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Chapter 1

Introduction

The Division of Automatic Control has produced annual reports of the current format since 1976. The first ones covered the fiscal and academic years from July to June, and since 1997 the reports have covered the fiscal years from January to December. The period June 1995 to December 1996 was covered in one report. The current annual report is consequently number 34 in the series.

It is also the last one of the current format. In the future we will rely on the web for archival facts and issue regular overviews of our research that are less technical and of more general interest.

As highlights for 2010 the following events could be mentioned:

- Our secretary since 1982, Ulla Salaneck retired on April 1, 2010. Lennart Ljung, who has been head of the control division since July 1, 1976, stepped down as head and was replaced by Svante Gunnarsson on July 1, 2010. Both these events were celebrated by a large garden party with most of the current and past co-workers of the division. See the pictures on the next page.
Figure 1.1: Photos from the celebration of Ulla and Lennart.
• Lennart Ljung received an honorary professorship of the Academy of Mathematics and Systems Science, the Chinese Academy of Sciences on July 28, 2010.

![Figure 1.2: Professor Lei Guo hands over the diploma to Lennart Ljung.](image)

• Henrik Ohlsson and Stig Moberg defended their doctoral theses.

• In addition, Rickard Falkeborn and Daniel Peterson completed their Techn. Lic. degrees.

• The SSF strategic research center MOVIII had final seminar with sophisticated visualizations in the Norrköping Visualization Dome on October 14, 2010.

• The new government national strategic research areas ELLIIT, and Security Link were launched under leadership from the group.
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: 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.
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. Svante Gunnarson is responsible for the program area EF (Electronics, Physics and Mathematics). This includes the “Y-program” (Applied Physics and Electrical Engineering), which is an award-winning Linköping engineering education program. Inger Klein is the leader of the program area DM (Data and Media), which includes the “D-program” (Computer Science and Engineering).

Report Outline

In the following pages the main research results obtained during 2010 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 section 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 in Appendix A together with a short personal presentation of each co-worker. 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 the generic email address

Automatic.Control@isy.liu.se
or AC@isy.liu.se for short.

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 WWW service. 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)
- [http://er-projects.gf.liu.se/~COFCLUO](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

Division of Automatic Control
1976–2010

During the period 1976 – 2010, 34 annual reports have been issued of the same format as the current one. Since future annual reports will have another format we will here summarize some aspects of the Division of Automatic Control over this period of 34 years, as it has been reflected in the annual reports.

2.1 Personnel

Over the years, the Division of Automatic Control has expanded from 7 to 55 employees. The development is illustrated in Figure 2.1. What has happened in recent years is primarily that the number of Post Docs and Assistant Professors (forskarassistentener) has increased significantly. The number of Ph. D. students has hovered around 20 to 30 for almost 20 years. This is in accordance with general trends in Swedish academia.
2.2 Scientific Production

The annual reports focus on the scientific results obtained during the years. How they are reported in books and other publications, and how they are received by fellow researchers is of course of major interest. These aspects are summarized in this section.

2.2.1 Books

Twenty books (28 different editions) have been produced by the group during the period:


2.2.2 Citations

Perhaps of more interest than the lists of publications themselves is to what extent they have influenced other researchers and engineers. The number of citations of the group’s publications per year is shown in Figure 2.2. The accumulated number of citations is about 12,800.

Remark. The plot shows the number of citations according to the Science Citation Index, Web of Science to publications by the current supervisors in the control group, so that each paper is counted only once. In that way it does not cover publications by Ph.D. students and Assistant Professors, that are not co-authored by a (former) supervisor. Likewise, the Linköping production by prolific, former employees is not covered (like Bo Wahlberg, Björn Ottersten, Mats Viberg, Tomas McKelvey, Jonas Sjöberg and Håkan Hjalmarsson).
2.3 Graduate Exams

One of the most important aspects of research is its link to the graduate education. During 1976 – 2010, 64 graduates student have received their Ph.D. exam and 77 have received a Techn.Lic. exam. They will be listed here with currently known affiliations. The total number of graduate exams delivered in 1976 – 2010 is 141. The degrees have been awarded to a total of 89 different people.

