LINKÖPING UNIVERSITY
DIVISIONS OF AUTOMATIC CONTROL AND COMMUNICATION SYSTEMS
ACTIVITY REPORT
2004

Contents

Chapter 1

Introduction

The Divisions of Automatic Control and Communication Systems consist of some thirty persons. We teach thirteen undergraduate courses to more than eleven hundred students. The courses cover both traditional control topics and more recent topics in model building and signal processing.

Our research interests are focused on the following areas:

– *System Identification*: We are interested in a number of aspects ranging from industrial applications, to aspects of the fundamental theory and properties of algorithms.

– *Non-Linear and Hybrid Systems*: Here we are interested both in developing theory for nonlinear systems and to understand and utilize how modern computer algebraic tools can be used for practical analysis and design. Hybrid systems is an important and emerging field covering problems of how to deal with systems with both discrete and continuous phenomena.

– *Sensor Fusion*: Techniques to merge information from several sensors are of increasing importance. We are involved in four different industrial application of this kind, at the same time as we try to abstract the common underlying ideas. Particle filters play an important role in this context.

– *Diagnosis and Detection Problems* are very important in today's complex automated world. Within the Competence Center ISIS we work with several industrial problems of this kind.

– *Communication Applications*: We have several applied and theoretical projects that deal with communication systems.

– *Robotics Applications*: Within ISIS we have a close cooperation with ABB Automation Technology Products – Robotics.

– *Optimization for Control and Signal Processing*: Convex optimization techniques are becoming more and more important for various control and signal processing applications. We study some such applications, in particular in connection with model predictive control.

Details of these research areas are given in the corresponding sections of this report.

Funding

We thank the Swedish Research Council (VR), the Swedish Agency for Innovation Systems (VINNOVA) and the Foundation for Strategic Research (SSF) for funding a major part of our research. The grant from SSF funds a research program VISIMOD, which is a joint program for research in Visualization, Modeling, System Identification, and Simulation. The participating groups are from the Departments of Electrical Engineering, Computer Science and from the Norrköping Visualization and Interaction Studio, NVIS. The program leader of VISIMOD is Lennart Ljung.

The Control and Communication Divisions take active part in the VINNOVA Competence Center ISIS (Information Systems for Industrial Control and Supervision), whose Director is Lennart Ljung. The ISIS Center started in November 1995. Phase III of this Competence center started January 1, 2001 and lasted to the end of 2003. Phase IV will cover 2004 and 2005.

The divisions are also central partners in the Research School ECSEL (Excellence Center for Computer Science and Systems Engineering in Linköping), which started its activities during 1996. This research school is funded by the Foundation for Strategic Research (SSF) and is a joint effort between the departments of Electrical Engineering and Computer Science.

Some Highlights

During the year Markus Gerdin, Andreas Eidehall, Erik Wernholt and Jonas Gillberg defended their Lic. Eng. dissertations.

Several distinctions were awarded to the researchers of the group. Fredrik Gustafsson received the Arnberg Prize from the Royal Swedish Academy of Sciences (KVA) for “outstanding technical research of great relevance for industrial applications”. Kent Hartman received the AF prize for his engagement in education at different levels. Lennart Ljung received honorary doctorates from the Universitè de Technologie de Troyes in France and from the Catholic University of Leuven in Belgium. He was also elected as foreign associate of the US National Academy of Engineering (NAE).

Figure 1.1: March 31: Fredrik Gustafsson receives the Arnberg Prize from the Royal Swedish Academy of Sciences (KVA).

Figure 1.2: September 15: Lennart Ljung delivers a lecture when receiving the Docteur Honoris Causa degree from Université de Technologie de Troyes, France.

Figure 1.3: October 2: Lennart Ljung receives the diploma at the induction to the US National Academy of Engineering (NAE). Left: William A. Wulf, President of NAE, Right: Craig Barrett, Chairman NAE and CEO of Intel.

Figure 1.4: October 12: Lennart Ljung receives the Ehredoctor Diploma from Professor A. B. Oosterlink, Rector of the Katholieke Universiteit Leuven. In the background, Professor Bart de Moor, promotor at the event.

Report Outline

In the following pages the main research results obtained during 2004 are summarized. More details about the results can be found in the list of articles and technical reports (See Appendices G and H. Numerals within brackets refer to the items of these appendices). These reports are available free of charge, most easily from our web-site. The next chapter describes how you can search for our publications in our data base and download any technical report.

We invite you to visit our home page:

`http://www.control.isy.liu.se`

The competence center ISIS has the home page

`http://vir.liu.se/isis`

and the VISIMOD Research Program is described in

`http://www.ida.liu.se/zope/portals/visimod`

For the research school ECSEL turn to

`http://vir.liu.se/ecsel`

Chapter 2

Network Services

There are a number of ways you can access the work produced at this group. Most convenient is probably to email the person you wish to contact. The email addresses are listed at the end of this activity report. Apart from these shorter but quite arbitrary email addresses you can always use the general form:

`Firstname.Lastname@isy.liu.se`

e.g., `Lennart.Ljung@isy.liu.se`.

We also have a generic email address:

`Automatic.Control@isy.liu.se`

or `AC@isy.liu.se` for short. Emails sent to this address are currently forwarded to our secretary Ulla Salaneck.

Finally, you can also retrieve reports and software electronically using our World Wide Web services. This is our preferred method of distributing reports.

2.1 World Wide Web

The most powerful way to get in touch with the group is probably by using our World Wide Web service (WWW). The address to our web pages is:

`http://www.control.isy.liu.se`

When you surf around in our WWW-environment you will find some general information over this group, the staff, seminars, information about undergraduate courses taught by the group and you have the opportunity to download technical reports produced at this group. This is the easiest way to access the group's work, just click and collect.

Our WWW service is always under development. We look forward to your feedback regarding this service. If you have any questions or comments, please send an email to our group of webmasters

`rt_www@isy.liu.se`

2.2 Publications Data Base

Selecting "Publications" in our web pages gives access to our publications data base. See Figure 2.1. It allows you to search for publications by author, area, year, and/or publication type. You can also search for words in the title. The result of the search is given either as a clickable list of publications (Choose HTML) or a list of BibTEX items (Choose Bibtex). See Figure 2.2 for an example of a search result. Clicking on the publication items brings you to the home page of the publication with further information. See Figure 2.3. Department reports can always be downloaded from the home page, while articles and conference papers refer to a related department report that can be downloaded in .ps or .pdf format.

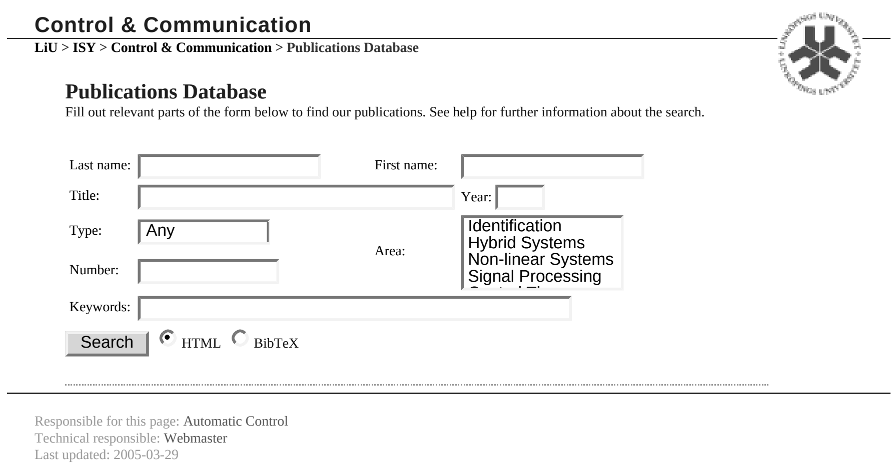
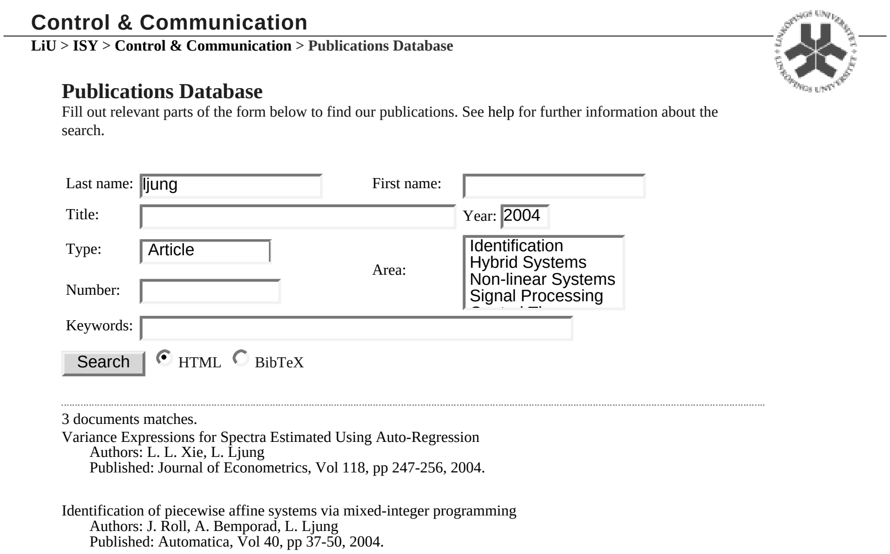


Figure 2.1: The publications data base interface.


Control & Communication

LiU > ISY > Control & Communication > Publications Database

Publications Database

Fill out relevant parts of the form below to find our publications. See help for further information about the search.

Last name: ljung First name:

Title: Year: 2004

Type: Article

Area: Identification / Hybrid Systems / Non-linear Systems / Signal Processing

Number:

Keywords:

Search HTML BibTeX

3 documents matches.

Variance Expressions for Spectra Estimated Using Auto-Regression
Authors: L. L. Xie, L. Ljung
Published: Journal of Econometrics, Vol 118, pp 247-256, 2004.

Identification of piecewise affine systems via mixed-integer programming
Authors: J. Roll, A. Bemporad, L. Ljung
Published: Automatica, Vol 40, pp 37-50, 2004.

Figure 2.2: Example of search result.

Control & Communication

LiU > ISY > Control & Communication > Publications Database

Educational aspects of identification software user interfaces
Author: L. Ljung
Published: Proc. 13th IFAC Symposium on System Identification, pp 1590 -1594, 2003.
Research area: Identification
Keywords: education, software
Related report

Abstract:

Apparently many users of identification techniques learn the topic only via use of commercial software. This may or may not include the software manual. This means that the software user interface -- graphical or not -- plays a major role in teaching identification theory and methodology to large number of users. This contribution deals with such educational / pedagogical aspects software user interfaces.
In particular we focus on issues to hide certain design variables as defaults, and what can be done in case no defaults are obvious. Other questions are how to force the user to appreciate and understand the quality of an identified model, and to know what optional design choices and methods that are available, in particular if there is no Graphical User Interface (GUI).

Bibentry:

```
@inproceedings{Ljung:03aaa,
   author = "Lennart Ljung",
   title = "Educational aspects of identification software user interfaces",
   year = "2003",
   month = "Aug",
   address = "Rotterdam,  The Netherlands",
   editor = "P. van der Hof, B. Wahlberg, S. Weiland",
   booktitle = "Proc. 13th IFAC Symposium on System Identification",
   pages = "1590 -1594",
}
```

Figure 2.3: Example of a publication home page.

Chapter 3

System Identification

3.1 Introduction

The research in System Identification covers a rather wide spectrum, from general principles to particular applications.

During 2004, two licentiate theses, [2], and [3] have been finished in this area. These will be described in the next few sections.

3.2 Estimation of Continuous Time Models

The licentiate thesis of Jonas Gillberg, [3] covers problems related to frequency-domain identification of continuous-time systems.

Input and output relationships in the physical sciences are often modelled in continuous time. The models can be devised from first principles and the parameters almost always have an intuitive physical interpretation. Traditionally identification of these continuous-time models have been carried out in the time domain, often via a discrete time version of the model. In the thesis methods are presented and analyzed for doing the identification in the frequency domain.

The first part of the work treats the identification of continuous-time autoregressive moving average (CARMA) models. Here a continuous-time counterpart to the discrete-time Whittle likelihood estimator

$$\hat{\theta} \triangleq \arg\min_{\theta} V_N^T(\theta, \hat{\hat{\Phi}}_c^T) \tag{3.1}$$

where

$$V_N^T(\theta, \hat{\hat{\Phi}}_c^T) \triangleq \sum_{k=1}^{N_\omega} \frac{\hat{\hat{\Phi}}_c^T(i\omega_k)}{\Phi_c(i\omega_k, \theta)} + \log \Phi_c(i\omega_k, \theta). \tag{3.2}$$

is analyzed and used. Here $\Phi_c(i\omega, \theta)$ is the signal spectrum for a model with parameter vector θ and $\hat{\hat{\Phi}}_c(i\omega)$ is the periodigram estimate from data. This method however needs an estimate of the continuous-time power spectral density $\hat{\hat{\Phi}}_c^T(i\omega_k)$, which in turn would require continuous-time measurements. This density is estimated from the discrete-time power spectral density

$$\hat{\hat{\Phi}}_c(i\omega) = \Phi_f^{(\ell)}(e^{i\omega T_s})\hat{\hat{\Phi}}_d(e^{i\omega T_s}) \tag{3.3}$$

with the non-causal prefilter

$$\Phi_f^{(\ell)}(e^{i\omega T_s}) \triangleq \frac{\left|\frac{e^{i\omega T_s}-1}{i\omega T_s}\right|^{2\ell}}{\left|\frac{B_{2\ell-1}(e^{i\omega T_s})}{(2\ell-1)!}\right|}. \tag{3.4}$$

The entities $B_{2\ell-1}(z)$ are the so called Euler-Frobenius polynomials. This is actually the frequency-domain version of the Wiener smoothing formulas if the system is of relative degree l and is approximated by a set of l integrators. Further on in the thesis a related, deterministic approach is derived for the case of a continuous-time output error (COE) model.

Another issue which is discussed in the thesis is the relationship between parameter bias and bias in the estimate of the continuous-time power spectral density.The central result is the expression

$$E(\hat{\theta} - \theta_0) \approx \sum_{k \in \mathcal{N}} S(i\omega_k)\Delta\Phi(i\omega_k).$$

where $\hat{\theta}$ are the estimated parameters and θ_0 are the true parameter values. The *relative bias* in the periodogram estimate of the power spectrum is defined as

$$\Delta\Phi(i\omega_k) = \frac{E\hat{\hat{\Phi}}(i\omega_k) - \Phi(i\omega_k, \theta_0)}{\Phi(i\omega_k, \theta_0)}$$

The *sensitivity* of the parameter estimates to the relative bias in the periodogram is

$$S(i\omega_k) = \Psi(\theta_0, \Phi)^{-1}\Psi_k(\theta_0, \Phi).$$

The so called *relative* sensitivity is defined as

$$\Psi_k(\theta_0, \Phi) = \frac{\Phi'_\theta(i\omega_k, \theta_0)}{\Phi(i\omega_k, \theta_0)}.$$

and

$$\Psi(\theta_0, \Phi) = \sum_{k \in \mathcal{N}} \Psi_k(\theta_0, \Phi)\Psi_k(\theta_0, \Phi)^T$$

Non-interfering disturbances can occur in areas where the model spectrum Φ is small and the relative bias can therefore be quite large. Hence in order to avoid parameter bias it is necessary to ignore information from frequencies where the relative bias and sensitivity are large.

3.3 Parameter Estimation in Differential-Algebraic Equations

Markus Gerdins licentiate thesis, [2] deals with parameter estimation in Differential-Algebraic Equations.

