LINKÖPING UNIVERSITY
DIVISION OF AUTOMATIC CONTROL
ACTIVITY REPORT
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Chapter 1

Introduction

The Division of Automatic Control consists of some forty persons. We teach thirteen undergraduate courses to more than a thousand students. The courses cover both traditional control topics and more recent topics in model building and signal processing.

During 2007 Kent Hartman, our long time director of studies left the group to become a leader of the school system in our local community. Another noteworthy event was that Fredrik Gustafsson was elected to the Royal Swedish Academy of Engineering Sciences.

During 2007 three PhD theses were defended: Andreas Eidehall, Frida Eng and Erik Wernholt all finished their doctoral degrees during 2007.

Moreover, Henrik Tidefelt and Stig Moberg completed the Techn.Lic degrees.

December was a month to celebrate and remember:

- On December 7th, VINNOVA granted a 10-year horizon Industry Excellence Center LINK-SIC to the division. It comprises the Automatic Control Division, the Vehicular Systems group and 5 companies (ABB CR, ABB Robotics, GM Powertrain Sweden AB, Saab AB and Scania AB).

- On December 13th, Lennart Ljung received the IEEE Control Systems Field Award (at the 46th CDC in New Orleans, LA).

- On December 18 we learnt that the Control Systems study area, (which to 80% consists of the Automatic Control Division) was selected as one of five National Centers of Excellence in Higher Education in Sweden,
by Högskoleverket (the Swedish National Agency for Higher Education).

Figure 1.1: Lennart Ljung receives the IEEE Control Systems Award from William Gruver, IEEE Division X Director.

**Research**

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.
– *Robotics Applications*: We have a close cooperation with ABB Robotics, and several projects concern modelling and control of industrial robots.

– *Optimisation for Control and Signal Processing*: Convex optimisation 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/SEFS) and the Foundation for Strategic Research (SSF) for funding a major part of our research. The strategic research center MOVIII is funded by SSF, as well the the project VISIMOD, which was finished during 2007.

The group is coordinating a major EU project, COFCLUO, regarding clearance of flight control laws. (Coordinator Anders Hansson.)

Moreover we have EU funding for participating in the European projects MATRIS and HYCON.

**Undergraduate Education**

As can be seen in Appendix B the Division of Automatic Control has extensive education activities with a large number of courses. The teaching staff of the division is also involved in education development and management of the engineering programs within Linköping University.

**Report Outline**

In the following pages the main research results obtained during 2007 are summarised. 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.
Network Services

Mail addresses

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.

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

The VISIMOD Research Program is described in

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

and the Strategic Research Center MOVIII has the home page

http://www.moviii.liu.se
The EU-project COFCLUO has the home page

http://er-projects.gf.liu.se/~COFCLUO

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

Publications Data Base

Selecting “Publications” in our web pages gives access to our publications data base. 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). Clicking on the publication items brings you to the home page of the publication with further information. 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 .pdf format.
Chapter 2

System Identification

2.1 Introduction

Our research in system identification covers a rather wide spectrum, from general principles to particular applications. Some identification applications are described in the chapter on Robotic Applications (Erik Wernholt’s PhD thesis, and related publications), and some other results on identification of DAE models are described in the next chapter.

2.2 Nonlinear System Identification

Nonlinearity Detection

Despite the fact that nonlinearities are present to some degree in most real-life systems, linear models are still used in most industrial applications of system identification. No matter the application, validation of an estimated model is always an important step in the identification procedure. Today, it is common practise to validate linear models using a number of techniques, e.g., cross-validation, residual analysis and comparisons with nonparametric impulse or frequency response estimates. However, these standard methods cannot detect contributions from unmodeled nonlinearities in the data.

In [23], a method for nonlinearity detection based on several correlation tests is presented. Using this method, nonlinearities in a system can be detected based on one dataset and with mild assumptions on the system, model and input signal. The purpose with the correlation tests is to check...
for dependencies between the model residuals and the square or the cube of the input signal, or vice versa. Unlike many previous approaches, the proposed method seems to be applicable to a wide range of systems and input signals. It can also distinguish between even and odd nonlinearities.

**A Weighting Method for Approximate Models**

Although it might be possible to find a model structure that contains the true system in some applications, most model structures will only be able to give an approximate model. In particular, this is usually the case when the system is nonlinear. Many approximation results in nonlinear system identification concern particular signal distributions. This seems to limit the applicability of these results to cases where the relevant signals have these distributions. However, by using a weighting method that modifies the cost function used in the identification method, the available approximation results can be used also for rather general classes of signal distributions [53, 22].

The key idea in this weighting method is to use importance weights in the cost function that is minimized in the identification algorithm. The approach is illustrated with an application to Hammerstein system identification. In this case, the weighting method can be used to obtain consistent estimates of the impulse response of a Hammerstein system with a general input signal without estimating or knowing the static nonlinearity in the system.

### 2.3 Manifold Learning

In the basic regression problem

\[ y(t) = f(x(t)) + e(t) \]

it may be the case that the regression vector \( x(t) \) belongs to a high-dimensional space, e.g. if it represents an image and \( y(t) \) is a corresponding feature. Even though \( x(t) \in \mathbb{R}^n \) with a large \( n \), it may be the case that the regressors are confined to a manifold \( x(t) \in \Omega \) with a much lower dimension than \( n \).