2.3.1 Ph.D. Exams

For the Ph.D. exams we also include the name of the “Opponent”. This is typically an international expert, who scrutinize the thesis during a public defense.

<table>
<thead>
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<th>YEAR</th>
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<th>CURRENT AFFILIATION</th>
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<tbody>
<tr>
<td>Mille Milnert</td>
<td>1982</td>
<td>A. Willsky</td>
<td>Director General, Swedish Research Council (VR)</td>
</tr>
<tr>
<td>Ton van Overbeek</td>
<td>1982</td>
<td>K. Glover</td>
<td>European Space Agency, Holland</td>
</tr>
<tr>
<td>Bengt Bengtsson</td>
<td>1982</td>
<td>A. Segall</td>
<td>Sectra AB, Linköping (retired)</td>
</tr>
<tr>
<td>Stefan Ljung</td>
<td>1983</td>
<td>A. Benveniste</td>
<td>ABB, Ludvika</td>
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<tr>
<td>Henrik Jonson</td>
<td>1983</td>
<td>B. Qvarnström</td>
<td>SAAB Dynamics, Linköping</td>
</tr>
<tr>
<td>Eva Trulsson</td>
<td>1984</td>
<td>K.J. Åström</td>
<td>Melerit, Linköping</td>
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<tr>
<td>(Skarman)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kjell Nordström</td>
<td>1987</td>
<td>B. Egardt</td>
<td>Consultant, Norrköping</td>
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<tr>
<td>Bo Wahlberg</td>
<td>1987</td>
<td>M. Gevers</td>
<td>Professor, KTH, Stockholm</td>
</tr>
<tr>
<td>Svante Gunnarsson</td>
<td>1988</td>
<td>T. Söderström</td>
<td>Professor, LiTH</td>
</tr>
<tr>
<td>Alf Isaksson</td>
<td>1988</td>
<td>B. Friedlander</td>
<td>ABB, Västerås &amp; Adjunct Professor, LiTH</td>
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<tr>
<td>Mats Viberg</td>
<td>1989</td>
<td>M. Kaveh</td>
<td>Professor, Chalmers</td>
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<td>Krister Forsman</td>
<td>1991</td>
<td>M. Hazewinkel</td>
<td>Perstorp AB</td>
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<td>Fredrik Gustafsson</td>
<td>1992</td>
<td>M. Basseville</td>
<td>Professor, LiTH</td>
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<td>Peter Nagy</td>
<td>1992</td>
<td>H. Broman</td>
<td>FOI, Linköping</td>
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<td>Tommy Svensson</td>
<td>1992</td>
<td>D. Atherton</td>
<td>SAAB Dynamics, Linköping</td>
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<td>(Linderstam)</td>
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<td></td>
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<tr>
<td>Sören Andersson</td>
<td>1992</td>
<td>J. Böhme</td>
<td>Ericsson, Stockholm</td>
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PhD-exams, cont’d