To make models of complex system, it is often desirable to combine physical modelling and system identification. This is called *grey box identification*. The classical approach to grey box identification has been to make state-space models with unknown parameters that are to be identified. However, modern modelling tools such as MODELICA are not based on state-space models. Instead the equations describing the system form a differential-algebraic equation (DAE),

$$F(\dot{\xi}(t), \xi(t), u(t), \theta) = 0. \tag{3.5}$$

Here $\xi(t)$ is a vector of physical variables, $u(t)$ is an input signal and θ is a vector of (possibly unknown) constant parameters. To be able to combine modern modelling tools with grey box identification, we examine how unknown variables θ in a DAE can be estimated from input and output data. The goal is that the user only should need to work with graphical models, such as the one in Figure 3.1. When the user has indicated which parameters that are unknown, where known inputs enter, where disturbances are present, and which signals that are measured and provided measurement data, the identification process should be fully automatic.

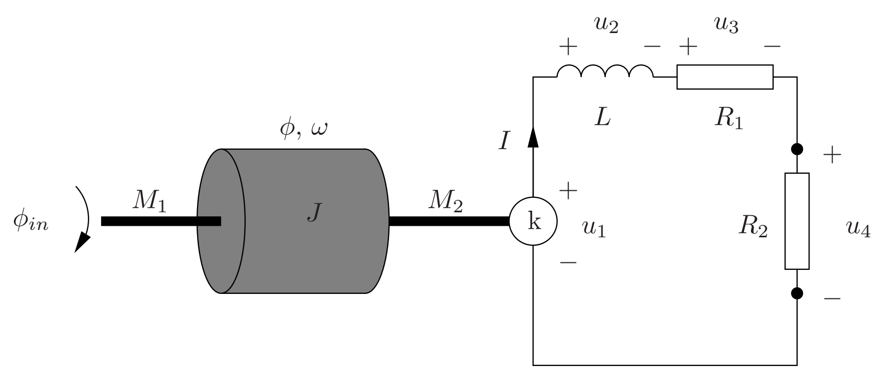


Figure 3.1: Modern modelling tools use graphical modelling. Research efforts are made to connect such modelling tools directly to identification software.

Several aspects of the case when the DAE is linear,

$$E(\theta)\dot{\xi}(t) = J(\theta)\xi(t) + K(\theta)u(t) \tag{3.6a}$$

$$y(t) = L(\theta)\xi(t), \tag{3.6b}$$

are discussed in the licentiate thesis [2]. To get a basic understanding of the properties of the model, and to lay the foundation for development of identification procedures, different transformations and canonical forms for the system (3.6) are reviewed. One important form is

$$\begin{bmatrix} I & 0 \\ 0 & N \end{bmatrix} \begin{bmatrix} \dot{z}_1(t) \\ \dot{z}_2(t) \end{bmatrix} = \begin{bmatrix} A & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix} + \begin{bmatrix} B \\ D \end{bmatrix} u(t) \tag{3.7a}$$

$$y(t) = \begin{bmatrix} C_1 & C_2 \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix} \tag{3.7b}$$

$$\xi(t) = Qz(t) \tag{3.7c}$$

where N is a nilpotent matrix and Q is an invertible matrix. One important characteristic of this form is that it can be computed efficiently using numerical software, which is important if it is going to be used in identification software. The computation of this form is discussed in [2] and in [29].

The transformed variants of the DAE can also be used to sample the model. An exact discrete time version of the continuous time model can be calculated if the inter-sample behaviour of the input is known. This can be useful for example when using discrete time measurements for identification.

Another important aspect of this form is that it shows the fact that the internal variables $\xi(t)$ may depend on derivatives of the input since the second row of (3.7a) gives that

$$z_2(t) = -Du(t) - \sum_{i=1}^{m-1} N^i D u^{(i)}(t). \tag{3.8}$$

The fact that the internal variables might depend on derivatives of the input implies that care must be taken when introducing noise in DAE systems. Since the derivative of white noise is not well defined, care must be taken so that all variables of interest are well defined after introduction of noise. Conditions for how noise can be added to the DAE (3.6) are discussed in [2]. If $u(t)$ is white noise in (3.8), we can for example see directly that it must be required that

$$ND = 0 \tag{3.9}$$

for all components of $z(t)$ to be well defined. This condition can also be stated in terms of the original system matrices in (3.6). When a noise model has been introduced, it is possible to implement prediction error and maximum likelihood estimation of the unknown parameters. Even if all parameters are known, it is interesting to model noise affecting the system, e.g., for state estimation using Kalman filters.

In [30], parts of the results are exemplified using measurements from a laboratory process. It is shown how a Modelica model and measurements from a physical process can be combined to estimate parameters and states.

The optimisation problems that are solved to find the parameters in grey box identification are often difficult to treat since they have several local minima. It is therefore important to have good starting values for the parameter search. One method to find starting values for linear DAE systems is discussed in [2]. It suggested that a polynomial which measures the difference between the grey box model and a black box model should be formed. Initial values for the parameters can then be found by minimising this polynomial.

3.4 Nonlinear System Identification via Direct Weight Optimization

In earlier Annual reports it has been described how a general non-linear regression function can be estimated from data by a method we have termed DWO – Direct Weight Opimization.

The basic nonlinear identification problem considered here can be phrased as follows: Assume that we are given data $y(t)$ and $\varphi(t)$, $t = 1, \ldots, N$ from the unknown nonlinear system

$$y(t) = f(\varphi(t)) + e(t)$$

where $e(t)$ is a noise term with known variance σ^2. Estimate $f(\varphi^*)$ for a given point φ^*, assuming only that f has a given Lipschitz bound on the derivative.

This type of identification problems arise, e.g., in the model-on-demand framework, where the main idea is not to bother about building a global model for a (possibly very complex) system, but instead keep a database of experimental data and build local models at specific points φ^* only when they are needed.

However, in practice the Lipschitz bound must be estimated. A strategy for how this could be done is presented in [45].

3.5 Identification and Verification of Piecewise Affine Systems

Piecewise affine systems are composed of several affine subsystems, between which switchings occur at different occasions. Such systems are obtained, for instance, whenever an otherwise linear system contains bounded signals, deadzones, or is controlled by discrete control laws. Piecewise affine systems can be found in many applications, and the research activities in the field have increased in the last decade.

Identification of piecewise affine systems is an area that is related to many other research fields within nonlinear system identification, and one can find several different methods and approaches which are applicable, or at least related to the piecewise affine system identification problem. However, until recently there have been few attempts to design special-purpose algorithms for these kinds of systems. In [14], such an algorithm, based on mixed-integer programming, is presented. This approach guarantees that an optimal model is found, at a price of greater computational complexity. To reduce the complexity, one can either restrict the model class or use a suboptimal optimization procedure. Both these alternatives have been investigated. Using piecewise affine Wiener models allows the complexity of the identification problem to be reduced considerably. For the special case where the estimation data only seldom switches between the different submodels, a way of trading off between optimality and complexity by using a change detection approach is proposed.

3.6 Linear Models of Nonlinear Systems

Linear models of nonlinear systems are used in many applications. For example, using standard system identification tools like the prediction-error method, it is very common to estimate approximative linear models also from measurements of the input and output signals of a nonlinear system. Systems with stationary stochastic input and output signals and linear time-invariant (LTI) approximations that are optimal in the mean-square error sense have been studied in a particular research project for a few years.

The reason for this choice of approximation type is that parameter estimates obtained by the prediction-error method under fairly general conditions will converge to values that correspond to mean-square error optimal LTI models when the number of measurements tends to infinity. The optimal LTI model can be called the LTI Second Order Equivalent (LTI-SOE), since it can explain the second order properties of the input and output signals. Some results about, and examples of, LTI-SOEs have previously been published in a licentiate thesis and in conference papers, and they have been described in earlier annual reports.

An interesting fact about LTI-SOEs is that they can be very sensitive to small nonlinearities in the sense that a small nonlinear part in the system might give a large contribution to the LTI-SOE. In previous publications, it has been shown that it is easy to construct a nonlinear system that exhibits this behavior. Consider the system

$$y(t) = y_l(t) + 0.01 y_n(t), \tag{3.10a}$$
$$y_l(t) = u(t), \tag{3.10b}$$
$$y_n(t) = u(t)^3 \tag{3.10c}$$

with the input

$$u(t) = e(t) - 1.980e(t-1) + 0.9801e(t-2),$$

where $e(t)$ is a white noise process with uniform distribution over the interval $[-1, 1]$. Since this input signal is bounded, the nonlinear contribution to the output is small. However, for this input signal, the system will have an LTI-SOE that is far from the linear part $y_l(t) = u(t)$ of the system.

In [28] and [27], it is shown that the sensitivity of an LTI-SOE to small nonlinearities depends on how non-Gaussian the input signal is. For example, consider the signal

$$u_M(t) = e_M(t) - 1.980e_M(t-1) + 0.9801e_M(t-2), \tag{3.11}$$

where

$$e_M(t) = \frac{1}{\sqrt{M}} \sum_{k=1}^{M} \tilde{e}_k(t), \quad M \in \mathbb{Z}_+.$$

The processes $\tilde{e}_k(t)$, $k = 1, \ldots, M$ are independent white signals with uniform distribution over the interval $[-1, 1]$ and zero mean. According to the central limit theorem, the signal $u_M(t)$ becomes more similar to a Gaussian signal for larger values of M.

Realizations with 50000 samples of the input and output signals have been generated and an output error model has been estimated for each pair of signals. The differences between the frequency responses of these estimated models are shown in Figure 3.2. Since the number of measurements is rather high, the estimated output error models are close to the corresponding LTI-SOEs. Hence, Figure 3.2 shows that the effects on the LTI-SOE from the nonlinearities in a certain system will become smaller if the input gets more Gaussian. These issues are also discussed in [68].

In control applications, the purpose of estimating a model of a system is often to use it for control design. Hence, it is interesting to know how an LTI-SOE can be made more useful for robust control design. This topic has been investigated during the year and some results concerning control design based on approximate linear models will be published in the future.

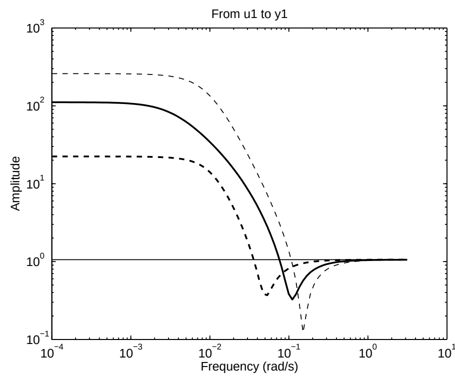


Figure 3.2: Bode plot showing the estimated output error models of the system (3.10) for a Gaussian input (thin solid) and for inputs u_M according to (3.11) with $M = 1$ (thin dashed), $M = 2$ (thick solid) and $M = 8$ (thick dashed).

3.7 Projection Techniques

3.7.1 Projection Techniques for Classification

In a broad variety of applications ranging from the information retrieval on the Internet to the processing of sensor signals, there is a constantly growing need to make use of patterns with very high dimensionality. One major task is of course the accurate *classification* of these patterns, but very important issues are also how to *compress* and how to *visualize* them. If numerical vectors represent the patterns, both these latter issues can be addressed by searching for special low-dimensional linear projections of the pattern vectors.

We usually assume every pattern is an observation of one of g populations. By *classification* we understand the task to infer which one of these populations a given pattern is an observation of. Usually, the pattern vector does *not* contain all information needed to make this inference fool proof. The uncertainties due to absent information will be manifested as noise that limits the possibility to distinguish between patterns from different populations. Given the probabilistic distribution of the noise, the *Bayes error* is a well-known definition for how confident the inference can be *at best*, despite the noise. No deterministic inference or classification rule can ever fall short of the uncertainty given by the Bayes error.

When pattern vectors are projected on a low-dimensional plane, valuable information is usually lost with an increase in noise magnitude and Bayes error as a consequence. This means it might not be possible to classify the low-dimensional representation of a pattern with the same confidence as allowed by the original pattern. Obviously, there is a whole set of k-dimensional projections in the original n-dimensional pattern space (we assume $k < n$). It is also rather obvious, that different projections in this set may result in different Bayes error. A natural and not very novel idea is to use the (particular) projection that gives the *lowest possible Bayes error*. However, it turns out that generally, this projection is very difficult to find. It is even difficult to compute the Bayes error for a given projection, and we are often resigned to use approximations.

In [10] we address the problem to find projections of two populations with equal or almost equal means, but with different covariance matrices. For this case the well known Fisher's linear discriminant analysis is not defined. The particular assumption in the work is that one population is "small" with little spread, while the other is "large". This is a problem structure encountered when one population models measurements on *good* or *normal* specimens, while the other models measurements on a more general class of *bad* or *abnormal* specimen.

In [10] we propose a method to find a linear projection from n to k dimensions where the spread of the good population is minimized with respect to the bad population. The objective function

$$\operatorname{trace}\left[(S^T\Sigma_g S)^{-1} S^T \Sigma_b S\right] \tag{3.12}$$

is maximized over different orthonormal projections $S \in \mathbf{R}^{n\times k}$. Here, Σ_g is the covariance matrix of the good population and Σ_b the cvariance matrix of the bad population. It is shown that with normal distributed populations with equal mean and $k = 1$, this projection has minimum Bayes error.

3.7.2 Projection Techniques for System Identification

Consider the nonlinear regression model

$$0 = f(\varphi_t) + v_t \tag{3.13}$$

where the regression vector is defined as

$$\varphi_t = \begin{bmatrix} y_t & y_{t-1} \cdots y_{t-n_a} & u_{t-n_k} & u_{t-n_k-1} \cdots u_{t-n_b-n_k+1} \end{bmatrix}^T . \tag{3.14}$$

This is a rather general model of a time-discrete SISO system with input u_t and output y_t, and the modelling objective is to find the function f that makes the expected magnitude of the residual v_t small in some sense. Typically, the dimension $n = n_a + n_b$ of the regression vector is too high to be directly visualized, and often high enough to make numerical aspects of the parameter estimation an issue that needs consideration.

For some systems it is meaningful to study *low-dimensional linear projections* of the regression vector,

$$\tilde{\varphi}_t = S^T \varphi_t, \tag{3.15}$$

where $S \in \mathbf{R}^{n \times k}$. A drained water tank is actually an example of such a nonlinear system. The linear projection may enable both visualization and efficient parameterization of the nonlinearity. The question is how to estimate S.

In [51] we develop the idea, that the residual magnitude (magnitude of v_t) is closely related to the area occupid by the points φ_t, or rather $\tilde{\varphi}_t$. A small area means that the points more or less lie on a curve in the column space of S. This area may be used as a non-parametric criterion by which the projection S is sought. In essence, the smaller area, the better projection S (a normality constraint on S is subsumed here). How large is the area occupid by a set of points? In [51] we use, inspired by Q. Zhang, the triangles of a *Delaunay triangulation* of the points φ_t to induce an area measure. The projection S is then found by minimizing this area measure.

It is found that the Delunay triangulation induce an excellent area measure. However, the resulting objective function is very complex with many local minima. The rather negative conclusion is that this criterion is less useful in practice when it comes to estimating the projection S.

3.7.3 Visualization Techniques for System Identification

System Identification is inherently an interactive art. Results from preliminary model building are studied by the user. Based on such studies, decisions about new model structures are taken. The studies are typically of visual nature, often simple 2-dimensional line plots of correlation functions and residuals. Visualization techniques have gone through a significant development during the past decade. It is an interesting problem to study what such new techniques may offer in terms of improved interaction in system identification, particularly when the identification involves nonlinear and time-varying dynamics.