It may then be beneficial to use that knowledge when estimating \( f \). The area of *manifold learning* is a recent research area, with roots in machine learning, where the manifold \( \Omega \) is inferred (typically by non-parametric methods) from measurements of \( x(t) \) and that knowledge is then used when forming \( f \).
In [36] techniques of manifold learning are applied to the estimation of $f$ for a variety of problems.

### 2.4 Applications to DAE Models

To estimate the parameters in a collection of differential algebraic equations is an important identification problem, that has been described in earlier annual reports. In [11] some basic results are given how to formulate the state and parameter estimation problem in a stochastic setting, with proper noise models.

Another question involving DAE models is how to relate identifiability properties of sub-models to global identifiability of the total model. That problem is discussed in [10].
Chapter 3

DAE models

DAE (differential algebraic equation) models consist of a mixture of equations with or without derivatives. They typically occur when using modern modeling tools where submodels from model libraries are put together. The individual submodels are often state space models but the interconnections add algebraic constraints. A general mathematical description is

\[
F(\dot{x}, x, u) = 0 \tag{3.1}
\]

where \(x\) is a vector of physical variables and \(u\) is a vector of inputs. Typically the vector \(x\) can be split in two set of variables, \(x_1\) and \(x_2\) so that (3.1) can be rewritten

\[
\dot{x}_1 = F_1(x_1, x_2, u, \dot{u}, ..) \tag{3.2}
\]

\[
0 = F_2(x_1, x_2, u, \dot{u}, ..) \tag{3.3}
\]

The transformation may require differentiations of some components of (3.1) which accounts for the possible presence of derivatives of \(u\). There are many structural questions for DAE models in particular when uncertainties in the original model (3.1) make different forms of (3.2), (3.3) possible. Several structural questions relating to this problem are treated in [5].

3.1 Well-posedness of models

The fact that derivatives sometimes appear in (3.2), (3.3) is often not apparent in (3.1). This is especially important in cases where \(u\) contains stochastic variables, since the derivative of a stochastic variable might not be well
defined mathematically. This leads to interesting questions regarding the well-posedness of estimation and identification problems for DAE models, a topic that is described in [11].

### 3.2 Identification

DAE models containing a parameter vector \( \theta \),

\[
F(\dot{x}, x, u; \theta) = 0
\]

can be identified in ways that are similar to those used for other types of models. In determining identifiability it could be useful to use the fact that the models have been often generated by connecting simpler submodels. In [10] it is described how several simplifications of the identifiability algorithms can be obtained by using the interconnection structure.

### 3.3 Optimal Control and Model Reduction

Model reduction for linear models can be performed using balanced realizations. The least controllable and observable states can then be removed. For nonlinear systems the corresponding calculations require the solution of optimal control problems and the associated Hamilton-Jacobi equations. In [43] this is done for DAE models using series expansion techniques. The method can be illustrated using a double pendulum.

The model is a DAE whose state space form has four state variables. A reduced nonlinear model with two state variables is compared to a linear reduced model with two state variables in figure 3.1. The reduced and full order
nonlinear models are indistinguishable while the linear model is a straight line.

The computing of practical optimal control for DAE models is often done using MPC techniques. One approach is described in [42].

3.4 Control of rigid bodies

Many control problems involve mechanical systems consisting of rigid bodies. An example is the control of aircraft. In [28] the vector equations for a rigid body are used to generate backstepping control laws. In cases where the motion does not converge to an equilibrium point many interesting phenomena occur. In [12] this is studied for a simple mechanical system: the so-called Tippe Top. The phase space of the final motion, consisting of rolling solutions is analyzed.

3.5 Properties of nonlinear step responses

Linear systems are often characterized by their step responses. In [25] explicit formulas for the settling time of nonlinear systems are presented. They are based on a transformation of the dynamics of the point of convergence to Poincaré-Dulac form.
Chapter 4

Sensor fusion

Highlights of the year are

• The PhD thesis of Frida Eng [2] and Andreas Eidehall [1], see Figure 4.1 and Sections 4.6 and 4.5, respectively.

• The scientific publications, including the journal papers [16, 7, 9, 8, 14, 11] and the conference papers [29, 32, 41, 40, 31, 30, 33, 24, 27, 37, 38, 21].

4.1 Project overview

Our research in sensor fusion covers the whole chain of problems, from sensors to applications as illustrated in Figure 4.2:

• Sensor and dynamic motion models.

Figure 4.1: The two PhD theses [2] and [1].
Sensor modeling is focused on inertial measurement units (IMU) and using cameras as sensors. The problems involve sensor error modelling, outlier detection and measurement uncertainty assessment.

Sensor-near signal processing problems needed between the sensors and the sensor fusion block are also essential.

Modeling for state estimation, including kinematic and dynamic models for the applications below. The field tests we are working on involve power measurements from received radio, acoustic, seismic and magnetic waves.

• State estimation.
  
  – Particle filtering. The theoretical research focuses on obtaining scalable and real-time algorithms for sensor fusion applications, where marginalization is the key tool.
  
  – Detection, localization and tracking in sensor networks.
  