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<th>NAME</th>
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<tr>
<td>Håkan Hjalmarsson</td>
<td>1993</td>
<td>R. Kosut</td>
<td>Professor, KTH</td>
</tr>
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<td>Inger Klein</td>
<td>1993</td>
<td>P. Caines</td>
<td>Associate Professor, LiTH</td>
</tr>
<tr>
<td>Jan-Erik Strömberg</td>
<td>1994</td>
<td>H. Paynter</td>
<td>DST AB, Linköping</td>
</tr>
<tr>
<td>Ke Wang Chen (Helmersson)</td>
<td>1994</td>
<td>P. Mäkilä</td>
<td>Ericsson, Linköping</td>
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<td>Thomas McKelvey</td>
<td>1995</td>
<td>J. Schoukens</td>
<td>Professor, Chalmers</td>
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<td>Jonas Sjöberg</td>
<td>1995</td>
<td>G. Dreyfus</td>
<td>Professor, Chalmers</td>
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<td>Roger Germundsson</td>
<td>1995</td>
<td>A. Benveniste</td>
<td>Wolfram Research, Champaign, USA</td>
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<td>Predrag Pucar</td>
<td>1995</td>
<td>B. Delyon</td>
<td>NIRA Dynamics</td>
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<td>Håkan Fortell</td>
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<td>H. Sira Ramirez</td>
<td>ABB Robotics, Västerås</td>
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<tr>
<td>Anders Helmersson</td>
<td>1995</td>
<td>J. Maciejowski</td>
<td>Ruag Space, Linköping &amp; Adjunct Professor, LiTH</td>
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<td>Peter Lindskog</td>
<td>1996</td>
<td>H. Koivo</td>
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<td>Johan Gunnarsson</td>
<td>1997</td>
<td>R.S. Sreenivas</td>
<td>Sörman AB</td>
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<td>Niclas Bergman</td>
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<td>V. Krishnamurthy</td>
<td>SAAB EDS</td>
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<td>Krister Edström</td>
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<td>G. Dauphin-Tanguy</td>
<td>Ericsson SR, Lund</td>
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<td>Magnus Larsson</td>
<td>1999</td>
<td>B. Neumann</td>
<td>ABB Robotics, Västerås</td>
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<td>Fredrik Gunnarsson</td>
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<td>J. Zander</td>
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<td>Valur Einarsson</td>
<td>2000</td>
<td>S. Kowalewski</td>
<td>Einfalt ehf., Iceland</td>
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<td>Mikael Norrlöf</td>
<td>2000</td>
<td>K. Moore</td>
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<td>Fredrik Tjärnström</td>
<td>2002</td>
<td>A. Vicino</td>
<td>Autoliv, Linköping</td>
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<td>Johan Löfberg</td>
<td>2003</td>
<td>B. Foss</td>
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<td>Jacob Roll</td>
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<td>M. Morari</td>
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<td>Jonas Elbornsson</td>
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<td>A. Zoubir</td>
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<td>Ola Härkegård</td>
<td>2003</td>
<td>M. Bodson</td>
<td>SAAB AB, Linköping</td>
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<td>Ragnar Wallin</td>
<td>2005</td>
<td>A. Garulli</td>
<td>Assistant Professor, LiTH</td>
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PhD-exams, cont’d