In [43] we give some illustrations of what can be achieved in this way. We describe an *experimental setup* where results from estimation and simulation in MATLAB are communicated to and displayed by a high-end visualization module built with AVS/Express. AVS/Express is a comprehensive and versatile data visualization tool with a graphical application development environment.

The experimental setup was developed in collaboration with the Norrköping Visualization and Interaction Studio (NVIS), Linköping University. NVIS conducts research within the areas of computer graphics, scientific visualization and virtual reality. At NVIS there is, among much other special equipment, a virtual reality theater with a cylindrical wall on which graphics are shown, for instance, system identification data. The wall is 10 meters wide and 3 meters high and covers about 150 degrees of the field of view. Each of the three CRT projectors covers a third of the wall and edge blending is used to join the three pictures into a single big picture. Stereoscopic vision is achieved using CrystalEyes glasses synchronized using infrared light.

Figure 3.3 shows an example, where time varying dynamics are revealed by plotting a 2-dimensional projection of the regression vector versus time. A *volume rendering* technique is used that gives the user the feel of both depth and density in data. The volume can be rotated interactively, and by the use of special 3-D glasses, the user has the feeling of beeing *immersed* into the data. In [44] the visualization techniques are described to the detail.

3.8 Using ANOVA for Selecting Regressors in Non-linear Models

Techniques to apply Analysis of Variance (ANOVA) to select regressors in non-linear models have been described in earlier annual reports. In general, system identification is data centred. Simple things are tried first; Is a linear model sufficient to describe the data? To invalidate a linear model, the residuals are examined with whiteness tests and the fit of the model on validation data is used to form an opinion of how good the model is. Thus, a linear model is often available, or easily computed.

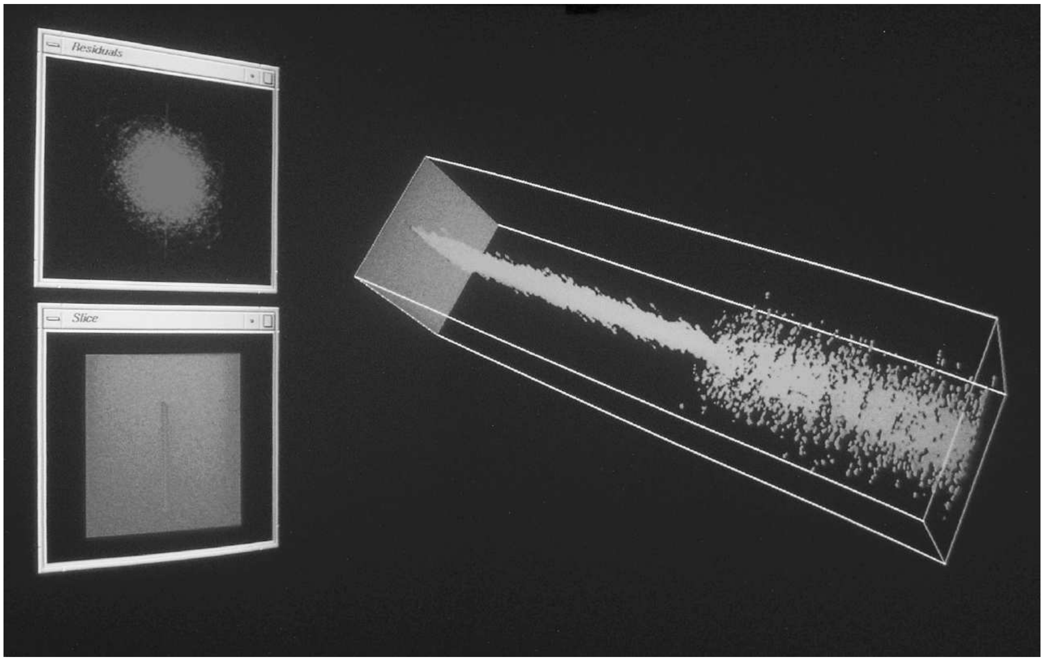


Figure 3.3: The experimental setup running on a semi-immersive display. This is a photograph of the screen in the NVIS virtual reality theater.

ANOVA can be used for finding proper regressors and model structure for a nonlinear model by fitting a locally constant model to the response surface of the data [96]. A clever parameterisation of a locally constant model makes it possible to perform hypothesis tests in a balanced and computationally very effective way. Let

$$\begin{aligned} y(t) &= g(u(t), u(t-T), \ldots, u(t-kT)) + e(t) \\ &= \theta_1^T \varphi_1(t) + g_2(\varphi_2(t)) + e(t) \end{aligned}$$

be a general nonlinear finite impulse response model with input $u(t)$ and output $y(t)$, sampled with sampling time T. Let $\varphi_1(t)$ be a vector containing the regressors that affect the output linearly (with parameters θ_1) and $\varphi_2(t)$ the regressors that affect $y(t)$ nonlinearly through the function $g_2(\cdot)$. Three main questions can be answered by both running ANOVA directly on identification data and running ANOVA on the residuals from a linear model:

- Should the regressor $u(t - k_i T)$ be included in the model at all, and should it be included in $\varphi_1(t)$ or $\varphi_2(t)$?

- What interaction pattern is present? Can $g(\cdot)$ be divided into additive parts containing only subsets of the regressors? What subsets?

- Are there nonlinear effects in the residuals from a linear model?

There are much to be gained by the division into a linear and a nonlinear subset of the regressors [54] instead of assuming a full nonlinear model. The complexity of any black-box type of model depends heavily on the size of $\varphi_2(t)$.

In [95], an idealised case is examined to quantify the difference between running ANOVA directly on identification data and first estimate an affine (linear with constant offset) model and then running ANOVA on its residuals. The purpose is to answer the questions above.

3.9 Subspace Methods

So called *Subspace methods* have been the subject of considerable recent interest in the literature on System Identification. The methods are intriguing, since they are numerically efficient, fast and do not require iterative search. At the same time they contain several design variable choices, and there is no full understanding about the best choices of these. We have reported on several aspects of subspace methods in earlier annual reports. A specific aspect is that subspace methods usually fail with closed loop data. A modification that takes care of that problem is described in [50]. The idea is to make an estimate of the innovations sequence, in order to avoid the correlation between past innovations and the input.

Chapter 4

Nonlinear Systems

4.1 Backstepping for rigid bodies

Backstepping is a Lyapunov based nonlinear control design method that provides an alternative to feedback linearization. In [75] a method for backstepping control of a rigid body is developed, based on a vector description of the dynamics. The control design gives insight into the controller structure and how it depends on the rigid body structure. In particular the method can be used for the design of controllers for aircraft dynamics.

4.2 Control allocation

Control allocation deals with the problem of distributing a given control demand among an available set of actuators. Most existing methods are static in the sense that the resulting control distribution depends only on the current control demand. In [9] a method for dynamic control allocation is proposed, in which the resulting control distribution also depends on the distribution in the previous sampling instant. The method extends regular quadratic programming control allocation by also penalizing the actuator rates. This leads to a frequency dependent control distribution which can be designed to, e.g., account for different actuator bandwidths. The control allocation problem is posed as a constrained quadratic program which provides automatic redistribution of the control effort when one actuator saturates in position or in rate. When no saturations occur, the resulting control distribution coincides with the control demand fed through a linear filter.

4.3 DAE models

General approaches to modeling, for instance using object-oriented software, lead to differential algebraic equations (DAE), also called implicit systems or descriptor syatems. For state estimation using observed system inputs and outputs in a stochastic framework similar to Kalman filtering, one needs to augment the DAE with stochastic disturbances (process noise). This might lead to mathematical difficulties because of hidden differentiations of the signals. In [30] it is discussed how such problems can be detected and avoided.

If some parameters in DAE models are unknown, one might need to estimate them from measured data from the modeled system. This is a form of system identification called gray box identification. In [2] it is investigated how gray box identification can be performed for linear descriptor systems. To solve the problem, some well-known canonical forms are used to examine how to transform the descriptor systems into state-space form. In general, the input must be redefined to make the transformation into state-space form possible. The implementation requires numerical software which is discussed in [29].

4.4 Robustness and model error models

Much attention in robust identification and control has been focused on linear low order models approximating high order linear systems. In [6] the more realistic situation with a linear model approximating a non-linear system is considered. It is described how a non-linear model error model can be developed, that allows a complete linear design process. The result is a closed loop system with performance robustness guarantees (in terms of gain from disturbance to output) against the nonlinear error. Clearly the design can be successful only if the linear model is a reasonably good approximation of the system. A particular aspect of the design process is to define a workable definition of "practical stability" for robust control design, with possible nonlinear model errors. For that purpose affine norms are used.

4.5 Nonlinear non-minimum phase systems

For nonlinear systems, instability of the zero dynamics is known to correspond to the non-minimum phase property of linear systems. For linear systems it is also known that non-minimum phase is associated with certain step response behavior e.g. undershoot. The corresponding step response properties of nonlinear systems are investigated in [31]. It is also investigated whether a certain nonlinear canonical form gives insight into the relation between step response and non-minimum phase behavior.

Chapter 5

Sensor fusion

This project is carried out by Division of Communication Systems and Division of Automatic Control in cooperation with our industrial partners SAAB (Dynamics and Gripen) Volvo (Cars), NIRA (Automotive algorithms) and FOI (laser scanning systems). Highlights of the year are

- The licentiate thesis by Andreas Eidehall [1].
- The sensor fusion work got international and national recognition by several major research grants which will support and extend the scope of the previous ISIS sensor fusion project:
  - FP5 IST project MATRIS for real-time tracking of cameras using inertial sensors and image information.
  - The Swedish research programme Intelligent Vehicle Safety System (IVSS) granted the application SEFS (SEnsor Fusion for Safety systems), where Chalmers and Volvo are partners.
  - The Swedish research council (VR) granted the project Sensor informatics and sensor fusion.

  These projects have in common that vision information is considered as a sensor in a sensor fusion framework.

5.1 Overview

We will here describe the general area of sensor informatics. We split the *sensor informatic problem* into

Motion dynamics	$x(t_{k+1}) = f(x(t_k), w(t_k))$	$\approx$	$x(t_{k+1}) = Ax(t_k) + w(t_k)$
Sensors: IS, GIS, Vision	$y(t_k) = h(x(t_k), e(t_k))$	$\approx$	$y(t_k) = Cx(t_k) + e(t_k)$
Filter	Approximate PF $\Rightarrow \hat{x}^{PF}$		"Exact" KF $\Rightarrow \hat{x}^{KF}$

Table 5.1: *Overview of a sensor fusion system with possible filtering approaches. The sensor delivers measurements $y(t_k)$ with time stamps t_k, which may come irregular in time and with jitter noise. This is the subject of Section 5.3. For almost linear models and Gaussian shaped noise, $\hat{x}^{KF}$ should be prefered, while for non-linear models or sensors with non-Gaussian error distributions should at least be $\hat{x}^{PF}$. The theoretical best choice and computational aspects are the subjects of Section 5.2.*

- high-level sensor fusion and
- low-level sensor sampling problem.

The reason for the latter is that it turns out to be a fundamental sensor fusion problem that must be solved when the data is not uniformly sampled or, due to bus communciation problems for instance, a sampling jitter is present.

The general problem of utilizing all available sensor information is called sensor fusion. Mostly, one assumes that the sensor measurements are related by a dynamic model, and we face a filtering problem. The optimal solution given by Bayes' law is well-known. In case the dynamic model is linear, the Kalman filter theory applies. In the non-linear case, several numerical approximations have appeared in the past, though quite few applications of these have been reported. It was first with the invention of the particle filter by Gordon *et al.* in 1993 that a general working solution with a sound theoretical basis that the signal processing community started to apply approximate non-linear filtering to real-world problems. During the past five years, many applications have been reported, and the theory has made substantial progress. Table 5.1 summarizes the sensor fusion model and the two choices of linear or non-linear filtering.

Pre-processing of sensor signals is in many cases decisive for the sensor fusion performance. We have found that for several inertial navigation problems, non-uniform sampling is in particular critical. In Table 5.1, non-uniform sampling is illustrated as explicit time stamps t_k attached to each measurement. In a model-based filtering framework, this does not pose a problem in itself. The main problems are random errors on t_k and deterministic jitter (cyclic unknown error) in t_k. Non-uniform sampling is a relatively unexplored area in signal processing where few hard facts are available.

5.2 Sensor fusion projects

The current projects include

- Particle filters for system identification. A wellknown general approach to system identification is to put the model structure on state space form, and extend the state vector with the parameters to be identified. The interesting question is how well the particle filter performs on such models, and it is not trivial to answer the question since the augmented state vector does not lead to an ergodic process which is one requirement for the particle filter theory. For linear model structures, this approach leads to a bilinear state space model, and then an important practical question is how to marginalize the state vector to get a lower-dimensional state vector. This is the subject of [56]. For instance, marginalizing the parameters avoids the problem of ergodicity mentioned above.

- The marginalized particle filter as a general tool has the potential of increasing estimation accuracy and reducing computational complexity at the same time. Complexity issues are analyzed in [49].

- Positioning of robot tools, [47, 48]. Using accelerometers at the tool of a robot and sensor fusion techniques, the accuracy of tool positioning can be increased.

- Fundamental limitations in filtering. What is the ultimate accuracy that can be achieved given infinite computational and memory resources? The Cramér-Rao lower bound gives once such accuracy bound for the second order moment. For linear systems with non-Gaussian noise, the Kalman filter is the linear filter that provides the best second order accuracy, but non-linear filters as the particle filter may give much better performance. In [39], explicit results are given for this case.

5.3 Non-uniform sampling

Non-uniform sampling naturally occurs in the following cases

- Event-based sampling as for instance the angular measurements that are done on rotating shafts. This occurs in the drive line and at the wheels ("ABS sensors") in vehicles and in robot arms, for instance. That means that the sensor delivers time instants t_k for a uniform angle grid $2\pi k/N$. Due to imperfect angle sensors, a regular jitter (offset to t_k) occurs. This jitter should be eliminated close to the sensor, since the error is hard or even impossible to estimate in (time-domain) sensor fusion.

- Using parallel computations for high-speed applications, as the project on parallel AD Converter structures, in Figure 5.1, a jitter effect occurs due to lack of exact synchronization of the computation blocks. That means, that the sampling times have a cyclic and unknown offset added to them.

- Stochastic sampling jitter occurs when time stamps of sensor measurements have unknown random errors. This occurs for instance in some communication protocols as CAN in vehicles and in high-speed applications where clock synchronization in not perfect. Theory of frequency analysis based on samples subject to stochastic jitter is developed in in [25, 33, 26], where an application to queue management control is given.

- System identification based on non-uniform samples with known sampling instants, is treated in [3].

5.4 Automotive collision avoidance

An automotive collision avoidance system incorporates many important sensor fusion aspects:

- Navigation for ego-motion estimation.

- Target tracking for situational awareness.

- Road prediction for hazard evaluation.

- Decision support.