  – Target tracking problems.

• Sensor fusion applications.
  
  – Localization and tracking The vision and mission are to position everything that moves. We have applications to aircraft, rockets, cars, surface ships, underwater vessels, film cameras, cellular phones and industrial robots. One leading theme is to consider cameras and Geographical Information Systems (GIS) as standard sensors in sensor fusion. A technical driver is to backup, support or replace GPS in critical integrated navigation systems. In some cases, the (Extended) Kalman filter is used in our application, but in particular when GIS are used, the particle filter and marginalized particle filter mentioned above are applied.
  
  – Simultaneous localization and mapping (SLAM). Our goal is to develop full 3D SLAM running on UAVs (SAAB, FOI).
  
  – Situation awareness and detection algorithms. In particular, collision mitigation and avoidance systems for cars (Volvo) and aircraft (SAAB).
The current funding comes from Swedish Research Council (VR), MOVIII (SSF excellence center), NFFP decisions based on uncertain data, NRFP fusion of IMU and GPS in rockets, ARCUS (TAIS) path planning of UAVs, FOCUS (Vinnova institute excellence centre): sensor networks, IVSS Sensor Fusion Systems.

4.2 Modeling

Algorithms and analysis of how to downsample non-uniformly sampled data is described in [21], and in the thesis overviewed in Section 4.6. The application in mind is a wheel speed sensor, measuring the time between individual cogs in a cogged wheel, and the goal is to compute the wheel speed signal with a moderate sampling rate.

The Harris detector is a standard tool in computer vision for detecting corners in images. In sensor fusion applications where the camera is seen as a sensor of objects and landmarks, each detected feature should have an associated covariance matrix. This is a nonstandard problem in the computer vision community. In [37], a statistical derivation of the covariance matrix is presented.

Estimation of AUV dynamics using field test data for sensor fusion applications is treated in [24]. The NLS algorithm is applied to the unknown parameters in the state space models for the yaw dynamics of the AUV, and a Kalman filter is used to provide predictions of the measured data.
4.3 State estimation

4.3.1 Particle filtering

The current projects include

- Our contributions to the marginalized particle filter is thoroughly over-viewed in previous publications. As a general tool, it has the potential of increasing estimation accuracy and reducing computational complexity at the same time. A new formulation of MPF/RBPF is given in [31]. The MPF theory has been applied to the SLAM problem, providing a general framework for SLAM applicable to general motion models [40]. A related marginalization idea for speeding up the PF in case of multi-rate sensors is presented in [41].

- One of the most important instruments for tuning the PF is the process noise covariance. This is by practitioners increased to mitigate sample impoverishment, and the procedure is called jittering or roughening with a quite vague theoretical justification. Risk sensitive particle filters [38] offers a sound theoretical ground where the outcome is the same, the covariance is increased, and the interpretation is that a certain risk criterion is modified.

- A software environment for target tracking is presented in [29].

- A novel convergence proof of the particle filter is presented in [32, 33]. The important contribution is that one strong condition in previous work is relaxed. The implication is that the convergence proof now holds for the state itself, not only bounded functions of the state.

- One of the world’s first implementations of a complete PF on a graphical processing unit (GPU) is reported in [30].

- Particle filters for differential algebraic equations pose a quite specific problem as described in the theses [11]. Basically, DAE:s appear from physical modeling, and in this context no process noise is usually included. However, for filtering by for instance the particle filter, certain process noise is needed for model errors, actuator noise and roughening of the filter. What is specific with DAE:s is that noise in certain subspaces correspond to non-causality, and the contribution is a contrutive way to determine in what subspace the state noise may reside.
4.3.2 Sensor networks

Localization of vehicles in sensor networks with acoustic, seismic and magnetic sensors is presented in [27]. The idea is that the received signal powers are compared, and a model that describes the logarithmic power as a linear function of logarithmic range is proposed.

4.4 Applications

Sensor fusion for augmented reality applications was performed in a EU project (Matris). The paper [16] presents the sensor fusion framework, and [7] gives a general project overview.

4.4.1 Decision support with uncertain data

Fault detection and situation awareness are two key areas between sensor fusion algorithms and higher level decision support systems.

The mathematical tools in fault detection literature is heavily biased to algebraic methods, and stochastic approaches are rare. A survey of existing work, and a novel framework for stochastic approaches to fault detection is presented in the survey paper [14].

Applications of sensor fusion to automotive collision avoidance systems are presented in [9, 8], and in the thesis overviewed in Section 4.5.

4.5 PhD: Tracking and threat assessment for automotive collision avoidance

The PhD thesis of Andreas Eidehall [1] is concerned with automotive active safety, and a central theme is a new safety function called Emergency Lane Assist (ELA). Automotive safety is often categorised into passive and active safety, where passive safety is concerned with reducing the effects of accidents and active safety aims at avoiding them. ELA detects lane departure manoeuvres that are likely to result in a collision and prevents them by applying a steering wheel torque. The ELA concept is based on traffic accident statistics, i.e., it is designed to give maximum safety based on information about real life traffic accidents. The ELA function puts tough requirements on the
accuracy of the information from the sensors, in particular the road shape and the position of surrounding objects, and on robust threat assessment. Several sensor fusion and signal processing methods have been developed and evaluated in order to improve the accuracy of the sensor information, and these improvements are also analysed in how they relate to the ELA requirements. Different threat assessment methods are also studied, and a common element in both sensor fusion and threat assessment is that they are based on driver behaviour models, i.e., they utilise the fact that depending on the traffic situation, drivers are more likely to behave in certain ways than others. Most of the methods are general and can be, and hopefully also will be, applied also in other safety systems, in particular when a complete picture of the vehicle surroundings is considered, including information about road and lane shape together with the position of vehicles and infrastructure. All methods in the thesis [1] have been evaluated on authentic sensor data from actual and relevant traffic environments.