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<tr>
<td>David Lindgren</td>
<td>2005</td>
<td>B. DeMoor</td>
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<tr>
<td>Rickard Karlsson</td>
<td>2005</td>
<td>N. Gordon</td>
<td>FOI, Linköping</td>
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<td>Jonas Jansson</td>
<td>2005</td>
<td>H. Christensen</td>
<td>VTI, Linköping</td>
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<td>Erik Geijer Lundin</td>
<td>2005</td>
<td>O. Salent</td>
<td>Scania AB</td>
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<td>Martin Enqvist</td>
<td>2005</td>
<td>R. Pintelon</td>
<td>Associate Professor, LiTH</td>
</tr>
<tr>
<td>Thomas Schön</td>
<td>2006</td>
<td>S. Godsill</td>
<td>Associate Professor, LiTH</td>
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<tr>
<td>Ingela Lind</td>
<td>2006</td>
<td>T. Söderström</td>
<td>SAAB AB, Linköping</td>
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<tr>
<td>Jonas Gillberg</td>
<td>2006</td>
<td>P. van den Hof</td>
<td>Nynä AB</td>
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<tr>
<td>Markus Gerdin</td>
<td>2006</td>
<td>M. Deistler</td>
<td>Imego AB, Göteborg</td>
</tr>
<tr>
<td>Christina Grönwall</td>
<td>2006</td>
<td>K. Åström</td>
<td>FOI, Linköping</td>
</tr>
<tr>
<td>Andreas Eidehall</td>
<td>2007</td>
<td>A. Polychronopoulos</td>
<td>Volvo AB, Göteborg</td>
</tr>
<tr>
<td>Frida Eng</td>
<td>2007</td>
<td>P. Ferreira</td>
<td>SP Devices, Linköping</td>
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<tr>
<td>Erik Wernholt</td>
<td>2007</td>
<td>J. Swevers</td>
<td>Autoliv, Linköping</td>
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<tr>
<td>Daniel Axehill</td>
<td>2008</td>
<td>M. Morari</td>
<td>Assistant Professor, LiTH</td>
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<tr>
<td>Gustaf Hendeby</td>
<td>2008</td>
<td>P.M. Djurić</td>
<td>DKFI, Kaiserslautern, Germany</td>
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<td>Johan Sjöberg</td>
<td>2008</td>
<td>X. Hu</td>
<td>ABB CR, Västerås</td>
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<td>David Törnqvist</td>
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<td>H. Durrand-Whyte</td>
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<td>Per-Johan Nordlund</td>
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<td>Henrik Ohlsson</td>
<td>2010</td>
<td>B. Wahlberg</td>
<td>Assistant Professor, LiTH</td>
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<tr>
<td>Stig Moberg</td>
<td>2010</td>
<td>B. Siciliano</td>
<td>ABB Robotics, Västerås</td>
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</table>

### 2.3.2 Techn. Lic. Exams

A “Techn. Lic.” degree (teknologie licentiat) is an intermediate degree between Masters and Ph. D., around half-way to the Ph. D. This is the list of persons who received the Techn. Lic. degree from the Division of Automatic Control in 1976 – 2010, and are not part of the list in the previous section.
<table>
<thead>
<tr>
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<td>Jonas Plantin</td>
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<td>Anders Ericsson</td>
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<td>Jan Palmqvist</td>
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<td>Magnus Andersson</td>
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<td>Jonas Blom</td>
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<td>Per Spångéus</td>
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<td>Anna Hagenblad</td>
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<tr>
<td>Måns Östring</td>
<td>2002</td>
<td>Lecturer, LiTH, Norrköping</td>
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<td>Claes Ohlsson</td>
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<td>Niclas Persson (Sjöstrand)</td>
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<td>ABB Robotics</td>
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<td>Svante Björklund</td>
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<td>2008</td>
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<td>Janne Harju Johansson</td>
<td>2008</td>
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<td>Richard Falkborn</td>
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<td>Mathcore, Linköping</td>
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<td>Daniel Petersson</td>
<td>2010</td>
<td>LiTH (Ph. D. student)</td>
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## 2.4 Undergraduate Teaching

### 2.4.1 Course Development

In the academic year 1976/77, the division offered two undergraduate courses with a total of 358 participants. These courses were:

1. **Reglerteknik** (Basic Control Course).

2. **Reglerteori** (Advanced Control Course).
Gradually, more and more undergraduate courses were introduced. In 2010 we had 1278 participants in 18 different courses. Since the first courses in 1976/77, they have been developed to include the following categories:

3. The basic control course has been adapted and is given in six different formats for the various study programs, and degrees offered.


10. Sensorfusion (Sensor Fusion), introduced in 2009.

See Section B.1 for the number of participants and undergraduate course material available during the year 2010.

2.4.2 Master’s Theses

Since 1976, 854 Master’s theses have been produced. In many cases a thesis is written by two students, so the number of Master’s thesis students examined is about 1200.

2.4.3 Quality Measures

- The students give the courses high rating in the course evaluations. As a result of that the teaching staff has received approximately 40 letters of recognition from the Dean of LiTH, distributed over thirteen staff
members. Such a letter is given to a course that gets rating 4.2 or more on a 1 to 5 scale for course quality. (Approximately 10% of the courses given within the engineering programs every year receive such a letter.) This is since 2002, when the Dean started this practice.

