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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.

As highlights for 2008 could be mentioned:

- The following four PhD-students defended their doctoral theses: Daniel Axehill, Gustaf Hendeby, Johan Sjöberg and David Törnqvist

- In addition, the following people completed their licentiate’s degrees: Johanna Wallén, Janne Harju Johansson, Jeroen Hol and Henrik Ohlsson

- On January 25, The Control Systems study area (which to 80% consists of the Automatic Control division) received the award as one of five National Centers of Excellence in Higher Education in Sweden by Högskoleverket (the Swedish National Agency for Higher Education)

- On April 2, Lennart Ljung receives an honorary doctorate from the Helsinki Institute or Technology.

- On June 18, The CADICS (Control, Autonomy, and Decision-making in Complex Systems) Linnaeus excellence center - of which the Automatic Control group is a member - was awarded funding for 10 years by the Swedish Research Council (VR) as one of twenty prominent Swedish research environments. The coordinator for CADICS is Lennart Ljung.
Figure 1.1: Svante Gunnarsson receives the Higher Education Award from Anders Flodström, The University Chancellor. In the background, Mille Millnert, the president of Linköping University.

Figure 1.2: Lennart Ljung is promoted to Doctor of Technology, h.c., at Helsinki Institute of Technology.
• The Swedish Foundation for Strategic Research (SSF) has granted money for a Center for integrated optimal planning and control in process industry: PIC-LI. The Automatic Control group is one of the partners involved in the project. The Program Director of PIC-LI is Alf Isaksson.

• In September the group hired two new University Lecturers, Martin Enqvist and Thomas Schön.

• On November 10, the VINNOVA Industry Excellence Center LINK-SIC had its kick-off workshop. LINK-SIC (Linköping Center for Sensor Informatics and Control) has been granted funding with a 10 year horizon from Vinnova and several companies. The center will be organized around the Automatic Control and Vehicular Systems research groups and the research projects involve five industrial partners: ABB Corporate Research, ABB Robotics, GM Powertrain Sweden AB, Saab AB and Scania AB.

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 applications 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) and the Foundation for Strategic Research (SSF) for funding a major part of our research. The strategic research center MOVIII is funded by SSF. The Linnaeus center CADICS is funded by VR and the Industry Excellence Center LINK-SIC is funded by Vinnova and industry.

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 2008 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 database 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 addresses to our main web page, as well as the web pages for the major centers are:

- [http://www.control.isy.liu.se](http://www.control.isy.liu.se)
- [http://www.moviii.liu.se](http://www.moviii.liu.se)
- [http://www.cadics.isy.liu.se](http://www.cadics.isy.liu.se)
- [http://www.linksic.isy.liu.se](http://www.linksic.isy.liu.se)
- [http://www.liu.se/pic](http://www.liu.se/pic)
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, and some in the chapter on Sensor Fusion.

A major event in System Identification was the plenary talk at the IFAC World Congress in Seoul, by Lennart Ljung, [51].

2.2 Nonlinear System Identification

Narx Models and ANOVA

As reported in earlier annual reports, the Analysis of Variance is a quite powerful methods to select regressors in nonlinear models of NARX-type. A complication is that with many potential regressors, the number of requires tests increases very rapidly. In [20] a procedure, TILIA, is suggested to organise these tests in an effective manner.

Block-structured Models

Many nonlinear systems can be described, at least approximately, using block-structured models. These types of models consist of interconnected linear time-invariant submodels and static nonlinearities and have been studied
for a long time in the system identification community. In [19], a procedure for structure identification of some block-oriented systems is proposed. By using dedicated experiments where either the power or the frequency content of the input signal is varied, it is possible to distinguish a number of common system structures.

An advantage with block-structured models is that the imposed structure reduces the number of parameters in the model. However, it can still be a challenging problem to obtain accurate initial estimates of these parameters. In [25], mean-square error optimal approximations of two interconnected Wiener systems are investigated. The result can be used to generate initial estimates for the linear submodels in Wiener-Hammerstein models.

**Wiener Models**

A Wiener model is a linear dynamical system followed by a static nonlinearity:

\[
z(t) = G(q, \theta)u(t) + v(t)
\]

\[
y(t) = f(z(t), \theta) + e(t)
\]

Here \(y\) and \(u\) are measured and the problem is to estimate \(\theta\). Such models have been discussed extensively in the literature, and many methods for estimating \(\theta\) have been suggested. Mostly, in the literature, then the “process noise” \(v(t)\) has been ignored. (Or in some cases, the measurement noise \(e(t)\) has been ignored). The most common method is the *output error* method:

\[
\hat{\theta} = \arg \min \sum \|y(t) - f(G(q, \theta)u(t), \theta)\|^2
\]

It is shown in [16] and [39] that this method generally leads to biased estimates in case process noise is present. An example is shown in figure 2.1.

The true maximum likelihood method can be derived for the model with process noise. It involves explicit integration over the pdf of \(e\), but can still be effectively implemented. The result is unbiased, as seen in Figure 2.2. When the process noise \(e\) is coloured the true maximum likelihood method becomes more difficult to implement efficiently. However, tests show that the results from the ML algorithm for white \(e\) still produce unbiased estimated in the coloured case.
Figure 2.1: 1000 estimated nonlinearities $f$ with the output error method. The true one is the thick line.

Figure 2.2: 1000 estimated nonlinearities $f$ with the maximum likelihood method. The true one is the thick line.
Identifying Nonlinear State-Space Models Using EM

The paper [80] considers the problem of identifying the parameters $\theta$ in the following relatively general class of nonlinear state-space models

\begin{align}
x_{t+1} &= f_t(x_t, u_t, \theta) + g_t(x_t, u_t, \theta)v_t, \\
y_t &= h_t(x_t, u_t, \theta) + e_t.
\end{align}

A Maximum Likelihood (ML) framework is employed, and it is illustrated how an Expectation Maximisation (EM) algorithm may be used to compute these ML estimates. The EM algorithm consists in two steps. First, the expectation step, where $Q(\theta, \theta') = E_{\theta'}\{\log p_\theta(X_N, Y_N)|Y_N\}$ is computed. Second, the maximisation step, where the new parameter estimate $\theta_{k+1}$ is computed by solving $\theta_{k+1} = \arg \max Q(\theta, \theta_k)$.