The ELA system developed within the thesis has been tested in a demonstrator, see Figure 4.3 for an illustration of a typical ELA intervention. People who used the system generally reacted very positively reactions. Many of the drivers felt that the intervention was very gentle and not at all dramatic. Even drivers who were afraid before the test drive that the intervention would be very dramatic agreed on this. Since the system brings the car back into the safe lane and leaves it in a safe position, it generally gives the driver a positive feeling of security.
4.6 PhD: Non-Uniform Sampling in Statistical Signal Processing

Non-uniform sampling comes natural in many applications, due to for example imperfect sensors, mismatched clocks or event-triggered phenomena. Examples can be found in automotive industry and data communication as well as medicine and astronomy. Yet, the literature on statistical signal processing to a large extent focuses on algorithms and analysis for uniformly, or regularly, sampled data. This work focuses on Fourier analysis, system identification and decimation of non-uniformly sampled data. In non-uniform sampling (NUS), signal amplitude and time stamps are delivered in pairs. Several methods to compute an approximate Fourier transform (AFT) have appeared in literature, and their posterior properties in terms of alias suppression and leakage have been addressed. In the thesis [2], the sampling times are assumed to be generated by a stochastic process, and the main idea is to use information about the stochastic sampling process to calculate a priori properties of approximate frequency transforms. These results are also used to give insight in frequency domain system identification and help with analysis of down-sampling algorithms.

The main result gives the prior distribution of several AFTs expressed in terms of the true Fourier transform and variants of the characteristic function of the sampling time distribution. The result extends leakage and alias suppression with bias and variance terms due to NUS. Based on this, decimation of non-uniformly sampled signals, using continuous-time anti-alias filters, is analyzed. The decimation is based on interpolation in different domains, and interpolation in the convolution integral proves particularly useful. The same idea is also used to investigate how stochastic unmeasurable sampling jitter noise affects the result of system identification. The result is a modification of known approaches to mitigate the bias and variance increase caused by the sampling jitter noise.

The bottom line is that, when non-uniform sampling is present, the approximate frequency transform, identified transfer function and anti-alias filter are all biased to what is expected from classical theory on uniform sampling. This work gives tools to analyze and correct for this bias.
Chapter 5

Robotics

5.1 Introduction

The research within the robotics area is to a large extent carried out in cooperation with ABB Robotics. The collaboration with ABB is a result of the competence center ISIS (Information Systems for Industrial Control and Supervision) which was supported by VINNOVA until 2005. The research during 2007 was mainly supported by the Swedish Research Council (VR). The overall aim of the work is to study and develop methods for improvement of the performance of robot control systems.

During the year Erik Wernholt defended his PhD thesis [3], and Stig Moberg presented his licentiate thesis [4].

5.2 Modeling and identification

An industrial robot represents a challenging task for system identification since it is a multivariable, nonlinear system operating in closed loop. In Erik Wernholt’s PhD thesis [3], a three-step procedure is proposed, based on intermediate nonparametric estimates of the frequency response function (FRF) in a number of operating points. The starting point then is a physically parameterized nonlinear grey-box model,

\[ \dot{x}(t) = f(x(t), u(t), \theta), \]  
\[ y(t) = h(x(t), u(t), \theta), \] (5.1)
of a six degrees-of-freedom industrial robot containing mechanical elasticities. Here, \( x(t) \) is the state vector, \( u(t) \in \mathbb{R}^{n_u} \) and \( y(t) \in \mathbb{R}^{n_y} \) the input and output vectors, \( \theta \) the parameter vector, and \( f(\cdot) \) and \( h(\cdot) \) are nonlinear functions that describe the dynamics. In the model some of the physical parameters are known a priori and some parameters, in particular the stiffness and damping of the elasticities, are to be determined by system identification.

The first step in the procedure is the selection of optimal operating points, i.e. positions and orientations of the robot tool. Given a nonlinear gray-box model (5.1), the information about the unknown parameters will vary depending on the operating point. Therefore, given a limited total measurement time, one should perform experiments around the operating point(s) that contribute the most to the information about the unknown parameters. In [47], this problem is formulated as a convex optimization problem by using a set of candidate operating points, obtained by gridding the workspace. It is also shown that the experiment design is efficiently solved by considering the dual problem. Given thousands of candidates, only a few operating points are selected in the optimum.