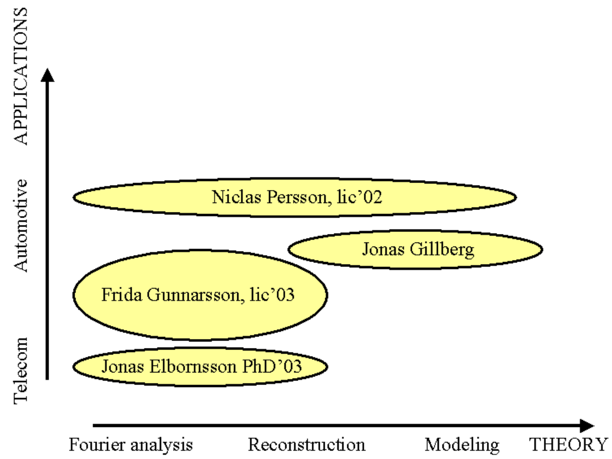


Figure 5.1: Previous research projects in non-uniform sampling

The challenge is to design these in a system showing an extremely low false alarm rate and good intervention performance. Our collaboration with Volvo Car Corp has given valuable knowledge, which has been substantiated in several demonstrator vehicles that have been tested extensively with successful result. The publications this year include the following projects:

- A sensor fusion framework for all three tasks of navigation, tracking and road prediction. This includes a curved coordinate system following the road [23], where the host vehicle's and tracked vehicles' lateral positions are given as deviations from the reference lane. In this way, all relevant parameters are collected in one state vector, where sensor inputs from own intertial sensors and wheel speeds are mixed with radar, lidar, IR and vision information in a common measurement model.

- Stochastic uncertainty for decision support is treated in [42].

- The paper [46] demonstrates how the particle filter can be used to utilize multiple radar reflections in tracked vehicles using a multi-modal probability density function for the radar measurement noise.

5.5 Laser radar systems

This project concerns target recognition methods and performance analysis of estimation algorithms based on data from a generic laser radar system. This year's work treated recognition of ground targets with complex shape.

Data processing methods in this area are usually developed separately for military or topographic applications, seldom with both application areas in mind. In civilian applications, ground surface estimation and classification of natural objects, for example trees, is common. Once the natural objects have been detected and classified, buildings can be reconstructed and vehicles can be recognized. In [41], an overview of methods from both areas is presented. By combining methods originating from civilian and military applications, we believe that the tools for scene analysis becomes available.

A first approach to recognition of ground targets from irregularly sampled laser radar data is presented in [32]. It is based on the fact that man-made objects of complex shape can be decomposed to a set of rectangles. The ground target recognition method consists of four steps; estimation of the target's 3D size and orientation, segmentation of the target into parts of approximately rectangular shape, identification of segments that contain the main parts of the target and matching the of target with CAD models. An example is shown in Figure 5.2. In [32], its application in a decision support system for ground target recognition is presented.

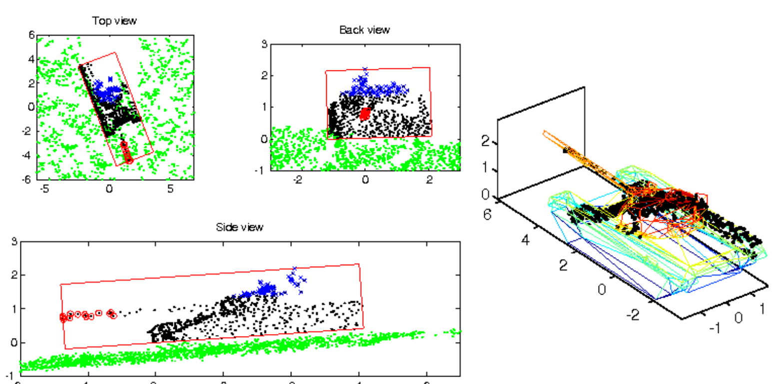


Figure 5.2: Target recognition of a tank. Left: 3D size and orientation estimation using rectangle fitting. The identified main parts are barrel (o) and turret (x). Right: Matching with low-resolution CAD model.

Chapter 6

Detection and Diagnosis

6.1 Fault Isolation in Control Systems with Object Oriented Architecture

Introduction

Developing control systems for complex systems is a difficult and increasingly important task. Large control systems have traditionally been developed using structured analysis and functional decomposition. Today, many large systems are designed using an object oriented approach. This has several advantages over traditional approaches, including better possibility to cope with complexity and to facilitate maintenance and reuse. It leads to new kinds of problems, though, and we concern ourselves with the problem of fault propagation caused by an object oriented software architecture. As basic inspiration and case study we have used a commercial control system for industrial robots developed by ABB Robotics; the system is highly configurable, programmable and has an object oriented architecture. More work on industrial robots is described in Chapter 8.

Object-oriented design goals such as *encapsulation* and *modularity* often stand in direct conflict with the need to generate concise information about a fault situation, and to avoid propagating error messages. Error messages are sent by individual objects to notify, e.g., an operator that an error condition has been detected. The aim to encapsulate information implies that individual objects, or groups of objects, in general do not know how close they are to the fault or if the fault has already been adequately reported by another part of the system. When a fault situation occurs, e.g, a hardware component failure, a broken communication link or a real-time fault, it is not a very desirable system behavior to present a multitude of error messages from different parts of the system to an operator. For the operator, who normally has no insight in the internal design of the control system, it can be very difficult to understand which error message that is most relevant and closest to the real fault. For objects that are close to each other it is possible to suppress error messages by information passing, but this is not always feasible.

There are two main objectives of our work: On the one hand we want to devise a method that can be used for operator support. The aim is then to single out the error message that explains the actual cause of the failure, or possibly an unobservable critical event explaining the observations. We aim to discard error messages which are definitely effects of other error messages, while trying to *isolate* error messages (or critical events) which explain all other messages. That is, we propose a fault handling scheme as an extra layer between the operator and the core control system, performing post-processing of the fault information from the system to achieve clear and concise fault information to the operator, without violating encapsulation and modularity. On the other hand, our method can also be used at design time. At the design level, we want to find out, at design-time, if the error log design is sufficient, that is, if enough error messages are produced to be able to isolate all faults.

The fault isolation is done in two steps. In the first phase a structural model fault isolation is done, and in a second phase a behavioral model fault isolation is used only if needed. If the structural model fault isolation is successful in finding a single cause of all the error messages, the second phase of behavioral model fault isolation is not needed.

The structural model is represented mainly by the class diagrams in UML (Unified Modeling Language). The main advantage with using a software engineering model is that it can be developed and maintained at a relatively low cost as it is an integrated part of the software development process. From the error messages in the error log we can find the cause-effect relation between the error messages. If there is no unique maximal element initially, we use the UML model, in particular the class diagrams, to extend the original graph. A prototype implementation of the structural approach has been made and tested on the ABB Robotics industrial robot control system.

Behavioral fault isolation

Since the structural model thus is an abstraction of all possible behaviors, it is not unlikely to have circular dependencies in the structural model without ever having circular dependencies in any specific scenario. When such a circular dependency occurs in the explanation graph the structural model is not sufficient to perform successful fault isolation, but having a behavioral model of the objects involved in the cycle we may be able to break the cycle. A dependency in the structural model, say class A depends on class B, means that there exists a scenario where an instance of class A depends on an instance of class B. It is not possible to deduce whether the dependency holds in the scenario at hand or not, since the model does not discriminate between different scenarios. By modeling also the behavior of the objects we get the opportunity to reason about dependencies that hold only under certain circumstances, i.e. in certain scenarios.

Our main focus lately has been to extend the structural approach to fault isolation using *behavioral methods* -more precisely we use UML state machines as notation for the behavioral model- and class instances rather than classes. We use the concept of *strong root candidate*. A strong root candidate is an event that is known to have occurred, and there is a run (consistent with the log) where this event is the first critical event.

When starting behavioral model fault isolation we have a limited set of root candidates, i.e. events in the scenario that are suspected to have caused the failure of the system. This set is an output from the structural model fault isolation.

We propose an approach to fault isolation based on *model checking* to locate strong root candidates (if they exist!). The property of being a strong root candidate is then expressed in the temporal logic CTL (normally used for verification). And we use an existing model checker to single out the strong root candidates. However, a main obstacle in model checking is the so-called state-space explosion–the number of global system states typically increases exponentially with the number of subsystems. Techniques have been proposed to stretch the limits of model checking (e.g., symbolic model checking and partial order reduction). However, in our case we do not solve a general model checking problem but a more specific problem. Consequently there are more efficient abstraction mechanisms for our particular problem, and we propose such a method in [94, 93]. The general idea is that we are only interested in the correlation between the first critical event and the set of messages that are logged during the execution. Hence, we can abstract away details not only about parallel object interleavings as in partial order reduction, but also ignore order of messages and dynamics that in the global system model does not change the set of messages sent or the order of critical events. For example, cyclic behavior where no critical events occur can be abstracted to a single state. Before applying model checking we perform abstraction, thus reducing the state space considerably and facilitating checking of the strong root candidates using model checking.

The result produced by our method is a table that maps all possible message logs to the corresponding strong root candidates. The table, called the fault isolation table, can of course be used for fault isolation; given a log and the fault isolation table, the strong root candidates can be found simply by table lookup. The primary use is in diagnosability analysis, though. The table partitions all possible system runs in equivalence classes of runs with the same logged messages. Each partition corresponds to a row in the table. If for such a row, there are several strong root candidates, we conclude that runs in the corresponding class are not diagnosable. If an error message is redundant, it will be evident from the table. If it depends on some other message, the two will only appear in certain configurations in consistent logs. The exponential size of the table indicates that it is not feasible to use it explicitly in general for systems with a large set of logged events. Then, abstractions of the table can be considered and presented to a user, for example the set of table rows that indicate non-diagnosability.

We have developed a prototype tool, StateTracer, that takes a description of a system as input and produces a fault isolation table as output along with visualizations of all merged objects. The system description is given in UML.

6.2 Fault detection and diagnosis in process control systems

This project is carried out by in cooperation with ABB Automation Systems and ABB Corporate Research. The aim is to study and develop methods for detection and diagnosis in process control applications.

This project focuses on fault detection and diagnosis in pulp and paper processes. Typical characteristics of these systems are that they are large systems with a large number of signals/sensors, and the physical models are of limited accuracy.

We investigate how to make a model of a system with a large number of signals, where furthermore only a small part of the signal space contains data under normal operations. PCA, principal component analysis is a promising method for this, where singular value decomposition is used to find the relevant parts of the signal space. The PCA model can then be used to compare measured process output with model output, and compute a test statistic, which will differ from zero when a fault has occurred.

Once a fault is detected, the next step in the fault detection and diagnosis is to find the faulty sensor. Using a probabilistic approach we can minimize the misclassification.

PCA has usually been employed for static systems, and for certain sampling rates, the pulp and paper process can be regarded as such. It is however also interesting to include dynamic information into the model, i.e., by including delayed versions of the signals in the regressor. This is known as dynamic PCA, dPCA, and closely related to subspace methods.

Another approach to fault detection is the parity space approach which is an elegant and general tool for additive faults in linear systems and is based on intuitively simple algebraic projections and geometry. It provides a tool to compute a residual vector that is zero when there is no fault in the system and reacts to different faults in different patterns, enabling a simple algorithm for diagnosis (deciding which fault actually occurred). Examples on simulated data often show very good results. A main drawback is that the approach does not take measurement errors and state noise into consideration as in the classical Kalman filter literature.

We mix the linear state space models used in fault detection and Kalman filtering, treating deterministic and stochastic disturbances in different ways.

In [36, 79] a comparison is made between the parity space analyzed in a stochastic setting and PCA. The result is thaty PCA has similar fault detection and isolation capabilities as the stochastic parity space approach.

Chapter 7

Communication Applications

7.1 Introduction

The third generation cellular radio systems is in many aspects conceptually different from the first and second generations. In these previous generations, resource management was to a large extent concentrated on channel allocation, where users share a fixed resource such as channels similar to classic work by Erlang et al. In the third generation (as well as in some upgraded second generation systems), the available resource is not fixed, but flexible and depend critically on the network deployment. The wireless communication system comprises many algorithms which have to be implemented in a distributed fashion but mutually affect each other. Also the information is distributed, and full observability of the system behavior is almost always not possible. Therefore, careful design and analysis of the various algorithms is crucial.

This project is carried out by Division of Communication Systems and Division of Automatic Control in cooperation with Ericsson Research. The aim is to apply methods from control theory and signal processing to algorithms on different layers in wireless communications systems.

One instructive approach is to separate the resource management in two segments:

- Radio resource management. This segment focuses on the radio access network to enable efficient transport of data from transmitters to receivers. Aspects, such as efficiency, feasibility, stability, fairness etc are central.

- Data network control. The data over the links is not continuous, and its flow depend on the behaviour of the core network run by the operator, and of other connected networks, such as the Internet. The data flow depends on both end-to-end transport protocols and on flow control mechanisms in nodes.

The activities are concentrated to:

- Identification and modeling of different network components and layers, based on control theory methodology. Primarily, the algorithms can be separated with respect to time constants, input and output signals, and physical location, to identify potential conflicts.

- Development of coordinating radio network algorithms. This also includes studying cross-couplings and conflicts between existing algorithms, as well as investigating robustness of distributed algorithms.

- Model data flow control to better relate to radio network properties.

7.2 Project Overview

The projects will be described using a top down approach, from flow control of data packets sent over the wireless links, via radio interface admission control of new users and finally to control of individual transmitter powers. The overall situation is depicted in Figure 7.1.

Data flow control primarily makes impacts on the core network and other connected networks, but also relates to radio network properties. Uplink load estimation and control addresses the situations at the base station, which is monitored in the RNC (Radio Network Controller). Control of individual transmitter powers mainly deals with the situation between the base station and the mobile situation.

7.3 Data Network Flow Control

Many people consider 3G as the technology that makes Internet generally available to mobile users. This means that the fields of telecommunications and data communications will overlap to a greater extent than before. While the paradigm in data communications is flexibility, the key word within

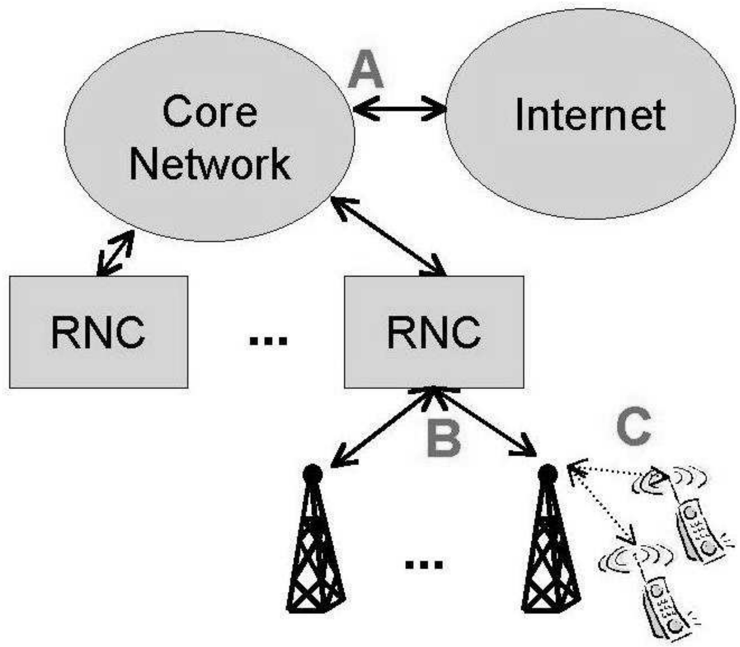


Figure 7.1: Radio network connected to a core network and the Internet

telecommunications is efficiency of the wireless link. Therefore, some flow control mechanisms used of wired Internet causes problems when used directly over wireless links. Furthermore, these flow control mechanisms were designed assuming different traffic characteristics than prevalent today. The field of data network control is "hot" within academia, and much effort is spent on modeling the control protocols and the queues of the switches and routers. The main idea with the project is to combine core knowledge in control theory and in telecommunications resource management, to form better understanding as well as better and more relevant models for the observed phenomena. One distinguishing property of the flow control problems is that new information becomes available upon packet arrivals, which means that the input signals are non-uniformly sampled in time. To better control queue lengths etc, a model of the observed data is instructive. [33] discusses frequency analysis of non-uniformly sampled data. The impact from the sampling can be seen as a frequency window applied to the continuous time Fourier transform to spread a distinct continuous time frequency over a frequency range.