In deriving an approximation for the E step, i.e. approximating $Q(\theta, \theta')$, the involved multi-dimensional integrals contains the smoothed state densities, more specifically $p_{\theta_k}(x_t|Y_N)$ and $p_{\theta_k}(x_{t+1}, x_t|Y_N)$. In order to compute approximations of the above mentioned integrals the smoothed state densities were successfully approximated using particle smoothers. The M step was solved using a standard Quasi-Newton type algorithm. Besides the theory, the paper also reports several successful numerical illustrations, where the proposed algorithm is used to successfully compute parameter estimates.

Direct Weight Optimisation and Piecewise linear models

Direct Weight Optimisation (DWO) as a method to estimate nonlinear models has been described in earlier annual reports. In [59] an overview of this approach is given, and in [61] it is shown how this can be applied to estimation of discontinuous functions.

A related result is that the solution paths to the DWO problem with respect to the “design” variables SNR and function smoothness can be expressed as piecewise linear segments, see [24] and [68]. Mathematically the problem is of the following kind

$$x^* = \arg \min_x J(x) + \lambda L(x)$$

where $J$ is piecewise quadratic and $L$ is piecewise affine. Then $x^*$ becomes a piecewise affine function of $\lambda$. 

10
The situation when the nonlinear model consists of piecewise linear segments is considered in [67].

2.3 Linear Models

ARX models

In [47] the much studied Least Squares algorithm for estimating ARX models is revisited. In particular it is studied how much “deterministic” signals that the white noise equation error noise may contain before the estimate becomes inconsistent.

In [55] the Nonnegative Garrote method is applied for order selection in ARX models. It has the advantage that the complexity of using more poles and more zeros can be individually assessed.

Correct Sampling and Identifiction of Continuous Time Models

The standard continuous time model is written as

\[ \dot{x}(t) = Ax(t) + Bu(t) + \dot{e}(t) \]
\[ \dot{y}(t) = Cx(t) + \dot{v}(t) \]

where \( \dot{e} \) and \( \dot{v} \) are white noises. (To be mathematically correct, the equations should be written as stochastic integrals.) This means that the output \( \dot{y} \) will have infinite variance, so the measured observed output \( z \) must me some low pass filtered variant of \( \dot{y} \). An often used model is that integrated sampling is used:

\[ z(t) = \frac{1}{\tau} \int_{t-\tau}^{t} \dot{y}(s) ds \]

The corresponding sampling formulas are well known, but have not been extensively used in the system identification context. A detailed discussion and illustration of this problem is given in [52]

2.4 Manifold Learning

The trend today is to use many inexpensive sensors instead of a few expensive ones, since the same accuracy can generally be obtained by fusing several
dependent measurements. It also follows that the robustness against failing sensors is improved. As a result, the need for high-dimensional regression techniques is increasing.

If measurements are dependent, the regressors will be constrained to some manifold. There is then a representation of the regressors, of the same dimension as the manifold, containing all predictive information. Since the manifold is commonly unknown, this representation has to be estimated using data. For this, manifold learning can be utilized. Having found a representation of the manifold constrained regressors, this low-dimensional representation can be used in an ordinary regression algorithm to find a prediction of the output. This has further been developed in the Weight Determination by Manifold Regularization (WDMR) approach.

WDMR, in contrast to most regression methods, has the property that it does not form an estimate by weighting together outputs of the closest regressors in an Euclidean sense. WDMR weight together the outputs of regressors close in a geodesic sense i.e., close along the manifold. This is many time a good assumption when dealing with manifold constrained regressors. The weights computed by WDMR for a one-dimensional manifold is shown in Figure 2.3. The development of WDMR are further described in [63, 8, 62].

![Figure 2.3](image)

Figure 2.3: The figure shows how the weighting kernel computed by WDMR adjusts to the manifold in a toy example. It can be seen that an estimation computed by WDMR will be based on geodesic rather than Euclidean distance. Black dots show estimation regressors and gray dots validation regressors. The two-dimensional regressors \([x_1, x_2]\) are placed along a u-shaped one-dimensional manifold. The kernel weights computed by WDMR for estimating the output of a validation regressor (marked with a red square) are shown with black bars.
In most regression problems, prior information can improve prediction results. This is also true for high-dimensional regression problems. Research to include physical prior knowledge in high-dimensional regression i.e., gray-box high-dimensional regression, has been rather limited, however. We have explored the possibilities to include prior knowledge in high-dimensional manifold constrained regression by the means of regularization. The result was called gray-box \textit{WDMR}. In gray-box WDMR we have the possibility to restrict ourselves to predictions which are physically plausible. This was done by incorporating dynamical models for how the regressors evolve on the manifold.

Figure 2.4 shows the estimated path of gray-box WDMR (red dashed curve) of the joint close to the tool of an industrial robot. The regressors used in this example were images of the robot, one of the regressor images is shown in Figure 2.4. In this example, the regressors (images of the robot) is constrained to a 6-dimensional manifold embedded in the 19,200 dimensional regressor space. The position of the joint was marked out by hand for 6 regressors and used for training. Gray-box WDMR is further described in [8].

![Figure 2.4: Tracked path of the joint close to the tool of the industrial robot. Dashed line: Gray-box WDMR. Solid line: WDMR.](image)

Another example with the needs of regression methods capable of handling very high-dimensional data is \textit{functional Magnetic Resonance Imaging}
(fMRI). Using fMRI, the brain activity in each cubic millimeter of the brain can today be measured as often as every second. For a human brain (see Figure 2.5), which has a volume of approximately 1.4 L, that gives 1 400 000 measurements per second or a 1 400 000-dimensional measurement each second. How the high-dimensional data of fMRI can be treated in regression is further discussed in [64].