In the second step, the multivariable nonparametric FRFs are estimated. Several methods for nonparametric FRF estimation exist and a number of them are analyzed in the thesis as well as in [46]. The simplest version is to perform \( n_u \) experiments and calculate the estimate from the DFT matrices \( Y(\omega_k) \in \mathbb{C}^{n_y \times n_u} \) and \( U(\omega_k) \in \mathbb{C}^{n_u \times n_u} \) like

\[
\hat{G}(e^{j\omega_k T_s}) = Y(\omega_k)U^{-1}(\omega_k),
\]

where each column of \( Y(\omega_k) \) and \( U(\omega_k) \) contain the DFT of the sampled data from each experiment. To obtain accurate estimates, it is crucial to use a good excitation signal. In the multivariable case, so-called orthogonal random phase multisine signals are used, which are periodic signals with certain properties that guarantee that \( U(\omega_k) \) is invertible and well conditioned. Another benefit from using multisine signals is that they enable quantification of the modeling errors that appear due to nonlinearities in the system. Such analysis is also carried out in the thesis.

In the third and final step, the optimal parameters are obtained by minimizing a criterion involving the difference between the estimated nonparametric FRFs and linearized approximations of the nonlinear grey-box model in the selected operating points. Different parameter estimators are compared, where the weighted logarithmic least squares estimator turns out to
Figure 5.1: Estimated nonparametric FRF (thin line, with one standard deviation shaded) and the FRF of the resulting gray-box model (thick line) in one of the positions. Input: 6 motor torques, output: 6 motor accelerations.

give the best result. Figure 5.1 illustrates the result by showing the magnitude of the estimated nonparametric FRF and the best parametric model for one of the positions. The identified model gives a good global description of the dynamics in the frequency range of interest.

5.3 Model based control

The performance requirements, in terms of cycle time and accuracy, of modern industrial robots require well designed control methods based on accurate dynamical models. Robot manipulators are traditionally described by the flexible joint model or the flexible link model. These models only consider elasticity in the rotational direction of each robot joint. When these models are used for control or simulation, the accuracy can be limited due to the model simplifications, since a real manipulator has a distributed flexibility in all directions. Stig Moberg’s licentiate thesis [4] treats various aspects of control and identification using a more general model, called the extended flexible joint model, see Figure 5.2. One of the topics is feed-forward control for this extended model. Feed-forward control requires the inverse dynamics
Figure 5.2: One example of an extended flexible joint model. The model has three actuated joints, two non-actuated joints, and eight degrees-of-freedom.

solution and in [88], an inverse dynamics method based on the solution of a high-index differential algebraic equation (DAE), is suggested.

Since an industrial robot typically carries out operations repeatedly this can be utilized in order to iteratively improve the accuracy of the control system. This control method, denoted iterative learning control (ILC), is discussed in [13] and [44]. In the first paper it is illustrated how an accelerometer can be used in an ILC algorithm when controlling a system containing mechanical elasticities. The second paper presents results from experiments using a six degrees-of-freedom commercial robot where a heuristically designed ILC algorithm is applied with the following updating structure

$$u_{k+1}(t) = Q(q)\left(u_k(t) + L(q)e_k(t)\right)$$

The filter $Q$ is chosen as a low-pass Butterworth filter, applied to give zero-phase characteristics. The filter $L$ is $L(q) = \gamma q^\delta$, which gives a learning gain $\gamma$ times a noncausal time shift of the error $e_k$. The ILC algorithm uses motor angle references and the available motor angle measurements from the robot to update the ILC control signal. The results are evaluated on the motor side where a substantial error reduction can be observed after only five iterations. The evaluation is done with respect to design parameters in the ILC algorithm but also the working point and programmed velocity is considered.
Chapter 6

Optimization for Control and Signal Processing

6.1 Introduction

The research in optimization for control and signal processing is currently focused on optimization modelling, optimization algorithms for robustness and stability analysis of control systems, and on model predictive control.

6.2 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 polytopic linear differential inclusions.

Typically standard SDP solvers cannot handle problems of more than small to medium size in reasonable time, typically the limit is about 50 state-variables, resulting in roughly 1000 optimization variables. The computational complexity stems from the cost of assembling and solving the equations for the search directions in the IP algorithms. The key to an efficient implementation is to use an infeasible IP method where the search directions are not computed exactly. A convergence proof for such an algorithm is presented in [59].

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6.3 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 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. Different relaxations have been investigated, and a quadratic programming solver has been tailored to the quadratic programming relaxations. The results are presented in [49, 50, 20, 19].

6.4 Optimization modelling

An important part of optimization based control and systems theory is easily used tools and frameworks for algorithm development. The optimization modelling language YALMIP, implemented as a free MATLAB toolbox, has been continuously developed and extended during the year. The current focus in the development is geared towards robust optimization with applications in Model Predictive Control. However, the toolbox is also used in completely different scenarios, such as experiment design [112] and machine learning [18].
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 and an IFAC Advisor, and associate editor of several journals. He has received honorary doctor’s degrees from the Baltic State Technical University in St. 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 is Professor of Nonlinear Control Systems in the department. He 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 in the department. His research interests include Nonlinear Systems, algebraic aspects of System Theory and Optimal Control.

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Svante Gunnarsson is Professor in the Control group, and 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 robotics, system identification, and iterative learning control.