In order to study the impact from modifications to queue management etc in combined fixed and wireless networks, additions to the network simulator *ns-2* has been made. The Master Thesis [131] describes recent modeling of radio resource management and investigates the impact from using too simlified models of either the fixed or the wireless part of the network. The conclusion is that in order to quantify end-to-end performance accurately, neither part can be represented by simplistic delay models.

Related to this project are also the two Master Theses [115, 149], which addresses the performance of evolved 3G systems for streaming services and in unlicenced frequency spectrum, respectively.

7.4 Uplink Load Estimation and Control in WCDMA

A prerequisite for proper behavior of radio network algorithms is that not more users than actually can be served are admitted into the system. This is of course intuitive, but with limited observability rather difficult to ensure. The situation is especially hard in the uplink communications from mobiles to the base stations, since the system has no absolute control of the transmitter powers of the mobiles. These depend in turn on the radio propagation conditions, which are subject to rapid changes. A relevant quantity is the total received power relative to the noise power, often referred to as the noise rise, NR. This can be associated to a cell load L, which is defined by

$$NR = \frac{1}{1-L}.$$

As also seen in Figure 7.2, it is very important to operate at moderate load levels. Fluctuations at high load levels have a critical impact on the noise rise.

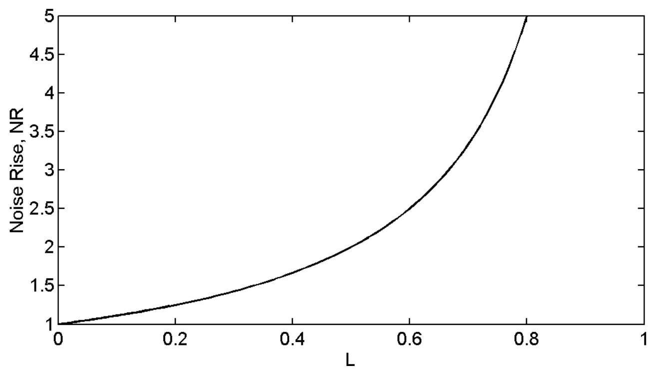


Figure 7.2: Relation between noise rise and load

A high level of noise rise means that many mobiles will have insufficient transmission power to transmit data successfully at the allocated service data rate (i.e. insufficient service coverage). It is also an indication of potential instability problems in the network. The key property is *feasibility*, which means that there exists finite transmission power levels for each uplink connection to meet the allocated service requirements. This is discussed in detail in [70, 5].

The load estimation accuracy can be improved if the channel activity is considered instead of using a full activity assumption. Some ideas relating activity estimation and load estimation are presented in [57].

Ensuring an efficient uplink communication is not only about ensuring proper admission and congestion control of potential users. There is also performance to gained by improving data transport over individual links.

Uplink Transmission Timing [59, 58] is a method based on statistical multiplexing of uplink usage, aiming at a certain channel activity for the individual links, and a dezentralized scheduling mechanism in the mobile that aim at the target channel activity, while selecting transmission instants carefully to minimize power consumption and thereby the uplink interference contribution.

Another plausible improvement is on the receiver side. The uplink reception is interfered by all other incoming connections to the same base station - connections that are known. Similar to noise cancelling, this interference can be at least partically cancelled using advanced multi-user receivers. Some system performance aspects of interference cancellation is discussed in [37].

7.5 Transmitter Power Control

The main resource in future 3G systems such as WCDMA is power and spectrum. Since the users share the same spectrum, power control is an important means to utilize the resources efficiently. The control of each transmitter power can be seen as distributed feedback control loops. As such, time delays, feedback bandwidth, sample rate etc. constitute fundamental limitations to the power control performance, which most naturally are analyzed using control theory methodology [8, 7]. Furthermore, control theory also facilitates the control design, and a compact discussion regarding the control theory aspects of power control is found in these publications.

7.6 Related Work

Some work bridges the reasearch projects. Positioning in wireless communication networks is one example where a sensor fusion approach is used to address the problem. Since nonlinearities and non-Gaussian noise are present, the particle filtering framework is plausible.

Chapter 8

Robotic Applications

8.1 Introduction

This work is to a large extent carried out in cooperation with ABB Robotics within the competence center ISIS (Information Systems for Industrial Control and Supervision). The overall aim of the work is to study and develop methods for improvement of the performance of robot control systems.

8.2 Multivariable and Nonlinear Identification of Industrial Robots

Erik Wernholt's licentiate thesis [4] treats various aspects of identification of industrial robots.

The ultimate goal for robot identification is to find an accurate global nonlinear flexible model, suitable for, e.g., control design (both the controller structure and tuning), simulation, analysis, and diagnosis. The identification of such a complex model is a huge task, both in finding suitable model structures and efficient identification procedures, and is still a topic for further research.

Figure 8.1 gives an overview of some common model structures and identification procedures. The global nonlinear flexible model is denoted $\mathcal{M}(\theta^{RB}, \theta^{FB}, \theta^{NL})$ where the parameter vector θ is divided into rigid body parameters, θ^{RB}, flexible body parameters, θ^{FB}, and parameters describing nonlinearities, θ^{NL} (for example, backlash, friction, and nonlinear stiffness).

The global nonlinear rigid model, $\mathcal{M}^{GNR}(\theta^{RB}, \theta^{NL})$, is obtained by ignoring flexibilities (denoted by $\theta^{FB} = 0$). For the local linear flexible model, $\mathcal{M}^{LLF}_{X_0}(\theta^{RB}, \theta^{FB})$, the global model $\mathcal{M}(\theta^{RB}, \theta^{FB}, \theta^{NL})$ is linearized around the operating point $X = X_0$ and nonlinearities are ignored (denoted by $\theta^{NL} = 0$).

A number of different identification methods exist, based on these model approximations. The main objective of Erik Wernholt's licentiate thesis [4] is the identification of flexibilities and nonlinearities (shaded boxes in Figure 8.1). In particular, a nonparametric frequency domain estimation method for the multivariable frequency response function (MFRF) is evaluated and analyzed. Nonlinear gray-box identification is also treated. Since identification in robotics is a much studied problem, one important part of the thesis also is to give an overview of earlier results.

For the MFRF estimation method, an approximate expression for the estimation error has been derived which describes how the estimate is affected by disturbances, the choice of excitation signal, the feedback and the properties of the system itself. The MFRF estimation method has been evaluated using both simulation data and experimental data from an ABB IRB 6600 robot. A number of different aspects regarding excitation signals and averaging techniques have been studied. It is shown, for instance, that the repetitive nature of the disturbances further limits the choice of excitation signals. Averaging the estimates over several periods of data or using experiments with identical excitation does not give any significant reduction due to the repetitive disturbances. The results are presented in [4] and [61].

A three-step identification procedure is also proposed in which parameters for rigid body dynamics, friction, and flexibilities can be identified only using measurements on the motor side of the flexibility. The main point is the last step, where the parameters of a nonlinear physically parameterized model (a nonlinear gray-box model) are identified directly in the time domain. The first two steps give special attention to the problem of finding good initial parameter estimates for the iterative optimization routine. The procedure is exemplified using real data from an experimental industrial robot. The results are presented in [4] and [106] and is also accepted for publication at the 2005 IFAC World Congress.

Another contribution to the area of robot identification is given in [18] where recursive grey-box identification is considered. A physically parameterized two-mass model of the movement around axis one is considered. Some of the physical parameters are assumed to be know and the remaining are estimated using a recursive prediction error algorithm.

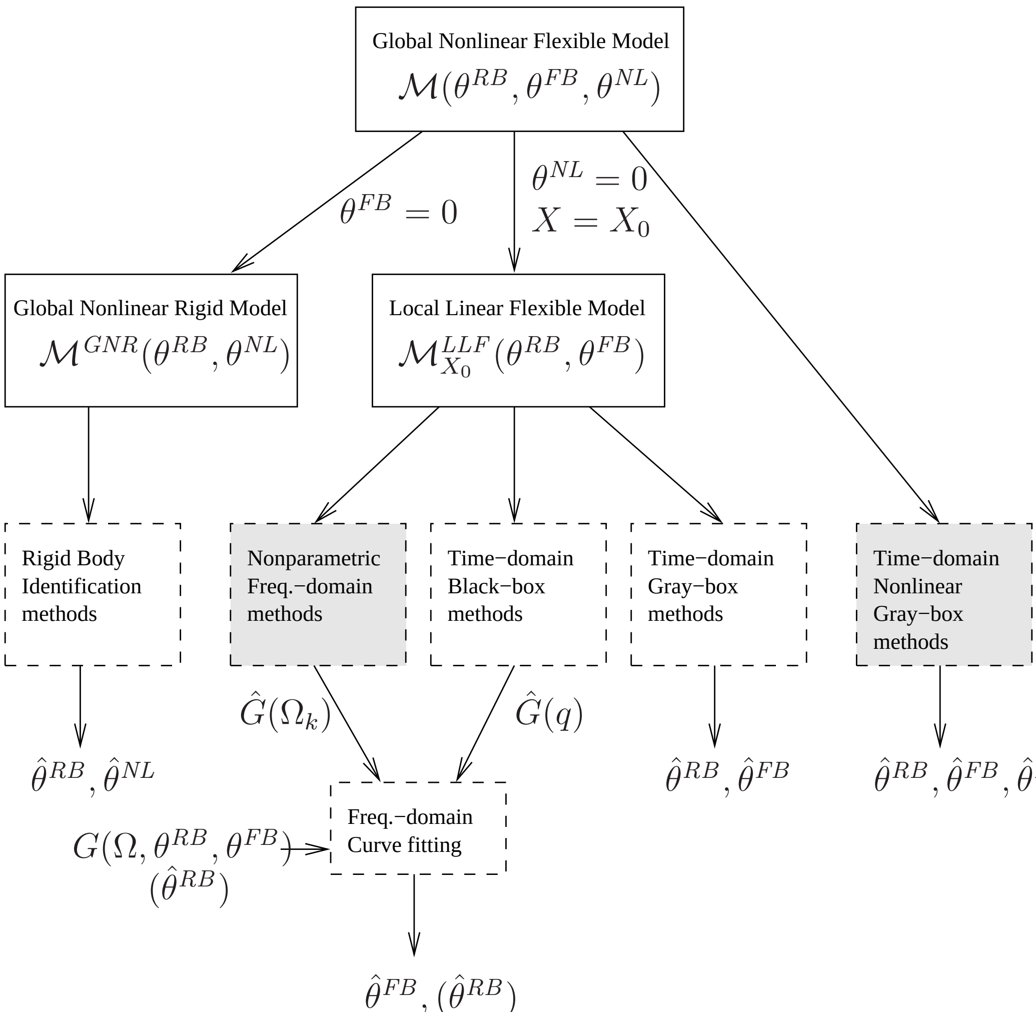


Figure 8.1: Overview of the robot identification problem and some common subproblems and identification methods. The shaded boxes denote what is treated in [4].

8.3 Iterative Learning Control

Iterative learning control (ILC) is a control method that utilizes a repetitive behavior that exists in many practical control applications, for example in the control of industrial manipulators. By using the error from previous iterations of the same action the error can be reduced. The structure of the problem is shown in Figure 8.2 where the output of the ILC algorithm is $u_{k+1}(t)$ defined for $0 \leq t \leq t_f$.

Mathematically the algorithm can be formulated as

$$u_{k+1} = Q(u_k + Le_k)$$

where u_k is the input to the controlled system and e_k is a measure of the control error. Q and L are operators that can be chosen by the user. When controlling a standard industrial robot only measurements from the motors are available although it is the arm that should be controlled. ILC on the motor does not always give a good result for the tool path tracking, and therefore additional sensors is a natural extension to increase the performance. In [35] some results from such an approach are presented. The process used in the experiments is a laboratory scale 1-DOF flexible joint process. Using a simple sensor fusion approach the information from the motor angle and the arm acceleration are merged into an estimate of the arm angle. This estimate is then using in an ILC algorithm with good result.

Another aspect of ILC is studied in [12], where the use of time-varying filters in the ILC-algorithm is considered. This comes as a logical consequence when a stochastic framework is applied to the problem. It is shown that zero error convergence can be achieved although the system model has an error of 100 % and there are stochastic disturbances acting on the output

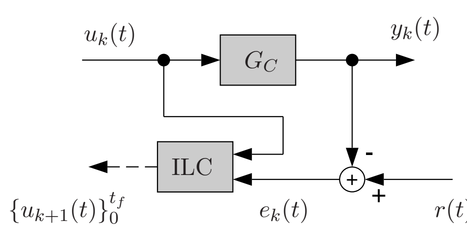


Figure 8.2: An example of a system controlled using ILC.

of the system. The trade-off between convergence speed and measurement disturbance sensitivity is also covered in [12].

8.4 Sensor integration

Modern industrial robot control is usually based only upon measurements from the motor angles of the manipulator. The ultimate goal however is to make the tool move according to some predefined path. During 2004 a new project was initiated where the aim has been to apply Bayesian estimation techniques for sensor fusion with application to robotics. In Figure 8.3 a robot equipped with a 3-axes accelerometer is shown.

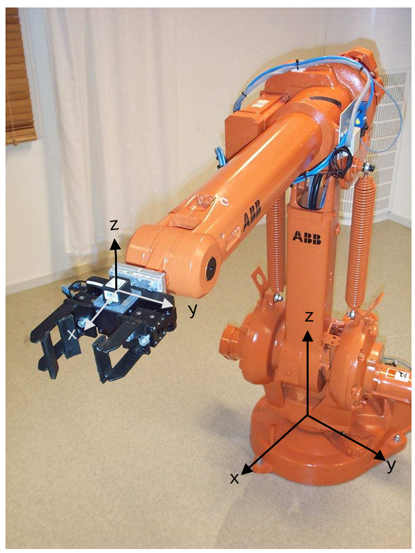


Figure 8.3: An ABB IRB1400 robot with a 3-axes accelerometer mounted on top of the gripper.

The Bayesian estimation techniques have been applied to a realistic flexible robot model in [48, 47, 88, 90]. In [48] measurements from the robot in Figure 8.3 are analyzed to support the modeling of the accelerometer sensor. Estimation using the *Extended Kalman Filter* (EKF) is also introduced and some preliminary results are reported. The estimation process is further developed in [47] where the EKF is compared to the particle filter estimation approach. In [88] and [90] modeling aspects are stressed and the sensitivity to parametric model errors is investigated. All the results so far are for a simulated robot, the next step will therefore be to do position estimation on a real robot.

8.5 Control

In [98] a realistic four mass model of one joint in an industrial robot is described. The model includes a nonlinear spring and a description of the uncertainties in the parameters that can be found in a practical robot system. The aim in [98] is also to present a control competition, organized by Stig Moberg and Jonas Öhr at ABB in Västerås. In the paper a detailed description of a design exercise is presented and the goal is to find a robust controller that effectively can reduce the effect of arm and motor disturbances.

A master thesis project [143] on control of a 3 degree-of-freedom robot arm using LQ and LQG techniques finished during 2004. This project serves as a continuation of a series of master's theses where the aim is to develop a platform for simulation studies of a realistic robot model and study different control strategies for multivaribale control.