Figure 2.5: A MR image showing the cross section of a skull.
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

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

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

\[ \dot{x}_1 = F_1(x_1, x_2, u, \dot{u}, ..) \]  
\[ 0 = F_2(x_1, x_2, u, \dot{u}, ..) \]

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. Many questions concerning the properties of such models are treated in [4].
3.1 Well-posedness and numerical properties of models

For nonlinear systems it is often assumed that the external signal enters the system affinely:

\[ \dot{x} = f(x) + g(x)u \]

This configuration is often easier to analyze than the general one. If \( u \) is a stochastic signal the relation between \( u \) and \( x \) has to be interpreted as a stochastic differential equation. The affine-in-\( u \) structure is then essential. The question then arises whether a model in DAE form can be rewritten as a differential equation with affine input. In [4] criteria that guarantee this to be possible are derived. They imply constraints on the addition of stochastic signals to DAE models. The theory is used in the study of particle filters for a mechanical system.

A problem closely related to well-posedness is that of numerical properties when some elements are small. This problem becomes important for DAE models of the form

\[ E\dot{x} = f(x) \]

when some elements of \( E \) are small and uncertain. In [73] it is shown how it is possible to guarantee reasonable behaviour of the solution even in the uncertain case. If \( f \) is linear it turns out to be possible to transform the system so that it is separated into fast and slow dynamics. In the limiting case when the relevant part of \( E \) becomes exactly zero, the fast dynamics becomes an algebraic equation. In the figure below it is shown how the slow dynamics varies because of the uncertainty of some elements in \( E \).
3.2 Optimal Control and Model Reduction

A classical problem in nonlinear design is optimal feedback control. For statespace models, it is well-known that the Hamilton-Jacobi-Bellman equation (HJB) can be used to calculate the optimal solution. For DAE models, a similar result exists where a Hamilton-Jacobi-Bellman-like equation is solved. This equation has an extra term in order to incorporate the algebraic equations. In [4] an interpretation of this extra term is given. A problem when using the HJB to find the optimal feedback law is that it involves solving a nonlinear partial differential equation. Often, this equation cannot be solved explicitly. An easier problem is to compute a locally optimal feedback law. For analytic nonlinear time-invariant state-space models, this problem was solved around 1960. In [71] and [4] these results are extended to analytic DAE models. Usually, the power series solution of the optimal feedback control problem consists of an infinite number of terms. In practice, an approximation with a finite number of terms is used. A problem is that for certain problems, the region in which the approximate solution is accurate may be small. Therefore, another parametrization of the optimal solution, namely rational functions, is studied, [70]. It is shown that for some problems, this parametrization gives a substantially better result than the power series. When the cost function contains a discounted cost the form of the Hamilton-Jacobi-Bellman equation is altered. This case is treated in [72].

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 [4] this is done for DAE models using series expansion techniques.

3.3 Properties of step responses

Linear systems are often characterized by their step responses. In the modeling of some biological systems the presence of a marked overshoot is a very noticeable feature. In [12] it is shown how this knowledge can be used to reject a number of otherwise possible models.
Chapter 4

Sensor fusion

Highlights of the year are

- The PhD thesis of Gustaf Hendeby [2] and David Törnqvist [5], see Figure 4.1, and Sections 4.5 and 4.6, respectively.

- The licentiate thesis of Jeroen Hol [7].

- The H.J. Woltring lecture [69].

- The scientific publications, including the journal papers [17, 23, 22, 13, 14, 15, 18] and the conference papers [38, 48, 54, 65, 66, 75, 33, 45, 69, 46, 44, 36, 60, 37, 74].

Figure 4.1: The two PhD theses [2] and [5].
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.**
  - *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

There are three journal papers on different signal processing aspects on non-uniformly (or irregularly) sampled data.

- The first one treats the fundamental properties in signal processing on non-uniformly data [14]. A frequency domain analysis extends the sampling theorem with explicit results on folding and reconstruction limitations.

- The implication of non-uniformly sampled data to system identification is described in [15]. Frequency domain expressions of the induced bias and variance are obtained.

- Algorithms and analysis of how to downsample non-uniformly sampled data is described in [13]. 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 papers [45, 46] are concerned with the problem of estimating the relative translation and orientation between an inertial measurement unit and a camera, which are rigidly connected. Accurate knowledge of this translation and orientation is important for high quality sensor fusion using the measurements from both sensors. The sensor unit used in this work was developed within the Matris project and it is shown in Figure 4.3. The key to the solution is to form this as an gray-box system identification problem. The new algorithm for estimating the relative translation and orientation does not require any additional hardware, except a piece of paper with a checkerboard pattern on it. The experimental results shows that the method works well in practice.

Robust feature detection in images is an important pre-processing step in sensor fusion applications such as SLAM. The approach in [75] is based on the parity space algorithm.
4.3 State estimation

4.3.1 Particle filtering

The current projects on the particle filter include

- 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 [23] 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.

The unscented Kalman filter (UKF) has become a popular alternative to the extended Kalman filter (EKF) and the particle filter during the past ten years. The UKF is based on the unscented transform (UT) for approximating a general nonlinear function of a Gaussian variable with a new Gaussian variable. The contribution in [44] is to show that the UT can be seen as a numerical Jacobian and Hessian approximation similar to a second order Taylor expansion. The conclusion is that UKF is closely related to a previous known second order EKF, but with a specific limitation.

4.3.2 Target tracking

The various topics relating to target tracking include the following publications:

- In classical target tracking literature, there is an implicit assumption that the speed of the target is negligible compared to the signal propagation speed. However, this is not the case when tracking vehicles based on acoustic or seismic wave propagation. This issue is addressed with a particle filter in [65].

- Tracking in sensor network becomes complicated when the observations are randomly delayed in the network and arrives out of sequence to a computing node. This problem has recently been addressed in a few papers. In [66], the requirement of that all particles back in time has to be stored is relaxed, leading to storage efficient particle filters.
• Maximum likelihood estimation of transition probabilities of jump Markov linear systems is described in [22].