- Members of the teaching staff have been nominated to the award Gyllene Moroten ("Teacher of the Year") nine times by the student union within LiTH. In 2009, Thomas Schön won the award.

- Members of the teaching staff have eight times received the award Iplom for high course ratings from the student within the program Industrial Engineering and Management.

- In 2007, the study area Control Systems in Linköping (which consists of the Automatic Control group and the Vehicular Systems group) received the award for “Excellent Education Environment” (Utmärkelsen “Framstående Utbildningsmiljö”) from the Swedish National Agency for Higher Education (Högskoleverket). The award was given to five such environments across all areas at all Swedish universities.

2.5 Major Grants and Research Centra

The need and expectations to bring in external research funds has increased dramatically over the period. The first external grant was given by STU (Styrelsen för Teknisk Utveckling) in 1979 and concerned fast solution of integral equations. Since then there has been many grants from STU, STUFF, NUTEK, TFR, VR, NFFP, VINNOVA, SSF and other funding agencies. Among major grants supporting broad centra (with the Division of Automatic Control as organizer and “Principal Investigator”) we may mention:


• ELLIIT (Excellence Center at Linköping-Lund in Information Technology). One of the Strategic Research Areas (SFO) that the government initiated 2010. It is focused on Information Technology and mobile communication. Horizon 2010 and onward.

• SECURITY LINK. Another of the SFOs focused on security issues in a broad sense. Horizon 2010 and onward.
Chapter 3

System Identification

The system identification research within the group concerns both theoretical aspects and applications in a number of areas, e.g., aircraft, industrial robots, medical imaging, and navigation sensors. During 2010, two Ph.D. theses about system identification were defended. Henrik Ohlsson’s thesis Regularization for Sparseness and Smoothness [2] is described in this chapter, while Stig Moberg’s thesis Modeling and Control of Flexible Manipulators [1] is described in Chapter 6.

During the year, also the perspective paper [26] was published. It is based on the 2008 plenary lecture at the IFAC World Congress in Seoul.

3.1 Regularization for Sparseness and Smoothness

Regularization shows up in a variety of different situations and is a well-known technique to handle ill-posed problems and to control for overfit. In statistics and machine learning, regularization has gained popularity due to modeling methods such as Support Vector Machines (SVM), ridge regression and lasso. But also when using a Bayesian approach to modeling, regularization often implicitly shows up and can be associated with the prior knowledge. Regularization has also had a great impact on many applications, and very much so in clinical imaging. In e.g., breast cancer imaging, the number of sensors is physically restricted, which leads to long scan times. Regularization and sparsity can be used to reduce that. In Magnetic Resonance Imaging (MRI), the number of scans is physically limited and to obtain
Henrik Ohlsson’s thesis [2] focuses on the use of regularization to obtain sparseness and smoothness and discusses novel developments relevant to system identification and signal processing. In regularization for sparsity a quantity is forced to contain elements equal to zero, or to be sparse. The quantity could e.g., be the regression parameter vector of a linear regression model and regularization would then result in a tool for variable selection. Sparsity has had a huge impact on neighboring disciplines, such as machine learning and signal processing, but rather limited effect on system identification. One of the major contributions of Henrik’s thesis is therefore the new developments in system identification using sparsity. In particular, a novel method for the estimation of segmented ARX models using regularization for sparsity is presented [30]. A technique for piecewise-affine system identification is also elaborated on, as well as several novel applications in control [62] and signal processing [61]. Another property that regularization can be used to impose is smoothness. To require the relation between regressors and predictions to be a smooth function is a way to control for overfit. Henrik has been particularly interested in regression problems with regressors constrained to limited regions in the regressor-space, e.g., a manifold. For this type of systems a new regression technique, Weight Determination by Manifold Regularization (WDMR, see e.g., Ohlsson and Ljung [29], Bauwens et al. [8]) was developed. WDMR is inspired by applications in biology and developments in manifold learning and uses regularization for smoothness to obtain smooth estimates. The use of regularization for smoothness in linear system identification is also discussed.