In [69] a gain scheduling control of a nonlinear system is presented. It is assumed that the reference trajectory is given in advance. Multiple frozen operating times are chosen on the reference trajectory and a linear time invariant model is obtained at each operating time. A linear parameter varying model is then constructed by interpolating the region between the neighboring frozen operating times. A gain scheduling state feedback law is designed by a linear matrix inequality formulation. The effectiveness is demonstrated in a numerical simulation of a tracking control of a two-link robot arm.

Chapter 9

Optimization for Control and Signal Processing

9.1 Introduction

The research in optimization for control and signal processing is currently focused on efficient optimization algorithms for robustness and stability analysis of control systems and for model predictive control. Also stability analysis of nonlinear systems with applications to flight control systems is investigated.

9.2 Optimization Algorithms for Robustness Analysis

In this project we study how to construct efficient Interior-Point (IP) algorithms for the Semidefinite Programs (SDPs) that originate from the Kalman-Yakubovich-Popov (KYP) lemma. They have several applications, e.g., linear system design and analysis, robust control analysis using integral quadratic constraints, quadratic Lyapunov function search, and filter design.

Typically standard SDP solvers cannot handle KYP-SDPs of more than small to medium size in reasonable time, typically the limit is about 50 state-variables, resulting in roughly 1000 optimization variables. With specially tailored KYP-SDP-solvers problems with several hundred state-variables, corresponding to roughly tenths of thousands of variables can be handled.

The computational complexity stems from the cost of assembling and solving the equations for the search directions in the IP algorithms. Two avenues have been investigated to circumvent this problem. One is to use decomposition algorithms. This work has been presented in [105]

Another way of attacking the above problem is to consider the dual problem and make use of an image representation of some of the constraints. This will reduce the number of variables in the dual problem such that the computation complexity is reduced with two orders of magnitude with respect to the state-dimension. A Matlab implementation of the code is publically available at `http://www.control.isy.liu.se/research/authors/reports/2517/kypd.html` and is described in [104, 60]. Ragnar Wallin received the best student paper award for [60] at the IEEE Conference on Computer Aided Control Systems, 2004. The solver is one of the solvers in YALMIP.

Applications related to the above mentioned methods for stability analysis of nonlinear systems and for clearance of flight control laws have been reported in [34, 38].

Further research on control applications of SDPs are presented in [40].

9.3 Model Predictive Control

Model Predictive Control (MPC) has proven to be very useful in process control applications. Efficient optimization routines to be used on-line is an active area of research. In [17] it is shown how to efficiently solve an optimal control problem with applications to model predictive control. The objective is quadratic and the constraints can be both linear and quadratic. The key to an efficient implementation is to rewrite the optimization problem as a second order cone program. This can be done in many different ways. However, done carefully, it is possible to use both very efficient scalings as well as Riccati recursions for computing the search directions.

In recent years the interest in controlling so-called hybrid dynamical systems has increased. Hybrid dynamical systems are systems with both continuous and discrete components. They are useful, e.g., when modeling systems containing logics, binary control signals or when approximating non-linear systems as piecewise linear systems. When MPC is used for control of hybrid systems, the optimization problem to solve at each sampling instant becomes a Mixed Integer Quadratic Programming (MIQP) problem. These problems have in general exponential computational complexity in the number of discrete variables and are known to be $\mathcal{NP}$-hard. In order to be able to solve such optimization problems in real time, it is necessary to decrease the computational effort needed. Research has been done on utilizing structure when solving these MIQP problems. The result is a preprocessing algorithm applicable to unconstrained MPC problems for systems with both real valued and binary control signals which may reduce the computational time considerably. The work is presented in [20, 21].

Appendix A

Personnel

Lennart Ljung is professor and head of the control group since 1976. He was born in 1946 and received his Ph. D. in Automatic Control from Lund Institute of Technology in 1974. He is a member of the Royal Swedish Academy of Engineering Sciences (IVA) and the Royal Swedish Academy of Sciences (KVA). He is an honorary member of the Hungarian Academy of Engineering, and a Foreign Associate of the US National Academy of Engineering (NAE). He is also an IEEE Fellow adn an IFAC Advisor, and associate editor of several journals. He has received honorary doctor's degrees from the Baltic State Technical University in S:t Petersburg, Russia (1996), from Uppsala University, Uppsala, Sweden (1998), from l'Université de Technologie de Troyes, France (2004) and from the Katholieke Universiteit in Leuven, Belgium (2004). In 2002 he received the Quazza medal from IFAC, and in 2003 the Hendryk W. Bode Lecture Prize from the IEEE Control Systems Society.

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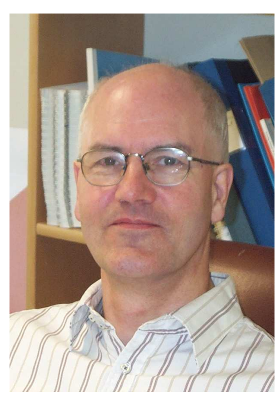
Torkel Glad was born in Lund, Sweden in 1947. He received his M. Sc. degree in engineering physics in 1970 and the Ph. D. degree in automatic control in 1976, both from the Lund Institute of Technology, Lund, Sweden. Since 1988 he is Professor of Nonlinear Control systems in the department. His research interests include Nonlinear Systems, algebraic aspects of System Theory and Optimal Control.



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Mille Millnert is a Professor in the department. He was born in 1952 and received his M. Sc. in 1977 and his Ph. D. in Automatic Control 1982 from Linköping University. His research interests are Model Based Signal Processing, Parameter Estimation and the Combination of Numerical and Symbolical techniques in Signal Processing and Control. From July 1996 he was Dean of the School of Engineering at Linköping University and from October 2003 he is president of Linköping University

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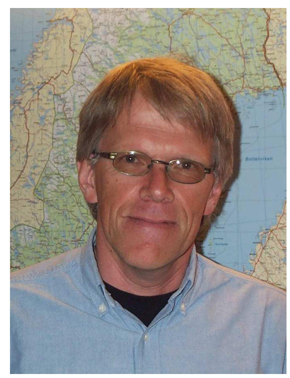
Svante Gunnarsson was born in 1959. He received his M. Sc. in 1983, his Lic. Eng. in 1986 and his Ph. D. in 1988 all from Linköping University. From 1989 he was associate professor at the department, and from 2002 professor. His research interests are system identification and adaptive control.



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Fredrik Gustafsson was born in 1964. He received the M. Sc. degree in electrical engineering in 1988 and the Ph. D. degree in automatic control in 1992, both from Linköping University, Sweden. He is currently professor in Communication Systems at the Department of Electrical Engineering at Linköping University. His research is focused on statistical methods in system identification, signal processing and adaptive filtering, with applications to communication, avionic and automotive systems.

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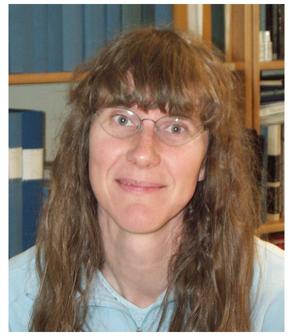
Inger Klein is a associate professor at the department. She was born in 1964. She received her M. Sc. in 1987, her Lic. Eng. in 1990, and her Ph. D. in 1993, all from Linköping University. Her research interest is diagnosis, fault detection and fault isolation, in particular for Discrete Event Systems.



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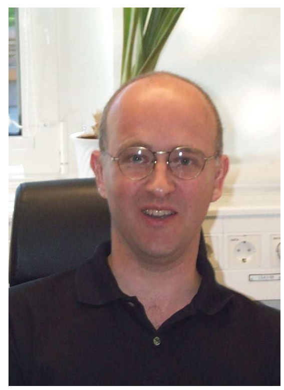
Anders Hansson was born in Trelleborg, Sweden, in 1964. He received the M. Sc. 1989, Lic. Eng. in 1991, and the Ph. D. in 1995, all from Lund University, Lund, Sweden. From 1995 to 1998 he was employed by the Information Systems Lab, Stanford University. From 1998 to 2000 he was associate professor at Automatic Control, KTH, Stockholm. From 2001 he is an associate professor at the Division of Automatic Control, Linköping University. His research interests are within the fields of optimal control, stochastic control, linear systems, signal processing, fuzzy logic, applications of control, image processing, and telecommunications.



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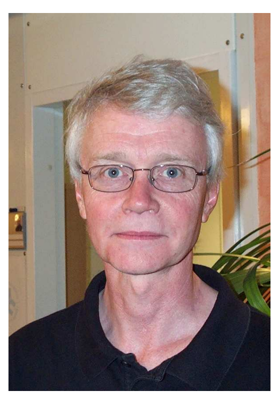
Kent Hartman was born in 1951. He received his M. Sc. in 1977 Applied Physics and Electrical Engineering at Linköping University, Department of Biomedical Engineering. He is an associate lecturer in the Control Group.



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Anders Helmersson was born in 1957. In 1981, he received his M. Sc. in Applied Physics at Lund Institute of Technology. He has been with Saab Ericsson Space since 1984. In 1993 he joined the Control Group where he received his Ph. D. in 1995. His research interest is mainly in robust control and gain scheduling. He is currently employed by Saab AB and is an adjunct professor at the Division of Automatic Control.

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Anna Hagenblad was born in Lycksele, Sweden, in 1971. She received her M. Sc. degree in Applied Physics and Electrical Engineering in 1995 and her Lic. Eng. in 1999. Her research interests are in the area of identification, particularly of the nonlinear Wiener model.

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Mikael Norrlöf was born in 1971. He received his M. Sc. in Computer Science and Engineering 1996, his Lic. Eng. in 1998 and his Ph. D. in 2000, all at Linköping University. His current research interests include Iterative Learning Control as well as modeling, nonlinear control, trajectory generation, and identification of industrial robots.

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Fredrik Gunnarsson was born in 1971 He received his M. Sc. in Applied Physics and Electrical Engineering in 1996 his Lic. Eng. in 1998 and his Ph. D. in 2000, all at Linköping University. His current research interests include control theory and signal processing aspects of wireless communications. He also works as a Senior Research Engineer at Ericsson Research.

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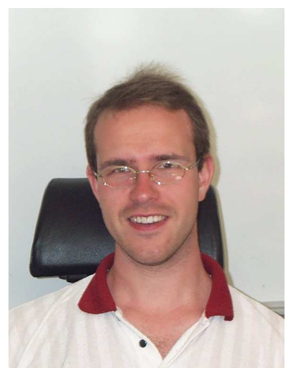

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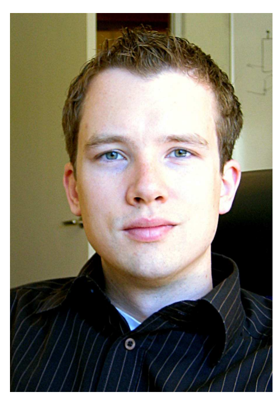

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Ulla Salaneck is the very valuable secretary for the control group.

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- Atsushi Fujimori, Department of Mechanical Engineering, Shizuoka University Hamamatsu, Japan visited the division from March 1, 2004 until January 29 2005.

- Didier Henrion, LAAS-CNRS, Toulous visited the division April 20–23.

- Graziano Chesi, Department of Information Engineering University of Siena Italy, visited May 4–8

- Graham Goodwin, The University of Newcastle Callaghan, NSW, AUSTRALIA visited the division from May 13–18.

- Alberto Bemporad, University of Siena, Siena, Italy, visited September 21–25.

- Dalius Navakauskas, Vilnius, Lithuania, spent the period November–December 2005 at the division of automatic control.

Appendix B

Courses

B.1 Undergraduate Courses

M.Sc. (civ.ing.)-program

- *Automatic Control* (Reglerteknik) The basic control course given for all engineering programs. *Contents*: The feedback concept, PID-controllers, Frequency domain design techniques, Sensitivity and robustness, State space models and state feedback controllers, Observers.

  M Mechanical Engineering. 165 participants. Lecturer: Inger Klein.

  Y Applied Physics and Electrical Engineering. 150 participants. Lecturer: Lennart Ljung.

  D Computer Engineering. 100 participants. Lecturer: Anna Hagenblad.

  I Industrial Engineering and Management. 175 participants. Lecturer: Svante Gunnarsson.

  TB, KB Engineering Biology and Chemical Biology Programs. 104 participants. Lecturer: Torkel Glad.

- *Control Theory Y* (Reglerteori Y). For the Applied Physics and Electrical Engineering and Computer Science and Engineering Programs. Multivariable systems, Fundamental limitations in feedback control systems, LQG-control, Loop transfer recovery, Loop shaping methods, Nonlinear systems, Optimal control. 98 participants. Lecturer: Torkel Glad.

- *Control Theory I* (Reglerteori I) For the Industrial Engineering and Management and Mechanical Engineering Programs. Multivariable systems, Sampled data systems, LQG-control. 12 Participants. Lecturer: Mikael Norrlöf.

- *Automatic Control M, advanced course* (Reglerteknik, fortsättningskurs M). For the Mechanical Engineering Program. Modelling, Bond graphs, System Identification, Nonlinear systems, Signal processing. 12 participants. Lecturer: Svante Gunnarsson.

- *Digital Signal Processing* (Digital Signalbehandling). For the Applied Physics and Electrical Engineering and Computer Science and Engineering Programs. Spectral analysis, Filtering, Signal Modeling, Wiener and Kalman filtering, Adaptive filters. 95 participants. Lecturer: Fredrik Gustafsson.

- *Modelling and Simulation* (Modellbygge och Simulering). For the Applied Physics and Electrical Engineering program. Physical system modelling, Bond graphs, Identification methods, Simulation. 82 participants. Lecturer: Torkel Glad.

- *Digital Control* (Digital Styrning). For the Applied Physics and Electrical Engineering, Computer Science and Engineering and Industrial Engineering and Management Programs. Numerical control, binary control and PLCS, process computers and applications of digital process control. 95 participants. Lecturer: Inger Klein.

- *Real Time Process Control* (Realtidsprocesser och reglering). For the Information Technology Program. Real time systems. PID control. 30 participants. Lecturer: Inger Klein.

- *Linear Feedback Systems* (Återkopplade linjära system). For the Information Technology Program. Linear systems, controllability, observability, feedback control. 30 participants. Lecturer: Inger Klein.

- *Control Project Laboratory* (Reglerteknisk projektkurs) For the Applied Physics and Electrical Engineering and Computer Science and Engineering Programs, Modelling and identification of laboratory processes, Controller design and implementation, 45 Participants. Lecturer: Anders Hansson.

- *Automatic Control Project Course* (Reglerteknik - projektkurs M) For the Mechanical Engineering Program. Project work, mainly carried out in industri. The projects involve modeling, controller design and implementation. 4 Participants. Lecturer: Svante Gunnarsson.

- *Introduction to MATLAB* (Introduktionskurs i MATLAB). Available for several Engineering Programs. 750 Participants. Lecturer: Fredrik Gustafsson.

- *Project work* (Ingenjörsprojekt Y). Develop an understanding of what engineering is all about and how the work is performed. - Administration, planning, communication, documentation and presentation of project work, 20 Participants. Lecturer: Anders Hansson and Kent Hartman.

- *Perspectives to computer technology* (Perspektiv på datateknik). Project work with focus on computer technology, 6 Participants. Lecturer: Kent Hartman.

B.Sc. (tekn.kand.)-program

- *Automatic control, EI* (Electrical Engineering) 5 units, 21 participants. Contents: Dynamical systems, the feedback principle, frequency domain analysis and design of control systems, robustness and sensitivity of control systems, sampling, implementation, some examples of nonlinearities in control systems. Simulation of dynamic systems. Lecturer: Kent Hartman.

- *Automatic control, advanced course, EI* 2 units, 21 participants. Contents: Sequential control and logic controllers. A typical industrial control system. Lecturer: Kent Hartman.