4.3.3 Sensor networks

Localization of vehicles in sensor networks with acoustic, seismic and magnetic sensors is presented in [36]. 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

Road geometry estimation and vehicle tracking using a single track model [54]. A multiple UAV system for vision-based search and localization is described in [74].

4.4.1 Simultaneous Localization and Mapping

Simultaneous Localization and Mapping (SLAM) has been considered as a sensor fusion application in the group before. From this year, there are several projects and a papers on this subject, motivating its own section.

The contribution [48] aims at unifying two recent trends in applied particle filtering (PF). The first trend is the major impact in simultaneous localization and mapping (SLAM) applications, utilizing the FastSLAM algorithm. The second one is the implications of the marginalized particle filter (MPF) or the Rao-Blackwellized particle filter (RBPF) in positioning and tracking applications. Using the standard FastSLAM algorithm, only low-dimensional vehicle models are computationally feasible. In this work, an algorithm is introduced which merges FastSLAM and MPF, and the result is an algorithm for SLAM applications, where state vectors of higher dimensions can be used. Results using experimental data from a UAV (helicopter) are presented. The algorithm fuses measurements from on-board inertial sensors (accelerometer and gyro) and vision in order to solve the SLAM problem, i.e., enable navigation over a long period of time. Figure 4.4 shows the algorithm in action with the particle cloud reprojected in the camera image.

Sensor fusion for augmented reality applications was performed in a EU project (MATRIS). The paper [38] presents the sensor fusion framework with
Figure 4.4: The scenario seen from the on-board vision sensor, together with particle clouds representing the landmarks/map features.

a general project overview in a video supported session at the IFAC world congress. Though this solution utilizes a partially known scen model, the ultimate goal is to create this model on the fly, that is, the SLAM problem.

Tree of Words for Visual Loop Closure Detection in Urban SLAM [33]

### 4.4.2 Decision support with uncertain data

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

A framework for decision support in collision avoidance system is presented in [18]. The key idea is to use Monte Carlo evaluation of risks, where the samples are taken from the posterior distribution delivered by sensor fusion tracking filters.

For detecting very small risks, the Monte Carlo approach above requires too many samples. One alternative proposed in [60] for airborne collision avoidance systems is to apply sound analytical approximations to the multi-dimensional integral expressions for the risk, followed by standard numerical algorithms for onedimensional integrals.
Nonlinear filtering is an important standard tool for information and sensor fusion applications, e.g., localization, navigation, and tracking. It is an essential component in surveillance systems and of increasing importance for standard consumer products, such as cellular phones with localization, car navigation systems, and augmented reality. The thesis [2] addresses several issues related to nonlinear filtering, including performance analysis of filtering and detection, algorithm analysis, and various implementation details. The most commonly used measure of filtering performance is the root mean square error (RMSE), which is bounded from below by the Cramér-Rao lower bound (CRLB). The thesis [2] presents a methodology to determine the effect different noise distributions have on the CRLB. This leads up to an analysis of the intrinsic accuracy (IA), the informativeness of a noise distribution. For linear systems the resulting expressions are direct and can be used to determine whether a problem is feasible or not, and to indicate the efficacy of nonlinear methods such as the particle filter (PF). A similar analysis is used for change detection performance analysis, which once again shows the importance of IA.

A problem with the RMSE evaluation is that it captures only one aspect of the resulting estimate and the distribution of the estimates can differ substantially. To solve this problem, the Kullback divergence has been evaluated demonstrating the shortcomings of pure RMSE evaluation.

Two estimation algorithms have been analyzed in more detail; the Rao-Blackwellized particle filter (RBPF), by some authors referred to as the marginalized particle filter (MPF), and the unscented Kalman filter (UKF). The RBPF analysis leads to a new way of presenting the algorithm, thereby making it easier to implement. In addition the presentation can possibly give new intuition for the RBPF as being a stochastic Kalman filter bank. In the analysis of the UKF the focus is on the unscented transform (UT). The results include several simulation studies and a comparison with the Gauss approximation of the first and second order in the limit case.

The thesis presents an implementation of a parallelized PF and outlines an object-oriented framework for filtering. The PF has been implemented on a graphics processing unit (GPU), i.e., a graphics card. The GPU is an inexpensive parallel computational resource available with most modern
computers and is rarely used to its full potential. Being able to implement the PF in parallel makes new applications, where speed and good performance are important, possible. The object-oriented filtering framework provides the flexibility and performance needed for large scale Monte Carlo simulations using modern software design methodology. It can also be used to help to efficiently turn a prototype into a finished product.

4.6 PhD thesis: Estimation and Detection with Applications to Navigation

The ability to navigate in an unknown environment is an enabler for truly autonomous systems. Such a system must be aware of its relative position to the surroundings using sensor measurements. It is instrumental that these measurements are monitored for disturbances and faults. Having correct measurements, the challenging problem for a robot is to estimate its own position and simultaneously build a map of the environment. This problem is referred to as the Simultaneous Localization and Mapping (SLAM) problem. The thesis [5] studies several topics related to SLAM, on-board sensor processing, exploration and disturbance detection. The particle filter (PF) solution to the SLAM problem is commonly referred to as FastSLAM and has been used extensively for ground robot applications. Having more complex vehicle models using for example flying robots extends the state dimension of the vehicle model and makes the existing solution computationally infeasible. The factorization of the problem made in the thesis [5] allows for a computationally tractable solution. Disturbance detection for magnetometers and detection of spurious features in image sensors must be done before these sensor measurements can be used for estimation. Disturbance detection based on comparing a batch of data with a model of the system using the generalized likelihood ratio test is considered. There are two approaches to this problem. One is based on the traditional parity space method, where the influence of the initial state is removed by projection, and the other on combining prior information with data in the batch. An efficient parameterization of incipient faults is given which is shown to improve the results considerably. Another common situation in robotics is to have different sampling rates of the sensors. More complex sensors such as cameras often have slower update rate than accelerometers and gyroscopes. An algorithm for
this situation is derived for a class of models with linear Gaussian dynamic model and sensors with different sampling rates, one slow with a non-linear and/or non-Gaussian measurement relation and one fast with a linear Gaussian measurement relation. For this case, the Kalman filter is used to process the information from the fast sensor and the information from the slow sensor is processed using the PF. The problem formulation covers the important special case of fast dynamics and one slow sensor, which appears in many navigation and tracking problems. Vision based target tracking is another important estimation problem in robotics. Distributed exploration with multi-aircraft flight experiments has demonstrated localization of a stationary target with estimate covariance on the order of meters. Grid-based estimation as well as the PF have been examined.
Chapter 5