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Fredrik Gustafsson is Professor in Sensor Informatics at Department of Electrical Engineering, Linköping University, since 2005. He was born in 1964 and he received the M.Sc. degree in electrical engineering 1988 and the Ph.D. degree in Automatic Control, 1992, both from Linköping University. During 1992-1999 he held various positions in automatic control, and in 1999 he got a professorship in Communication Systems. His research interests are in statistical signal processing, adaptive filtering and change detection, with applications to vehicular, airborne, communication and audio systems. He was associate editor for IEEE Transactions of Signal Processing 2000-2006 and is currently associate editor for EURASIP Journal on Applied Signal Processing and International Journal of Navigation and Observation.

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Anders Hansson is a Professor in the Control group, and he 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 was an associate professor at the Division of Automatic Control, Linköping University. From 2006 he is professor at the same division. He was associate editor of IEEE Transactions on Automatic control 2006-2007. His research interests are applications of optimization to control and signal processing.
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Mille Millner 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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**Anders Helmersson** is an Adjunct Professor at the Division of Automatic Control. He was born in 1957. In 1981, he received his M. Sc. in Applied Physics at Lund Institute of Technology. He has been with Saab 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 RUAG Aerospace Sweden AB (formerly Saab Space).

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**Alf Isaksson** is an Adjunct Professor at the Division of Automatic Control. He was born in 1959, and he received his M. Sc. in 1983, his Lic. Eng. in 1986 and his Ph. D. in 1988, all from Linköping University. He is currently employed by ABB AB.

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**Inger Klein** is an 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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Kent Hartman is a Junior Lecturer (universitetsadjunkt) in the Control Group. He was born in 1951, and received his M. Sc. in 1977 Applied Physics and Electrical Engineering at Linköping University, Department of Biomedical Engineering. He has been Director of Studies since 2000.
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Anna Hagenblad is a Junior Lecturer in the Control Group. She was born in Lycksele, Sweden, in 1971, and 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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Fredrik Gunnarsson is an Adjunct Lecturer in the division. He 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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Mikael Norrlöf is a Research Assistant in the Control Group. He was born in 1971. He received his M. Sc. in Computer Science and Engineering 1996, his Lic. Eng. in 1998, his Ph. D. in 2000 and he became Docent in 2005, all at Linköping University. In 2007 Mikael became an employee at ABB Robotics in Västerås and works part time at ABB and LiU. His current research interests include Iterative Learning Control, modeling, nonlinear control, trajectory generation, sensor fusion applications, and identification of industrial robots.
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Johan Löfberg is the Director of Studies since August 2007 and a Research Assistant in the Control Group, and he was born in 1974. He received his M.Sc. in Mechanical Engineering in 1998 and his Lic.Eng. in 2001 and his PhD in 2003 all at Linköping University. During 2003 - 2006 he was employed as a post doctoral fellow at ETH, Zürich. His research interests are mainly within the area of optimization and model predictive control.
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Jacob Roll is a Research Assistant in the Control Group. He was born in 1974. He received his M. Sc. in Applied Physics and Electrical Engineering in 1999 and his Lic. Eng. in 2001 and his Ph. D. in 2003 all at Linköping University. His research interests are in system identification and hybrid systems.
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Rickard Karlsson is a Research Assistant in the Division of Automatic Control, and he was born in 1970. He received his M. Sc. in Applied Physics and Electrical Engineering in 1996, his Lic. Eng. in 2002 and his Ph. D. in 2005 all at Linköping University.
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Martin Enqvist is a Research Assistant in the Control Group. He was born in 1976 and received his M. Sc. in Applied Physics and Electrical Engineering in 2000, his Lic. Eng. in 2003 and his Ph. D. in 2005 all at Linköping University. During 2006, he was employed as a postdoc researcher at Vrije Universiteit Brussel in Belgium. His research interests are mainly within the area of system identification.
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Ragnar Wallin is a Research Assistant at the department. He was born in 1962. He received his M. Sc. in Electrical Engineering in 1998 and his Lic. Eng. in 2000 both from the Royal Institute of Technology, Stockholm and his Ph. D. in 2005 at Linköping University. His research interests are in optimization algorithms, mainly for gain scheduling applications.
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Thomas Schön is a research associate at the department. He was born in 1977. He received the Ph. D. degree in Automatic Control in 2006, the M. Sc. degree in Applied Physics and Electrical Engineering in 2001 and the B. Sc. degree in Business Administration and Economics in 2001, all from Linköping University, Linköping, Sweden. He has held visiting positions at the University of Cambridge (UK) and the University of Newcastle (Australia). His research interests are mainly within the areas of sensor fusion, signal processing and system identification, with applications mainly to the automotive and aerospace industry.

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Erik Wernholt is a researcher associated with the Control Group. He was born in 1975. He received his M. Sc. in Applied Physics and Electrical Engineering in 2001, his Lic. Eng. in 2004 and his Ph. D. in 2007, all at Linköping University. His research interests are in system identification, mainly for industrial robots.