- *Automatic control, MI/KI* (Mechanical Engineering and Chemical Engineering) 4 units, 55 participants. Contents: Sequential control and logic controllers. Fundamentals of automatic control, dynamical systems, feedback, differential equations, frequency analysis, Bode plots, stability, simple controllers, sampling, implementation, simulation of dynamic systems. Lecturer: Kent Hartman.

B.2 Graduate Courses

- *System Identification.* Lecturer Lennart Ljung, Literature: L. Ljung: System Identification: Theory for the User. Prentice Hall 1999, 2nd ed.

- *Optimal Filtering.* Lecturer Fredrik Gustafsson, Literature: Kailath, Sayed, Hassibi: Linear Estimation; Steven Kay: Fundamentals of statistical signal processing: estimation theory.

- *Convex Optimization for Control.* Lecturer Anders Hansson . Literature: Boyd, S. and L. Vandenberghe: "Convex Optimization", Cambridge University Press, 2004.

- *Linear Systems.* Lecturer Torkel Glad. Literature: Wilson J. Rugh, Linear System Theory, Prentice Hall, 1996.

Appendix C

Seminars

- *Large-scale reverse engineering by the Lasso.* **Michael Hörnquist**, Linköpings universitet, February 5, 2004.
- *Systems Biology and Dynamic Pathway Modeling.* **Kwang-Hyun Cho**, University of Ulsan, Korea, February 12, 2004.
- *Probabilistic and Statistical Methods in Advanced Control.* **Rudolf Kulhavy**, Honeywell Automation & Control Solutions, February 16, 2004.
- *A Flight Control Design of an Unmanned Space Vehicle Using Gain-Scheduling.* **Atsushi Fujimori**, Shizuoka University, Japan, March 11, 2004.
- *Robotstyrning; Om multipla sensorplattformar i nätverk.* **Åke Wernersson**, FOI, Linköping, March 25, 2004.
- *Multiple Robot Control — Why and How.* **Håkan Fortell**, ABB Robotics, April 1, 2004.
- *Några reglerproblem inom bioteknik (Control problems in bio technology).* **Per Hagander**, Lund University, April 15, 2004.
- *GloptiPoly 3 - a Matlab package for globally optimizing polynomial moments.* **Didier Henrion**, LAAS-CNRS, France, April 22, 2004.
- *Verifying Safety with Barriers.* **Stephen Prajna**, California Institute of Technology, April 29, 2004.

- *Generating Exponentially Stable Oscillations in Nonlinear Systems by Feedback with Application to Walking Mechanisms.* **Anton Shiriaev**, Umeå universitet, May 5, 2004.

- *Some recent LMI-based results in the analysis of dynamical systems.* **Graziano Chesi**, University of Siena, Italy, May 5, 2004.

- *Delta Operator Formulations of Estimation and Control.* **Graham C. Goodwin**, University of Newcastle, Australia, May 14, 2004.

- *Theory and Application of Constrained Estimation.* **Graham C. Goodwin**, University of Newcastle, Australia, May 17, 2004.

- *What do Elvis Presley, Mobile Phones and Lap Top Computers have in Common?* **Graham C. Goodwin**, University of Newcastle, Australia, May 18, 2004.

- *Overview of the Research at Nihon University in the field of Automotive Engineering & ITS.* **Ichiro Kageyama**, Nihon University, June 10. 2004.

- *Direction-dependent dynamics — theory and application.* **Fredrik Rosenqvist**, Chalmers University of Technology, September 16, 2004.

- *Robot Path Planning: An Object-Oriented Approach.* **Morten Strandberg**, S3, KTH, October 7, 2004.

- *A Well-posed Approach to ARMA Estimation and Hinf Control Synthesis.* **Anders Blomqvist**, Optimization and Systems Theory, KTH, October 28, 2004.

- *Design and Analysis of Feedback Structures in Chemical Plants and Biochemical Systems.* **Henning Schmidt**, Fraunhofer-Chalmers Research Centre, November 18, 2004.

- *Model Reduction for Linear Time-Varying Systems.* **Henrik Sandberg**, Lund University, November 11, 2004.

- *Regleroptimering ger förbättringar i processindustrin.* **Krister Forsman**, ReglerDoktorn, December 2, 2004.

Appendix D

Travel and Conferences

Daniel Axehill participated at Reglermöte 2004, Göteborg, May 2004, 43th IEEE Conference on Decision and Control, Paradise Island, December, 2004.

Andreas Eidehall participated at the IEEE Intelligent Vehicles Symposium, Parma, Italy, June 2004.

Frida Eng participated in 2004 in the International Conference on Acoustics, Speech and Signal Processing, Montreal, Canada, and in Reglermötet, Göteborg, Sweden, as well as in the Fifth conference on Computer Science and Systems Engineering, Norrköping, Sweden.

Martin Enqvist participated in Reglermöte 2004 in Gothenburg, Sweden, May, 2004 and in the 6th IFAC Symposium on Nonlinear Control Systems in Stuttgart, Germany, September, 2004.

Erik Geijer Lundin participated at Reglermöte, Göteborg, May,2004, HYCON kick-off meeting, Paris, October, 2004, the 10th Annual Swedish Workshop on Wireless Systems 2004, Smådalarö, December, 2004.

Markus Gerdin participated at Reglermöte 2004, Göteborg, May 2004, Fifth Conference on Computer Science and Systems Engineering, Norrköping, October 2004.

Fredrik Gunnarsson participated in Vehicular Technology Conference in Milan, Italy, May 2004, and the 10th Annual Swedish Workshop on Wireless Systems 2004, Smådalarö, December, 2004.

Svante Gunnarsson attended the CDIO meetings at US Naval Academy, Annapolis, Maryland, June 2004, and Queens University, Belfast, UK, September 2004.

Anna Hagenblad participated in Reglermöte'04, Göteborg, May 26–27, 2004.

Anders Hansson participated in Reglermöte '04 in Göteborg, visited ONERA, Toulouse, France, February 18, and LAAS, Toulouse, France, February 19, 2004 as well as the 43rd IEEE Conference on Decision and Control, Paradise Island, The Bahamas, December 14, 2004.

Kent Hartman participated at the TEKIT-dagen, Linköping, April 2004, Samverkansgruppen för högskoleingenjörsutbildningarna, Växjö, April 2004, Reglermötet, Göteborg, May 2004, CUL-dagen, Linköping, November 2004.

Anders Helmersson participated at 2nd Chinese-Swedish Conference on Control, Beijing, China, October 16-17, 2004.

Gustaf Hendeby participated at Reglermöte 2004, Gothenburg, May, 2004.

Ola Härkegård participated at Reglermöte 2004, Gothenburg, May, 2004.

Rickard Karlsson participated at the AmericanControl Conference, Boston, MA, USA, June, 2004.

Inger Klein participated in Reglermöte 2002, Gothenburg, Sweden, May, 2004.

Ingela Lind participated at the ERNSI Workshop System Identification, Dobogokõ, Hungary, 3–6 October 2004.

Lennart Ljung participated in the 1st International Symposium on Control, Communications and Signal Processing in Mammamet, Tunisia March 21–24. June 7–8 he participated in the conference Systems and Control: Challenges in the 21st Century, organized in connection with the inaguration of the new control group at Delft University in the Netherlands. On June 13–17 he participated in and coorganised Rediscover '04 in Savtat, Croatia and June 30 to July 3 he participated in the American Control Conference in Boston, MA, USA. From September 1 to September 3 he took part in the IFAC symposium on Nonlinear Control, NOLCOS in Stuttgart, Germany and September 14–16 he visited the Universite de Technologie de Troyes, UTT, France to receive an honorary doctoral degree. September 30 to October 5 he visited Washington DC, in order to be inducted into the US National Academy of Engineering, (NAE). And October 10–14 he visited Katholieke Universiteit Leuven, Belgium to receive another honorary doctoral degree. Ljung participated in the Second Chinese-Swedish Workshop on Control in Beijing, China, October 14–20 and visited Tsinghua University on October 19. December 13–17 he took part in the IEEE Conference on Decision and Control, Paradise Island, the Bahamas.

Mikael Norrlöf visited Center for Dynamics of Complex Systems, Universita degli Studi di Firenze, Italy, April 13, participated at the Reglermöte 2004, Gothenburg, May 2004, IEEE Conference on Control Applications, Taipei, Taiwan, September, 2004, and the VINNOVA Competence Center Workshop 2004, Stockholm, November, 2004.

Jacob Roll participated at the ERNSI Workshop, Dobogoko, Hungary, October 2004, HYCON kickoff meeting, Paris, October 2004, and Nordita Workshop, Copenhagen, December 2004.

Ulla Salaneck particiapted in Reglermöte'04, Göteborg, May 26–27, 2004, ERNSI, October 3–6, 2004 and the Second Chinese - Swedish Control Conference, Beijing, China, October 16-17, 2005

Thomas Schön visited DaimlerChrysler, Department for Research and Technology, Powertrain Control, Stuttgart, Germany, February 13, participated at Reglermötet, Göteborg, Sweden, May 26–27, participated at the 7th International Conference on Information Fusion, Stockholm, Sweden, June 2004, participated at ERNSI Workshop System Identification, Budapest, Hungary, October 4–6, participated at the fifth Conference on Computer Science and Systems Engineering, Norrköping, Sweden, October 20–21, participated at project meetings (EU project, MATRIS) Darmstadt, Germany, February 12, London, United Kingdom, April 26–28, Kiel, Germany, November 8–10.

David Törnqvist participated at Reglermöte 2004, May, 2004, The American Control Conference 2004, Boston, USA, June/July, 2004 and Fifth

Conference on Computer Science and Systems engineering, October, 2004.

Ragnar Wallin participated at the International Symposium on Computer Aided Control System Design, Taipei, Taiwan, September, 2004.

Erik Wernholt participated in Reglermöte 2004 in Göteborg, Sweden, May 2004, and in the 43rd IEEE Conference on Decision and Control, Paradise Island, The Bahamas, December 14-17, 2004.

Appendix E

Lectures by the Staff

- Daniel Axehill: *Adaptive Cruise Control for Heavy Vehicles*, Reglermöte'04, Göteborg, Sweden, May 26, 2004.

- Daniel Axehill: *A Preprocessing Algorithm with Applications to MPC*, Fifth Conference on Computer Science and Systems Engineering, Norrköping, Sweden, October 21, 2004.

- Daniel Axehill: *A Preprocessing Algorithm with Applications to MPC*, 43th IEEE Conference on Decision and Control, Atlantis, Bahamas, December 15, 2004.

- Frida Eng (née Gunnarsson): *Frequency analysis using non-uniform sampling with application to active queue management*, International Conference on Acoustics, Speech and Signal Processing, Montreal, Canada, May, 2004.

  Also held at Reglermötet, Göteborg, Sweden, 2004 and Fifth conference on Computer Science and Systems Engineering, Norrköping, Sweden, 2004.

- Frida Eng: *On Modeling and Control of Network Queue Dynamics*. Guest lecture in a PhD course on Communication, September, 2004 and in an undergraduate course on Automatic Control, October, 2004.

- Martin Enqvist: *Some Results on Linear Models of Nonlinear Systems*, Department of Signals, Sensors and Systems, Royal Institute of Technology (KTH), Stockholm, Sweden, March 11, 2004.

- Martin Enqvist: *LTI Approximations of Slightly Nonlinear Systems: Some Intriguing Examples*, Reglermöte 2004, Gothenburg, Sweden, May 26, 2004.

- Martin Enqvist: *LTI Approximations of Slightly Nonlinear Systems: Some Intriguing Examples*, 6th IFAC Symposium on Nonlinear Control Systems, Stuttgart, Germany, September 3, 2004.

- Markus Gerdin: *Computation of a Canonical Form for Linear Differential-Algebraic Equations*, Reglermöte 2004, Göteborg, Sweden, May 26, 2004.

- Torkel Glad: *Stability Analysis of Nonlinear Systems using Frozen Stationary Linearization*, American Control Conference, Boston, USA June 30, 2004. *Step responses of nonlinear non-minimum phase systems*, NOLCOS'04, Stuttgart, Germany, September 3, 2004.

- Fredrik Gunnarsson: *Post-processing of Drive Test Measurements using Spatial Filtering*, Vehicular Technology Conference, Milan, Italy, May, 2004.

- Fredrik Gunnarsson: *Aspects of Power Control in Wireless Communications Networks*, KTH, October 6, 2004.

- Fredrik Gustafsson: *Sensorkluster, sensorfusion och virtuella sensorer*, Conference presentation at Transportforum in Linköping. January 15, 2004.

- Fredrik Gustafsson: *The particle filter with applications*, Uppsala University, January 28, 2004.

- Fredrik Gustafsson: *Particle filtering with positioning applications* and *Automotive Safety Systems*, Two plenary lectures at the 23rd Benelux meeting on Systems and Control in Helvoirt, Belgium, March 17, 2004.

- Fredrik Gustafsson: *Tutorial on sensor fusion and particle filtering*, for the EU FP5 project Matris partners in London, April 27, 2004.

- Fredrik Gustafsson: *Numerical methods for navigation*, Conference lecture at Avigen in Linköping, September 9, 2004.

- Anders Hansson: *The KYP-SDP solver KYPD*, ONERA, Toulouse, France, February 18, 2004.

- Anders Hansson: *Stability of Nonlinear Systems using Frozen Stationary Linearization*, LAAS, Toulouse, France, February 19, 2004.

- Anders Helmersson: *Reduced-order LMI-based H_∞ synthesis*, 2nd Chinese-Swedish Conference on Control, Beijing, China, October 16-17, 2004.

- Rickard Karlsson: *Model-based Statistical Tracking and Decision Making for Collision Avoidance Application*, American Control Conference, Boston, MA, USA, June, 2004

- Rickard Karlsson: *Particle Filtering in Practice – Sensor Fusion, Positioning, and Tracking*, ISIS Annual Workshop Linköping, November 4, 2004.

- Lennart Ljung: *Challanges of Nonlinear System Identification*, ICSSSP 2004, Hammamet, Tunisia, March 23, 2004.

- Lennart Ljung: *Univeristy Cooperation with Industry: Formats and Results*, DCSC Symposium: Systems and Control: Challenges in the 21st Century, Delft, The Netherlands, June 8, 2004.

- Lennart Ljung: *Identification of Nonlinear Systems: Possibilities and Problems*, Rediscover Clip'04, Cavtat, Croatia, June 16, 2004.

- Lennart Ljung: *State of the Art in Linear System Identification - Time and Frequency Domain Methods*, The American Control Conference, Boston, MA, June 30, 2004.

- Lennart Ljung: *Integrated Frequency-Time Domain Tools for System Identification* The American Control Conference, Boston, MA, July 2, 2004.

- Lennart Ljung: *Estimation of Gray Box and Black Box Models from Nonlinear Circuit Data* IFAC Symposium on Nonlinear Control Systems, NOLCOS, Stuttgart, Germany, September 1, 2004.

- Lennart Ljung: *Adaptive DWO Estimator of a Regression Function*, IFAC Symposium on Nonlinear Control Systems, NOLCOS, Stuttgart, Germany, September 3, 2004.

- Lennart Ljung: *Models and Reality*, Speech at the Acceptance of the Honorary Doctoral Degree at the Universite de Technologie de Troyes, France, September 15, 2004.

- Lennart Ljung: *Nonlinear System Identification: Possibilities and Problems* Workshop on System Identification and Data Modeling, on the occasion of the Honoris Causa, awarded to Professor Dr Lennart Ljung, Katholieke Universiteit Leuven, Belgium, Belgium, October 12, 2004.