Robotics

5.1 Introduction

The research within the robotics area is to a large extent carried out in close cooperation with ABB Robotics and ABB Corporate Research. From 2008 the collaboration is carried out within the Industry Excellence Center LINK-SIC (Linköping Center for Sensor Informatics and Control) supported by VINNOVA. The overall aim of the center is to generate results that are of both high scientific quality and industrial relevance. An example of the industrial impact of the robotics research is presented in [32].

During 2008 Johanna Wallén completed her licentiate’s degree by the licenciate thesis [9].

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. The research in this area is based on an approach where the starting point is a physically parameterized nonlinear grey-box model of a six degrees-of-freedom industrial robot containing mechanical elasticities. 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 approach consists of a three-step procedure, where, in the first step, suitable operating points are selected. In the second step multivariable nonparametric frequency response functions (FRFs) are estimated
in the selected operating points using multi-sine excitation signals. Several methods for nonparametric FRF estimation exist and a number of them are analyzed in [79]. In the third and final step, the nonlinear grey-box model is fitted to the nonparametric models 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. An in depth description of the three-step method is presented in [78]. A benefit from using multi-sine signals is that they enable quantification of the modeling errors that appear due to nonlinearities in the system. Illustrations of how this can be used in identification of industrial robots are given in [27].

5.3 Model based control

The performance requirements, in terms of cycle time and accuracy, of modern industrial robots require carefully designed control methods based on accurate dynamical models. Control of industrial robots has been an active research area for many years, and a large number of design methods have been proposed. There is still a gap between the academic research and the industrial practice, and it is hence an ambition in this research area to bridge over this gap. This is done by proposing industrial relevant benchmark problems to the academic world, and the latest contribution of this kind is a multivariable benchmark problem presented in [58]. Another approach is to expose proposed control methods to conditions that are present in industry. An example of this can be found in [57] where a discrete-time implementation of the feedback linearization approach is compared to a feedforward approach.

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), has been an active research area within the group for several years. The interest during the recent years has been concentrated to ILC applied to robots containing mechanical flexibilities. The big challenge in such a case is that the controlled variables are different from the measured variables. In standard industrial robots the controlled variables are the position and the orientation of the tool, while the measured variables are the angles of the motors that generate the motion. This situation implies that good performance when studying the measured variables does not necessarily imply good performance
of the controlled variables. This phenomenon has been studied using both theoretical studies, simulations and experiments in Johanna Wallén’s licen-
tiate thesis [9], and is also discussed in [77] and [76]. The simulation study
in [9] is made using a flexible two-mass model of a single robot joint, and
performance and robustness issues are discussed. Experimental results are
presented in [77], where the ILC algorithm is based on measurements of the
motor angles, as is schematically illustrated in Figure 5.1. In addition to the
conventional evaluation of the ILC algorithm based on the motor-side error,
the tool-path error on the arm side is evaluated using a laser-measurement
system. To achieve even better performance, especially in difficult operating
points, it is concluded that an arm side measurement, from for example an
accelerometer, needs to be included in the learning.

\[
\sum_{k} u_k(t) + e(t) + \sum_{k} u_k(t) = \sum_{k} r_m(t) + e(t) + \sum_{k} u_k(t)
\]

Figure 5.1: Illustration of the ILC algorithm applied to the robot system.
The ILC update \( u_k \) at iteration \( k \) is added to the motor angle reference \( r_m \).
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 the Kalman-Yakubovich-Popov (KYP) lemma and from analysis of polytopic linear differential inclusions. They have several applications, e.g., linear system design and analysis, robust control analysis using integral quadratic constraints, Lyapunov function search, and filter design.

Typically standard SDP solvers cannot handle problems of more than small to medium size in reasonable time. The computational complexity stems from the cost of assembling and solving the equations for the search directions in the IP algorithms.

For analysis of polytopic differential inclusions the key to an efficient implementation is to use an infeasible IP method where the search directions
are not computed exactly, [85, 86, 6, 40, 41, 42]. For KYP-SDPs one approach to reduce the computational time is to use decomposition methods, [26]

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 [1, 81, 83, 29, 28].

6.4 Multiuser Detection

When the optimal multiuser detection problem is formulated as a maximum likelihood problem, a binary quadratic programming problem has to be solved. A preprocessing algorithm has been developed which is able to compute almost all variables in the problem, even though the system is heavily loaded and affected by noise. The results have been presented in [82, 11].

6.5 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. The toolbox now features support for automatically deriving certain counterparts of optimization models involving uncertainty [53], thus allowing us to formulate and solve worst-case and min-max problems easily. These additions to the toolbox have been extensively exploited when deriving new model predictive control algorithms for linear parameter-varying systems [30, 31].

In addition to the evolving development of the robust optimization framework in YALMIP, the support for matrix-valued sum-of-squares decompositions of sparse matrix polynomials has also been improved, relying on methods described in [91].
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 S:t Petersburg, Russia (1996), from Uppsala University, Uppsala, Sweden (1998), from l’Université de Technologie de Troyes, France (2004), from the Katholieke Universiteit in Leuven, Belgium (2004) and from Helsinki Institute of Technology (2008). In 2002 he received the Quazza medal from IFAC, in 2003 the Hendryk W. Bode Lecture Prize from the IEEE Control Systems Society, and in 2007 the IEEE Control Systems Field Award.