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**Umut Orguner** is a postdoctoral associate at the Division of Automatic Control. He was born in 1977. He received B. Sc., M. Sc. and Ph. D. degrees all in electrical engineering from Middle East Technical University, Ankara, Turkey in 1999, 2002 and 2006 respectively. Between 1999 and 2007, he was with the Department of Electrical and Electronics Engineering of the same university as a teaching and research assistant. His research interests include estimation theory, multiple-model estimation, target tracking and information fusion.
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**Christos Papagiorgiou** was a postdoc during 2007 and the first half of 2008.
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**Xiao-Li H** was a postdoc at the Division from August 2006 - August 2007.
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Sören Hansson is employed as research engineer at the Division on a part time basis, where he is responsible for the laboratory equipment.
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Ulla Salaneck is the secretary for the control group.
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Visitors

Kjell-Magne Fauske  Ph.D. student at the Norwegian University of Science and Technology (NTNU) and the University graduate center (UniK), located at Kjeller, from visited the division from October 2006 to March 2007.
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. 141 participants. Lecturer: Johan Löfberg.


  I Industrial Engineering and Management. 147 participants. Lecturer: Svante Gunnarsson.

TB, KB Engineering Biology and Chemical Biology Programs. 85 participants. Lecturer: Thomas Schön.

• **Control Theory I** (Reglerteori I) For the Industrial Engineering and Management and Mechanical Engineering Programs. Multivariable systems, Sampled data systems, LQG-control. 4 participants. Lecturer: Torkel Glad.

• **Automatic Control M, advanced course** (Reglerteknik, fortsättningskurs M). For the Mechanical Engineering Program. Multivariable systems, Nonlinear systems, Signal processing. 15 participants. Lecturer: Svante Gunnarsson.


• **Modelling and Simulation** (Modellbygge och Simulering). For the Applied Physics and Electrical Engineering program. Physical system modelling, Bond graphs, Identification methods, Simulation. 89 participants. Lecturer: Jacob Roll.

• **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. 70 participants. Lecturer: Martin Enqvist.

• **Real Time Process Control** (Realtidsprocesser och reglering). For the Information Technology Program. Real time systems. PID control. 20 participants. Lecturer: Inger Klein.

• **Linear Feedback Systems** (Återkopplade linjära system). For the Information Technology Program. Linear systems, controllability, observability, feedback control. 20 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, 67 Participants. Lecturer: Anders Hansson.
• Introduction to MATLAB (Introduktionskurs i MATLAB). Available for several Engineering Programs. 540 participants. Lecturer: Ragnar Wallin/Anna Hagenblad.

• 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, 12 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, 19 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, 64 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, 64 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 and Ragnar Wallin.

B.2 Graduate Courses

• Sensor fusion Lecturer: Fredrik Gustafsson

• Process Control Lecturer: Alf Isaksson Literature: Lecture Notes.


• Non-linear systems. Lecturer: Torkel Glad. Literature: Lecture notes.
Appendix C

Seminars


• *Model-based decision support for integrated management of coastal lagoons.* Simone Paoletti, Universita’ degli Studi di Siena, Siena, Italy. February 8, 2007.


• *Active vehicle safety system design and verification in driving.* Jonas Jansson, VTI. October 25, 2007.

• *ARMA system identification methods based on matching of covariances, cepstrum and Markov parameters* Per Enqvist, Royal Institute of Technology, Stockholm. November 1, 2007.


• *Graph-Based Control of Heterogeneous Robot Networks: From Controllability to Optimal Control.* Magnus Egerstedt, Georgia Institute of Technology. November 15, 2007.


Appendix D

Travels and Conferences

Daniel Axehill participated in the 7th IFAC Symposium on Nonlinear Control Systems, Pretoria, South Africa, August 22–24 and in the 46th IEEE Conference on Decision and Control, New Orleans, USA, December 12–14.

Martin Enqvist participated in the IEEE Instrumentation and Measurement Technology Conference, Warsaw, Poland, May 1–3; the 16th ERNSI Workshop on System Identification, Venice, Italy, October 1–3; and the 46th IEEE Conference on Decision and Control, New Orleans, USA, December 12–14.

Torkel Glad participated in the 7th IFAC Symposium on Nonlinear Control Systems, Pretoria, South Africa, August 22–24.


Fredrik Gustafsson attended the conference on Information Fusion, Quebec, July.

Anders Hansson participated in the European Control Conference, Kos, Greece, July 2-5.

Lennart Ljung participated in the microsymposium on System Identification at VUB, Brussels, February 27-28, and visited Reading University May 31 - June 1. He participated in the 16th ERNSI Workshop in Venice, Italy on October 1–3 and in the Fest for Georgio Picci in Venice, October 4 – 5. On November 7 – 8 he took part in the Data Driven Modelling Workshop at VUB in Brussels, and December 11 – 15 he was at the 46th CDC in New Orleans.

Christian Lyzell participated in the 16th ERNSI Workshop on System Identification, Venice, Italy, October 1–3.

Johan Löfberg participated in the Second Mathematical Programming Society International Conference on Continuous Optimization, Hamilton, Canada, August 13-17. He also participated and co-organized a workshop on Model Predictive Control at the 16th International Conference on Process Control, Slovakia, June 11-14.

Stig Moberg participated in the IEEE International Conference on Robotics and Automation, Roma, Italy. April 10–14.