- Lennart Ljung: *University in Cooperation with Industry: Formats and Results.* second Chinese-Swedish Workshop on Control, Beijing, China, October 17, 2004.

- Lennart Ljung: *Nonlinear System Identification: Possibilities and Problems* Tsinghua University, Beijing, China, October 19, 2004.

- Lennart Ljung: *OSIRIS, A Proposal for a VINN Excellence Center*, ISIS Workshop, Linköping, November 4, 2004.

- Mikael Norrlöf: *Position estimation of an industrial robot using accelerometers and sensor fusion techniques*, ABB Automation Technologies AB, Västerås, Sweden, March 23, 2004.

- Mikael Norrlöf: *Some challenges in industrial robot modeling and control*, Center for Dynamics of Complex Systems, Universita degli Studi di Firenze, Italy, April 13, 2004.

- Mikael Norrlöf: *Bayesian Position Estimation of an Industrial Robot using Multiple Sensors*, IEEE Conference on Control Applications, Taipei, Taiwan, September 2, 2004.

- Mikael Norrlöf: *Iterative Learning Control of a Flexible Robot Arm Using Accelerometers*, IEEE Conference on Control Applications, Taipei, Taiwan, September 3, 2004.

- Mikael Norrlöf: *Towards improved performance for industrial robots*, ISIS Workshop, Linköping University, Sweden, September 2, 2004.

- Mikael Norrlöf: *Världens noggrannaste robotstyrning*, VINNOVA Competence Center Workshop, Riksdagshuset, Stockholm, Sweden, September 17, 2004.

- Mikael Norrlöf: *Some fundamental limitations in CITE Iterative Learning Control*, Department of Automatic Control, Lund Institute of Technology, Lund, Sweden, October 28, 2004.

- Thomas Schön: *Nonlinear Estimation Using the Particle Filter*, DaimlerChrysler, Research and Technology, Powertrain Control, Stuttgart, Germany, February 13, 2004.

- Thomas Schön: *Sensor Fusion for the MATRIS Project*, BBC R&D, London, United Kingdom, April 27, 2004.

- Thomas Schön: *Particle Filter for System Identification*, Reglermötet, Göteborg, Sweden, May 26, 2004.

- David Törnqvist: *Transmission Timing — A Control Approach to Distributed Uplink Scheduling in WCDMA*, American Control Conference 2004, Boston, USA, June 30, 2004.

- Ragnar Wallin: *Efficiently solving semidefinite programs originating from the Kalman-Yakubovich-Popov lemma using general purpose SDP solvers*, Optimization and systems theory, Department of Mathematics, KTH, Stockholm, Sweden, March 12, 2004.

- Ragnar Wallin: *KYPD: A solver for semidefinite programs derived from the Kalman-Yakubovich-Popov lemma*, IEEE International Symposium on Computer Aided Control System Design, Taipei, Taiwan, September 2, 2004.

- Erik Wernholt: *On the Use of a Multivariable Frequency Response Estimation Method for Closed Loop Identification*, 43rd IEEE Conference on Decision and Control, Paradise Island, The Bahamas, December 14, 2004.

Appendix F

Publications

Licentiate Theses

[1] A. Eidehall. An automotive lane guidance system. Technical Report Licentiate Thesis no. 1122, Department of Electrical Engineering, Linköping University, SE-581 83 Linköping, Sweden, Nov 2004.

[2] M. Gerdin. Parameter estimation in linear descriptor systems. Technical Report Licentiate Thesis no. 1085, Department of Electrical Engineering, Linköping University, SE-581 83 Linköping, Sweden, Apr 2004.

[3] J. Gillberg. Methods for frequency domain estimation of continuous-time models. Technical Report Licentiate Thesis no. 1133, Department of Electrical Engineering, Linköping University, SE-581 83 Linköping, Sweden, Dec 2004.

[4] E. Wernholt. On multivariable and nonlinear identification of industrial robots. Technical Report Licentiate Thesis no. 1131, Department of Electrical Engineering, Linköping University, SE-581 83 Linköping, Sweden, Dec 2004.

Journal Papers and Book Chapters

[5] E. Geijer Lundin and F. Gunnarsson. Characterizing uplink load — concepts and algorithms. In M. Guizani, editor, *Wireless Commu-*

nications Systems and Networks, chapter 14, pages 425–441. Kluwer Academics, 2004.

[6] T. Glad, A. Helmersson, and L. Ljung. Robustness gurantees for linear control designs with an estimated nonlinear model error model. *International Journal of Robust and Nonlinear Control*, 14:959–970, Aug 2004.

[7] F. Gunnarsson. Fundamental limitations of power control and radio resource management in wireless networks. *Wireless Communications and Mobile Computing*, 4(5):579–591, Aug 2004.

[8] F. Gunnarsson. Power control in wireless networks - characteristics and fundamentals. In M. Guizani, editor, *Wireless Communication Systems and Networks*, chapter 7, pages 179–208. Kluwer Academics, 2004.

[9] O. Härkegård. Dynamic control allocation using constrained quadratic programming. *Journal of Guidance, Control, and Dynamics*, 27(6):1028–1034, Nov 2004.

[10] D. Lindgren and P. Spångéus. A novel feature extraction algorithm for asymmetric classification. *IEEE Sensors Journal*, 4(5), Oct 2004.

[11] T. McKelvey, A. Helmersson, and T. Ribarits. Data driven local coordinates for multivariable linear systems and their application to system identification. *Automatica*, 40(9):1629–1635, Sep 2004.

[12] M. Norrlöf. Disturbance rejection using an ILC algorithm with iteration varying filters. *Asian Journal of Control*, 6(3):432–438, Feb 2004.

[13] M. Norrlöf and S. Gunnarsson. A note on causal and CITE iterative learning control algorithms. *Automatica*, Apr 2004.

[14] J. Roll, A. Bemporad, and L. Ljung. Identification of piecewise affine systems via mixed-integer programming. *Automatica*, 40(1):37–50, Jan 2004.

[15] A. Stenman, F. Gustafsson, and K. Forsman. A segmentation based approach for detection of stiction in control valves. *Journal of Signal Processing and Adaptive Control*, 17(7-9), Feb 2004.

[16] L. L. Xie and L. Ljung. Variance expressions for spectra estimated using auto-regression. *Journal of Econometrics*, 118(1-2):247–256, Jan 2004.

[17] M. Åkerblad and A. Hansson. Efficient solution of second order cone program for model predictive control. *International Journal of Control*, 77(1), Jan 2004.

[18] M. Östring and S. Gunnarsson. Recursive identification of physical parameters in a flexible robot arm. *Asian Journal of Control*, 6, Feb 2004.

Conference Papers

[19] M. Amirijoo, J. Hansson, S. Son, and S. Gunnarsson. Robust quality management for differentiated imprecise data services. In *Proceedings of the 25th IEEE International Real-time systems symposium*, Lisabon, Portugal, Dec 2004.

[20] D. Axehill and A. Hansson. A preprocessing algorithm for MIQP solvers with applications to MPC. In *Proceedings of Reglermöte 2004*, Göteborg, Sweden, May 2004.

[21] D. Axehill and A. Hansson. A preprocessing algorithm for MIQP solvers with applications to MPC. In *Proceedings of the 43th IEEE Conference on Decision and Control*, pages 2497–2502, Atlantis, Paradise Island, Bahamas, Dec 2004.

[22] D. Axehill, J. Sjöberg, and K. Lindqvist. Adaptive cruise control for heavy vehicles. In *Proceedings of Reglermöte 2004*, Göteborg, Sweden, May 2004.

[23] A. Eidehall and F. Gustafsson. Combined road prediction and target tracking in collision avoidance. In *Proceedings of IEEE Intelligent Vehicles Symposium*, pages 619–624, Parma, Italy, June 2004.

[24] A. Eidehall and F. Gustafsson. Combined road prediction and target tracking in collision avoidance. In *Proceedings of IEEE Intelligent Vehicles Symposium*, pages 619–624, Parma, Italy, Nov 2004.

[25] F. Eng and F. Gustafsson. Frequency analysis using non-uniform sampling with application to active queue management, extended. In *Proceedings of Reglermöte 2004*, May 2004.

[26] F. Eng and F. Gustafsson. Frequency analysis using non-uniform sampling with application to active queue management, extended. In *Fifth conference on Computer Science and Systems Engineering, CCSSE04*, pages 147–151, Dec 2004.

[27] M. Enqvist and L. Ljung. LTI approximations of slightly nonlinear systems: Some intriguing examples. In *Proc. NOLCOS 2004 - IFAC Symposium on Nonlinear Control Systems*, Stuttgart, Germany, Sep 2004.

[28] M. Enqvist and L. Ljung. LTI approximations of slightly nonlinear systems: Some intriguing examples. In *Reglermöte 2004*, May 2004.

[29] M. Gerdin. Computation of a canonical form for linear differential-algebraic equations. In *Proceedings of Reglermöte 2004*, Göteborg, Sweden, May 2004.

[30] M. Gerdin and T. Schön. Noise modeling, state estimation and system identification in linear differential-algebraic equations. In *Fifth Conference on Computer Science and Systems Engineering*, pages 153 – 163, Norrköping, Sweden, Oct 2004.

[31] T. Glad. Step responses of nonlinear non-minimum phase systems. In *Preprints, 6th IFAC Symposium on Nonlinear Control Systems, NOLCOS 2004*, pages 1445–1449, Stuttgart, Germany, Sep 2004.

[32] C. Gronwall, T. R. Chevalier, A. Persson, M. Elmqvist, S. Ahlberg, L. M. Klasen, and P. Andersson. An overview of methods for recognition of natural and man-made objects using laser radar data. In *Proc. SPIE*, volume 5412, pages 310–320. SPIE, 2004.

[33] F. Gunnarsson, F. Gustafsson, and F. Gunnarsson. Frequency analysis using non-uniform sampling with application to active queue management. In *International Conference on Acoustics, Speech and Signal Processing, 2004*, May 2004.

[34] K. S. Gunnarsson, J. Hansson, F. Karlsson, A. Hansson, and R. Wallin. Clearance of flight control laws using linear fractional transformations. In *Proceedings of AIAA Guidance, Navigation, and Control Conference and Exhibit*, Providence, Rhode Island, Aug 2004.

[35] S. Gunnarsson and M. Norrlöf. Iterative learning control of a flexible robot arm using accelerometers. In *IEEE Conference on Control Applications*, Taipei, Taiwan, Sep 2004.

[36] A. Hagenblad, F. Gustafsson, and I. Klein. A comparison of two methods for stochastic fault detection: the parity space approach and principal component analysis. In *Proceedings of Reglermöte 2004*, May 2004.

[37] B. Hagerman, F. Gunnarsson, H. Murai, M. Tadenuma, and J. Karlsson. WCDMA uplink interference cancellation performance - field measurements and system simulations. In *Proc. Nordic Radio Symposium*, Oulu, Finland, Mar 2004.

[38] A. Hansson, A. Helmersson, and T. Glad. Stability analysis of nonlinear systems using frozen stationary linearization. In *2004 American Control Conference*, pages 424–429, Boston, Massachusetts, USA, Jul 2004.

[39] G. Hendeby and F. Gustafsson. On performance measures for approximative parameter estimation. In *Reglermöte 2004*, May 2004.

[40] D. Henrion, A. Hansson, and R. Wallin. Reduced lmis for fixed-order polynomial controller design. In *Preprints of the Sixteenth International Symposium on Mathematical Theory of Networks and Systems*, Katholieke Universiteit Leuven, Belgium, Jul 2004.

[41] T. Horney, J. Ahlberg, C. Gronwall, M. Folkesson, K. Silvervarg, J. Fransson, L. Klasen, E. Jungert, F. Lantz, and M. Ulvklo. An information system for target recognition. In *Proc. SPIE*, volume 5434, pages 163–175. SPIE, 2004.

[42] J. Jansson. Dealing with uncertainty in automotive collision avoidance. In J. Valldorf and W. Gessner, editors, *Advanced Microsystems for Automotive Applications 2004*, pages 165–175, Berlin, Germany, Apr 2004. Springer Verlag.

[43] J. Johansson, D. Lindgren, M. Cooper, and L. Ljung. Interactive analysis of time-varying systems using volume graphics. In *Proc. of the 43st IEEE Conference on Decision and Control*, Dec 2004.

[44] J. Johansson, P. Ljung, D. Lindgren, and M. Cooper. Interactive visualization approaches to the analysis of system identification data. In *Proceedings IEEE Symposium on Information Visualization*, Oct 2004.

[45] A. Juditsky, A. Nazin, J. Roll, and L. Ljung. Adaptive dwo estimator of a regression function. In *Proc. NOLCOS 2004 - IFAC Symposium on Nonlinear Control Systems*, Stuttgart, Germany, Sep 2004.

[46] R. Karlsson, J. Jansson, and F. Gustafsson. Model-based statistical tracking and decision making for collision avoidance application. In *Proceedings of the 2004 American Control Conference*, pages 1–6, Boston, MA, Jul 2004.

[47] R. Karlsson and M. Norrlöf. Bayesian position estimation of an industrial robot using multiple sensors. In *IEEE Conference on Control Applications*, Taipei, Taiwan, Sep 2004.

[48] R. Karlsson and M. Norrlöf. Sensor fusion for position estimation of an industrial robot. In *Preprints Reglermöte 2004*, Göteborg, Sweden, May 2004.

[49] R. Karlsson, T. Schön, and F. Gustafsson. Complexity analysis of the marginalized particle filter. In *Fifth Conference on Computer Science and Systems Engineering*, pages 169–173, Oct 2004.

[50] W. Lin, S. J. Qin, and L. Ljung. On consistency of closed-loop subspace identification with innovation estimation. In *Proc. 43rd IEEE Conference on Decision and Control*, page Paper WeB11.2, Paradise Island, Bahamas, Dec 2004.

[51] D. Lindgren and L. Ljung. Nonlinear dynamics isolated by delaunay triangulation criteria. In *Proc. of the 43st IEEE Conference on Decision and Control*, Dec 2004.

[52] L. Ljung. Integrated frequency-time domain tools for system identification. In *Proc of the 2004 American Control Conference*, Boston, MA, Jul 2004.

[53] L. Ljung. State of the art in linear system identification: Time and frequency domain methods. In *Proceedings of the 2004 American Control Conference*, page Paper WeM01.1, Boston, MA, Jul 2004.

[54] L. Ljung, Q. Zhang, P. Lindskog, and A. Juditsky. Modeling a nonlinear electric circuit with black box and grey box models. In *Proc. NOLCOS 2004 - IFAC Symposium on Nonlinear Control Systems*, Stuttgart, Germany, Sep 2004.

[55] M. Lundevall, J. Eriksson, F. Eng, B. Olin, N. Wiberg, and S. Wänstedt. Streaming applications over HSDPA in mixed service scenarios. In *Vehicular Technology Conference Fall. Proceedings of the IEEE*, Sep 2004.

[56] T. Schön and F. Gustafsson. Particle filters for system identification of state-space models linear in either parameters or states. In *Proceedings of Reglermöte 2004*, pages 1–6, May 2004.

[57] C. Tidestav, F. Gunnarsson, and N. Wiberg. Activity based uplink load estimation in WCDMA. In *Proc. IEEE Global Telecommunications Conference*, San Francisco, CA, USA, Nov 2004.

[58] D. Törnqvist, E. Geijer Lundin, F. Gunnarsson, and F. Gustafsson. Transmission timing — a control approach to distributed uplink scheduling in WCDMA. In *Proc. American Control Conference*, Boston, MA, USA, June 2004.

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