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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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Visitors

Gabriele Bleser  Fraunhofer IGD, Fraunhoferstr.5, 64283 Darmstadt, Germany visited the division during March – July 2008.

Jésica Escobar  Control Automatica, Cinvestav, Mexico, visited the division during March – July 2008.
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. 113 participants. Lecturer: Johan Löfberg.


  I Industrial Engineering and Management. 162 participants. Lecturer: Svante Gunnarsson.


• **Industrial Control** (Industriell Reglerteknik). 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, model predictive control, monitoring and applications of digital process control. 64 participants. Lecturer: Martin Enqvist.

• **Real Time Process Control** (Realtidsprocesser och reglering). For the Information Technology Program. Real time systems. PID control. 24 participants. Lecturer: Inger Klein.

• **Linear Feedback Systems** (Återkopplade linjära system). For the Information Technology Program. Linear systems, controllability, observability, feedback control. 24 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, 55 Participants. Lecturer: Daniel Axehill.

• **Introduction to MATLAB** (Introduktionskurs i MATLAB). Available for several Engineering Programs. 324 participants. Lecturer: Ragnar Wallin/Gustaf Hendeby.
- *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: Svante Gunnarsson.

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

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

- *Automatic control.* 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. 60 participants. Lecturer: Ragnar Wallin.

- *Automatic control.* Sequential control and logic controllers. A typical industrial control system. 42 participants. Lecturer: Thomas Schön.

**B.2 Graduate Courses**


- *Sensor Fusion.* Lecturer: Fredrik Gustafsson.


- *Robotik.* Lecturer: Mikael Norrlöf.


• *Robust and Adaptive Control*. Short course, September 2–4, 2008. Lecturer: Naira Hovakimyan, Virignia Tech, Blacksburg, USA; Eugene Lavretsky and Kevin A. Wise, Phantom Works, Boeing, USA.
Appendix C

Seminars

- Aerodynamic modeling using flight mechanical simulations, flight tests and optimization. Roger Larsson, Saab AB. January 17, 2008.

- Presentation of the latest developments of the 5-DOF Gantry-Tau prototype and other robotics activities at the University of Agder. Geir Hovland, University of Agder, Norway. January 24, 2008.


- Control of hybrid systems: Theory, computation and applications. Manfred Morari, ETH, Zürich, Switzerland. February 27, 2008.

• **Time varying matrix estimation for stochastic systems using the "equivalent control" concept.** Jésica Escobar, Control Automatica, Cinvestav, Mexico. March 19, 2008.

• **Hybrid systems: The continuous meets the discrete in systems and control.** Peter Caines, McGill University, Montreal, Canada. March 27, 2008.

• **Hybrid systems: System identification with quantized & information theoretic control for mobile sensing.** Le Yi Wang, Wayne State University, Detroit and Allison Ryan, Vehicle Dynamics Lab, University of California, Berkeley. March 31, 2008.


• **Real-time markerless camera tracking for mobile augmented reality.** Gabrielle Bleser, Fraunhofer IGD, Darmstadt, Germany. May 21, 2008.

• **Use of optimization in power system analysis.** Lennart Söder and Valery Knatzkins, Royal Institute of Technology, Stockholm, Sweden May 22, 2008.

• **Interior-point methods for nuclear norm minimization.** Lieven Vandenberghe, University of California, Los Angeles. May 26, 2008.

• **A fix-up for the EKF parameter estimator.** Donald Wiberg, University of California, Santa Cruz. May 28, 2008.

• **Astronomy, cosmology and control systems: Instrumentation for understanding the universe through adaptive optics.** Donald Wiberg, University of California, Santa Cruz. May 29, 2008.
• Homogeneous polynomial Lyapunov functions for robustness analysis of uncertain systems. Andrea Garulli, Università di Siena, Siena, Italy. June 10, 2008.


• On efficient on-line implementation of off-line MPC for hybrid systems. Michal Kvasnica, Slovak University of Technology, Slovakia. June 18, 2008.

• Dirichlet process mixtures and its application to multistate tracking. Emre Özkan, Middle East Technical University, Ankara, Turkey. August 28, 2008.

• Trajectory prediction and wind estimation using multiple aircraft. Ioannis Lymperopoulos, ETH, Zürich, Switzerland. September 11, 2008.

• A nonlinear observer for rigid body attitude estimation on SO(3) using internal measurements and vector observations. José Vasconcelos, Instituto Superior Técnico, Lisbon, Portugal. September 18, 2008.


• Synchronization and coordination of multi-agent systems. Mark W. Spong, University of Illinois at Urbana-Champaign, USA. October 20, 2008.


• Treating populations and landscapes as signals: applied on (1) spread of disease, (2) animal welfare vs transport, (3) endangered species, and (4) climate effects on lichens. A step towards research collaborations? Uno Wennergren, Department of Biology, Linköpings universitet. November 13, 2008.


• How to control Vattenfall. Mikael Nordlander, Vattenfall. November 27, 2008.

• The elements of weather forecasting – from observations through physical principles to computational modelling. Per Undén, SMHI. December 4, 2008.

Appendix D

Travels and Conferences

Daniel Axehill visited the Automatic Control Laboratory, ETH Zurich, Switzerland, May 19–23. He participated in Reglermöte 2008, Luleå, June 4–5 and the 47th IEEE Conference on Decision and Control, Cancun, Mexico, December 9–11.

Martin Enqvist participated in the 17th ERNSI Workshop on System Identification, Sigtuna, Sweden, October 1–3.


Torkel Glad participated in Reglermöte 2008, Luleå, June 4–5; took part in the 17th IFAC World Congress in Seoul, Korea, July 7–11 and the 47th IEEE Conference on Decision and Control, Cancun, Mexico, December 9–11.

Svante Gunnarsson attended the 4th Chinese-Swedish Conference on Control, Hong Kong, China, January 10–11; the 4th International CDIO Conference, Gent, Belgium, June 17–18; and Nätverket Ingenjörsutbildningarnas Utvecklingskonferens, Stockholm, Sweden, November 26–27.