Henrik’s thesis also presents a real-time functional Magnetic Resonance Imaging (fMRI) bio-feedback setup. The setup has served as proof of concept and been the foundation for several real-time fMRI studies, e.g., Nguyen et al. [59], Eklund et al. [42, 41].

3.2 Nonlinear Systems

Identification of nonlinear systems is a vast subject, with many suggested model structures and algorithms. The area has sometime been called “non-elephant” zoology, to pinpoint how difficult it is to characterise and classify it. An attempt to provide some kind of structure into the field is given in [55].
3.2.1 State-space Descriptions

During the last decade or so, nonlinear system identification techniques based on sequential Monte Carlo (SMC) methods, such as particle filters, have appeared at an increasing rate and with increasingly better performance. In the papers [60, 53] we have continued this line of work. More specifically, we employ the standard Maximum Likelihood (ML) framework and derive an Expectation Maximization (EM) type algorithm. This involves the solution of a nonlinear smoothing problem for the state variables.

In the work [60] we provide a novel approach to the estimation of a general class of dynamic nonlinear system models. The main contribution is the use of a tool from mathematical statistics, known as Fishers’ identity, to establish how an EM type quantity can be used to compute gradients of maximum-likelihood and associated prediction error cost criteria.

Furthermore, in [53] we developed an identification method capable of identifying parameters in so called mixed linear/nonlinear state-space models, containing conditionally linear Gaussian substructures. For this cause, we develop a so called Rao-Blackwellized particle smoother (RBPS), designed to exploit the structure present in a mixed linear/nonlinear state-space model. By doing so, we can obtain better estimates than what is provided by a standard particle smoother, using the same number of particles.

The EM algorithm has proven to be effective for a range of identification problems. Unfortunately, the way in which the EM algorithm has previously been applied has proven unsuitable for the commonly employed innovations form model structure. In the work [74] we address this problem, and present a previously unexamined method of EM algorithm employment. The results are profiled, which indicate that a hybrid EM/gradient-search technique may in some cases outperform either a pure EM or a pure gradient-based search approach.

3.2.2 Block-oriented Systems

A block-oriented system consists of a combination of linear dynamic sub-systems and static nonlinearities, connected either in series or in parallel. This system class contains well-known and well-studied sub-classes, such as Wiener, Hammerstein and Wiener-Hammerstein systems. Many of the existing methods for these types of systems are based on, or benefit from, a theoretical result known as the invariance property. For example, Bussgang’s
classic theorem shows that this property holds for a static nonlinearity with a Gaussian input signal. The book chapter [13] contains an introduction to the invariance property and explains why it is so useful for identification of block-oriented systems.

The special problem of a Wiener model concerns the case of a linear dynamic system followed by a static nonlinearity. In [32] it is shown how to formulate the ML criterion for this structure, also in the case additive colored noise enters into or after the linear system. Handling this criterion numerically is non-trivial, but in the paper it is pointed out how to deal with the problem using particle filtering. As an extra benefit, also follows a method to deal with blind Wiener models, that is systems without measurable inputs, which obey the structure: white noise entering an unknown linear dynamic system, followed by a nonlinear static block.

3.3 Continuous-time Models

3.3.1 Sampling Continuous-time Models with Stochastic Disturbances

The basic continuous-time (CT) model

\[
\dot{x} = Ax + Bu + w \\
y = Cx + e
\]

is an idealisation that contains mathematically sophisticated objects like CT white noises \(w\) and \(e\). Sampling such models to describe real world discrete time signals must involve some kind of low-pass filtering of \(y\). In connection with system identification of CT models from sampled data, this process is often approximated (or “mishandled”) to some extent. In [27] it is discussed how a proper method should work and to what extent the usual methods capture or not the essential features.
3.3.2 Estimation of Continuous-time Models using Frequency Domain Techniques

The two companion papers [14] and [15] concern the problem of estimating a CT model

\[ y(t) = \frac{B(p)}{F(p)} u(t) \]  

(3.1)

where \( p \) is the differentiation operator, from sampled data sequences \( y(t_k), u(t_k), k = 1, \ldots, N \).

