrix} T_s B \\ 0 \end{pmatrix} u_t, \tag{4a}$$

$$y_t = (C \;\; 0) \begin{pmatrix} x_t \\ q_t \end{pmatrix}, \tag{4b}$$

where

$$A = \left.\frac{\partial f}{\partial x}\right|_{\substack{x=x_0 \\ u=u_0}}, \quad B = \left.\frac{\partial f}{\partial u}\right|_{\substack{x=x_0 \\ u=u_0}} \quad \text{and} \quad C = \left.\frac{\partial h}{\partial x}\right|_{\substack{x=x_0 \\ u=u_0}}.$$