Fredrik Gustafsson participated in the 17th ERNSI Workshop on System Identification, Sigtuna, Sweden, October 1–3.
Anders Hansson attended Regelmöte 2008, Luleå, June 4–5; COFCLUO Workshop on Clearance of Flight Control Laws, Siena, Italy, September 26; Flygtekniskt seminarium, Kolmården, November 5–6; IEEE Conference on Decision and Control, Mexico, December 9–11.

Anders Helmersson attended the 4th Chinese-Swedish Conference on Control, Hong Kong, China, January 10–11.


Inger Klein attended the 4th Chinese-Swedish Conference on Control, Hong Kong, China, January 10–11; Regelmöte 2008, Luleå, June 4–5; and Nätverket Ingenjörsutbildningarnas Utvecklingskonferens, Stockholm, Sweden, November 26–27.

Roger Larsson attended the AIAA Guidance, Navigation and Control conference, Honolulu, USA, August 18-21; the Flygtekniskt seminarium, Kolmården, November 5–6.

Lennart Ljung participated in the 4th Chinese-Swedish Control Conference in Hongkong, January 9-11, in the COFCLOU advisory committee meeting in Toulouse, February 7, and in the International Conference on Avionics (ICAS-08), Hyderabad, India, February 22-23. He also visited the International Institute of Information Technology in Hyderabad. He took part in the Microsymposium on System Identification at VUB, Brussels, March 11-12. He was at the Helsinki Institute of Technology, Finland, to receive an honorary doctorate on April 1-2, and he took part in the Institute for Systems Research Symposium and Review Day at University of Maryland, April 10-11, as well as in the John Baras Fest at UMD on April 12. He visited the University of California at San Diego to give the Penner Lecture, April 13-16. On June 3-5 he participated in the biannual Swedish Control Meeting (Regelmöte 2008) in Luleå, and on July 7-11 he took part in the 17th IFAC World Congress in Seoul, Korea. He was at the 17th ERNSI Workshop in Sigtuna, October 1-2, and was in the Jury of Laurent Mervel in Rennes on
October 22. Finally, he was at the 47th IEEE Conference on Decision and Control, Cancun, Mexico, December 9–11.


**Christian Lyzell** participated in Reglermöte 2008, Luleå, June 4–5; the 17th ERNSI Workshop on System Identification, Sigtuna, Sweden, October 1–3; and the 47th IEEE Conference on Decision and Control, Cancun, Mexico, December 9–11.

**Johan Löfberg** participated in Reglermöte 2008, Luleå, June 4–5; The 17th IFAC World Congress, Seoul, Korea, July 6–11; Workshop on Clearance of Flight Control Laws, Siena, Italy, September 26; SAAB Flygteknikseminarium, Kolmården, Sweden, November 5–6.

**Stig Moberg** participated in the 17th IFAC World Congress, Seoul, Korea, July 6–11. He also visited University West, Trollhättan, Sweden, November 25.

**Henrik Ohlsson** participated in Reglermöte 2008, Luleå, June 4–5; the 17th ERNSI Workshop on System Identification, Sigtuna, Sweden, October 1–3; and the 47th IEEE Conference on Decision and Control, Cancun, Mexico, December 9–11.

**Umut Orguner** participated in the 11th International Conference of Information Fusion, Cologne, Germany, June 30–July 03.

**Daniel Petersson** participated in Reglermöte 2008, Luleå, June 4–5; Workshop on Clearance of Flight Control Laws, Siena, Italy, September 26; SAAB Flygteknikseminarium, Kolmården, Sweden, November 5–6.

**Ulla Salaneck** attended the 4th Chinese-Swedish Conference on Control, Hong Kong, China, January 10–1; Reglermöte 2008, Luleå, Sweden, June 4–5: the ‘Riksskreterarmötet´in Rome, Italy, September 27–29 and the 17th ERNSI Workshop on System Identification, Sigtuna, Sweden, October 1–3.

**Thomas Schön** participated in the IEEE Intelligent Vehicles Symposium, Eindhoven, The Netherlands, June 4–6; the 17th IFAC World Congress, Seoul, South Korea, July 6–11; the 17th ERNSI Workshop on System

**Johan Sjöberg** participated at Reglermöte 2008, Luleå, Sweden, June 4–5; the 17th IFAC World Congress, Seoul, Korea, July 6–11.

**Henrik Tidefelt** participated in the 17th IFAC World Congress, Seoul, Korea, July 6–11.


**Johanna Wallén** participated in Reglermöte 2008, Luleå, June 4–5 and the 17th IFAC World Congress, Seoul, Korea, July 6–11.


**Erik Wernholt** visited the group of Optimization and Systems Theory, KTH, Stockholm, Sweden, February 15. He also participated in Reglermöte 2008, Luleå, June 4–5, the 17th IFAC World Congress, Seoul, Korea, July 6–11, and the 17th ERNSI Workshop on System Identification, Sigtuna, Sweden, October 1–3.
Appendix E

Lectures by the Staff

- Daniel Axehill: *Integer quadratic programming for control*, Automatic Control Laboratory, ETH Zurich, Switzerland, May 20.


- Rikard Falkeborn: *Formulation of flight clearance criteria as convex optimization problems*, SAAB Flygteknikseminarium, Kolmården, Sweden, November 6.


- Svante Gunnarsson: *Some Aspects of System Identification in Robotics*, 4th Chinese-Swedish Conference on Control, Hong Kong, China, January 11.

- Svante Gunnarsson: *Computer Supported Learning and Assessment in Engineering Education*, 4th International CDIO Conference, Gent, Belgium, June 18.
• Svante Gunnarsson: *Framstående utbildningsmiljö - Hur blir man det?*, Nätverket Ingenjörsutbildningarnas Utvecklingskonferens, Stockholm, Sweden, November 27.

• Fredrik Gustafsson: *Sensor fusion projects in autonomous vehicles* Saabteknikdagarna, Kolmården, Sweden, November 06.