Mikael Norrlöf visited Lund Institute of Technology, Lund, Sweden, April 4, when he was member of examination board for the dissertation, "High-Speed Vision and Force Feedback for Motion-Controlled Industrial Manipulators" by Tomas Olsson, Department of Automatic Control.

Henrik Ohlsson participated in the 7th IFAC Symposium on Nonlinear Control Systems, Pretoria, South Africa, August 22–24; and the 16th ERNSI Workshop on System Identification, Venice, Italy, October 1–3.

Umut Orguner participated in the IEEE Statistical Signal Processing Workshop (SSP’07), Madison, WI, August 26–29.

Jacob Roll participated in the 10th International Conference on Hybrid Systems: Computation and Control, Pisa, Italy, April 3-5, in the 16th ERNSI Workshop on System Identification, Venice, Italy, October 1-3, and in the 46th IEEE Conference on Decision and Control, New Orleans, USA, December 12-14.
Ulla Salaneck participated in the ‘Rikssekreterarmötet’ in Budapest, Hungary, September 21–24 and the 16th ERNSI Workshop on System Identification, Venice, Italy, October 1–3.

Thomas Schön participated in the 7th IFAC Symposium on Nonlinear Control Systems, Pretoria, South Africa, August 22–24; the 16th ERNSI Workshop on System Identification, Venice, Italy, October 1–3; and the 46th IEEE Conference on Decision and Control, New Orleans, USA, December 12–14; the Prevent Workshop, Paris, France, March 14-15. He visited Volvo Technology, Göteborg, Sweden, January 15; the Department of Mathematics at the Royal Institute of Technology, Stockholm, Sweden, October 22; Volvo Technology, Göteborg, Sweden, November 6.

Johan Sjöberg participated in the 7th IFAC Symposium on Nonlinear Control Systems, Pretoria, South Africa, August 22–24;

Henrik Tidefelt attended the 7th IFAC Symposium on Nonlinear Control Systems, Pretoria, South Africa, August 22–24.

David Törnqvist visited Australian Centre for Field Robotics (ACFR), University of Sydney, Australia, January–April; visited Center for Collaborative Control of Unmanned Vehicles (C3UV), University of California, Berkeley, CA, USA, July–August.


Erik Wernholt participated in the 46th IEEE Conference on Decision and Control, New Orleans, USA, December 12–14.
Appendix E

Lectures by the Staff


- Torkel Glad: *Computing the settling time for nonlinear step responses*, 7th IFAC Symposium on Nonlinear Control Systems (NOLCOS), Pretoria, South Africa, August 22.

- Svante Gunnarsson: *Large-Scale Use of the CDIO Syllabus in the Formulation of Program and Course Goals*, 4th International CDIO Con-
• Fredrik Gustafsson: *A Marginalized Particle Filtering Framework for Simultaneous Localization And Mapping (SLAM)* Conference on Information Fusion, Quebec, July.

• Fredrik Gustafsson: *Localization in Sensor Networks Based on Log Range Observations* Conference on Information Fusion, Quebec, July.


• Fredrik Gustafsson: *Modeling for Kalman filtering is very different from identification for control*, ERNSI Workshop, Stockholm, October 1.


• Lennart Ljung: *Global Identifiability of Complex Models, Constructed from Simple Submodels*, Picci Fest, Venice, October 4.


• Henrik Ohlsson: *How manifold learning can be used in nonlinear identification*, ERNSI Workshop, Venice, Italy, October 3.

• Thomas Schön: *A Basic Convergence Result for Particle Filtering*, 7th IFAC Symposium on Nonlinear Control Systems (NOLCOS), Pretoria, South Africa, August 22.

• Thomas Schön: *New Convergence Results for Particle Filters*, ERNSI Workshop, Venice, Italy, October 3.

• Thomas Schön: *An Introduction to the Particle Filter and Its Applications*, Department of Mathematics, Royal Institute of Technology, Stockholm, Sweden, October 22.


• Thomas Schön: *A Robust Particle Filter for State Estimation - with Convergence Results*, 46th IEEE Conference on Decision and Control (CDC), New Orleans, LA, USA, December 12.


• David Törnqvist: *Navigation Research in Linköping*, Univeristy of Sydney, Australia, February.

• David Törnqvist: *Particle Filters and Simultaneous Localization and Mapping*, University of California, Berkeley, CA, USA, July 6.

• Johanna Wallén: *Experimental evaluation of ILC applied to a six degrees-of-freedom industrial robot*, European Control Conference, Kos, Greece, July 4.


• Erik Wernholt: *Experiment Design for Identification of Nonlinear Gray-Box Models with Application to Industrial Robots*, 46th IEEE Conference on Decision and Control, New Orleans, USA, December 14.


Appendix F

Publications

Phd Theses


Licentiate Theses


**Journal Papers and Book Chapters**


**Conference Papers**


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Appendix G

Technical Reports


[52] F. Eng, F. Gustafsson, and F. Gunnarsson. Frequency domain analysis of signals with stochastic sampling times. Technical Report LiTH-ISY-R-2772, Department of Electrical Engineering, Linköping University,


E. Wernholt and J. Löfberg. Experiment design for identification of nonlinear gray-box models with application to industrial robots. Technical Report LiTH-ISY-R-2774, Department of Electrical Engineering,


Appendix H

Master’s Theses