• Fredrik Gustafsson: *Modeling for Kalman filtering is very different from identification for control*, ERNSI Workshop, Stockholm, October 3.


• Inger Klein: *Fault Isolation in Object Oriented Control Systems*, 4th Chinese-Swedish Conference on Control, Hong Kong, China, January 11.

• Larsson Roger: *Vad gör en aerodynamiker på Saab*, Royal Institute of Technology. March 10.


• Lennart Ljung *System Identification: From Data to Model – With Applications to Aircraft Modeling*, International Conference on Avionics (ICAS-08), Hyderabad, India. February 22.

• Lennart Ljung *The MOVIII Strategic Research Center*, International Institute of Information Technology, Hyderabad, India. February 23.

• Lennart Ljung *Maximum Likelihood Estimation of Wiener Models*, John Baras Fest, University of Maryland, USA. April 12.
• Lennart Ljung *System Identification: From Data to Model*, The Penner Lecture, University of California at San Diego, USA. April 14.


• Lennart Ljung *Piecewise Linear Solutions Paths for Parametric Piecewise Quadratic Programs*, (For Jacob Roll). 17th IFAC World Congress, Seoul, Korea. July 8.

• Lennart Ljung *New Convergence Results for the Least Squares Identification Algorithm*, 17th IFAC World Congress, Seoul, Korea. July 8.


• Lennart Ljung *Trends and Challenges in System Identification*, S2-Dagen, Chalmers Institute of Technology, Göteborg, October 29.


• Lennart Ljung *Dynamic Test Selection for Reconfigurable Diagnosis*, (For Jacob Roll), 47th IEEE Conference on Decision and Control, Cancun, Mexico, December 9.

• Christian Lyzell: *The Use of Nonnegative Garrote for Order Selection of ARX Models*, 47th IEEE Conference on Decision and Control, Cancun, Mexico, December 10. Also held at Reglermöte 2008, Luleå, June 5.

• Johan Löfberg: *Advanced Optimization Modeling in YALMIP*, CORE, Louvain-la-Neuve, Belgium. April 22.


• Stig Moberg: *A Benchmark Problem for Robust Control of a Multivariable Nonlinear Flexible Manipulator*, 17th IFAC World Congress, Seoul, Korea. July 7.


• Stig Moberg: *A New Concept for Motion Control of Industrial Robots*, 17th IFAC World Congress, Seoul, Korea. July 11.

• Stig Moberg: *Robot Motion Control*, University West Trollhättan, Sweden. November 25.


• Henrik Ohlsson: *Direct Weight Optimization Applied to Discontinuous Functions*, 47th IEEE Conference on Decision and Control, Cancun, Mexico, December 9.


• Umut Orguner: *Storage Efficient Particle Filters for the Out of Sequence Measurement Problem*, 11th International Conference of Information Fusion, Cologne, Germany, July 1.

• Umut Orguner: *Target Tracking Using Delayed Measurements with Implicit Constraints*, 11th International Conference of Information Fusion, Cologne, Germany, July 1.

• Daniel Petersson: *New approaches to LPV generation*, Workshop on Clearance of Flight Control Laws, Siena, Italy, September 26. Also held at SAAB Flygteknikseminarium, Kolmården, Sweden, November 6.


• Thomas Schön: *The Particle Filter - Applications and Theory*, Automatic Control Laboratory, ETH Zurich, Switzerland, April 22.


• Thomas Schön: *Sensor Fusion for Augmented Reality*, 17th IFAC World Congress, Seoul, South Korea. July 10.

• Thomas Schön: *Introducing the Particle Filter*, Autoliv Electronics AB, Linköping, Sweden, August 27.

• Thomas Schön: *A New Algorithm For Calibrating a Combined Camera and IMU Sensor Unit*, ERNSI Workshop, Sigtuna, Sweden, October 3.

• Thomas Schön: *Fusing Data From Different Sources*, 10th International Symposium on 3D Analysis of Human Movement (plenary lecture), Amsterdam, The Netherlands, October 29.
• Thomas Schön: *Particle Filter SLAM with UAV Applications*, Flygtekni
skt seminarium, Kolmården, Sweden, November 6.

• Thomas Schön: *Overview of the SLAM Problem*, Computer Vision Lab-
oratory, Linköping University Linköping, Sweden, November 7.

• Thomas Schön: *A New Algorithm for Calibrating a Combined Cam-

• Henrik Tidefelt: *Index reduction of index 1 DAE under uncertainty*, 17th IFAC World Congress, Seoul, Korea. July 8.

• David Törnqvist: *Utilizing Model Structure for Efficient Simultane-
ous Localization and Mapping for a UAV Application*, IEEE Aerospace Conference, Big Sky, MT, USA, March 7.


• David Törnqvist: *A Multiple UAV System for Vision-Based Search and Localization*, American Control Conference, Seattle, WA, USA, June 12.

• David Törnqvist: *Detecting Spurious Features using Parity Space*, Interna

• Johanna Wallén: *On Kinematic Modelling and Iterative Learning Con-
trol of Industrial Robots*, Lic. Eng. presentation at Linköping University, Sweden, January 25.

• Johanna Wallén: *On Kinematic Modelling and Iterative Learning Con-

• Johanna Wallén: *Arm-side Evaluation of ILC Applied to a Six-degrees-
of-freedom Industrial Robot*, 17th IFAC World Congress, Seoul, Korea, July 11.


• Johan Sjöberg: *Optimal Feedback Control of nonlinear DAE models*, Department of Automatic Control, Lund University, May.


• Johan Sjöberg: *Rational Approximation of Nonlinear Optimal Control Problems*, the 17th IFAC World Congress, Seoul, Korea, July 6–11.
Appendix F

Publications

Phd Theses


Licentiate Theses


Journal Papers and Book Chapters


Conference Papers


[65] U. Orguner and F. Gustafsson. Target tracking using delayed measurements with implicit constraints. In Proceedings of 11th International Conference on Information Fusion, pages 1–8, Cologne, Ger-


Appendix G

Technical Reports


Appendix H

Master’s Theses