The basic approach is to form the discrete Fourier transforms (DFT) of the input output data, and see how they can be used to obtain good estimates of the true (continuous-time) Fourier transforms. Then frequency domain criteria can be used to estimate (3.1). Part I of the two papers [14, 15] concerns the case of uniformly sampled data \( (t_k = kT) \), while part II deals with the general, non-uniformly sampled case.

3.4 Applications

The paper [23] is concerned with the problem of estimating the relative translation and orientation of an inertial measurement unit and a camera, which are rigidly connected. The key is to realize that this problem is in fact a gray-box system identification problem, the paper is also discussed in Chapter 5 on sensor fusion. Another system identification type problem appears in [51], where we provide a novel method for calibrating an Ultra-Wideband (UWB) indoor positioning system. This is again further explained in the chapter on sensor fusion, since it also involves interesting sensor fusion aspects.

Gray-box identification of industrial robots is described in [31] and in Stig Moberg’s Ph.D. thesis [1]. More information about this application is available in Chapter 6.

An application of identification to systems biology is described in [9]. The model describes insulin signaling in human cells and the problem is to reject certain choices of structure. More details are given in Chapter 4 on nonlinear and DAE models.
Chapter 4
Nonlinear and DAE Models

4.1 Structure of DAE Models

An important structural property of a differential algebraic equation (DAE),
\[ F(\dot{x}, x, t) = 0 \]

is the number of hidden implicit differentiations. This is closely related to the practical difficulty of rewriting the DAE as an explicit ordinary differential equation (ODE). A widely used measure of this difficulty is the Kunkel-Mehrmann strangeness index. A relaxation of the strangeness index that has a very simple characterization was presented in the previous annual report for 2009. In [118] the properties of this simplified index were developed further.

4.2 Rejection of Models based on Qualitative Properties

Consider a fairly general model of a physical system
\[ \dot{x} = f(x, \theta), \quad y = h(x, \theta) \]

where \( y \) is the measured output, \( x \) is the state vector and \( \theta \) is a vector of constant parameters. Often the modeling problem has the two phases of first choosing the function \( f \), which relates to the structure of the system, and then finding suitable values for \( \theta \). Sometimes it is useful to reject a model
structure, i.e., to show that, for a given $f$, there is no physically reasonable choice of $\theta$ that is compatible with the measured values of $y$.

One application where this problem comes up is systems biology. A typical model can be described by a diagram like the one shown in Figure 4.1, that describes how the concentrations of four different proteins affect each other.

\begin{equation*}
\begin{align*}
\dot{x}_1 &= -v_1(x_1) + v_4(x_4) \\
\dot{x}_2 &= -v_2(x_2) + v_1(x_1) \\
\dot{x}_3 &= -v_3(x_3) + v_2(x_2) \\
\dot{x}_4 &= -v_4(x_4) + v_3(x_3)
\end{align*}
\end{equation*}

where the state variables are the protein concentrations and the functions $v_i$ are the reaction velocities. Models of this type can be used to describe insulin signaling in cells, as shown in [9]. In the simplest models the velocities are modeled as being linear, but more realistic models include saturation effects. In experiments $x_1$ is initialized with a certain concentration and one of the other concentrations is measured. The response then shows a pronounced overshoot. The question is then: when can a model of this form have an overshoot? In the linear case this question is closely related to the placement of poles and zeros. For instance one can show that when $v_3$ is much smaller than the other velocities there can be no overshoot in a measurement of $x_4$, but there will be a large overshoot in $x_2$, associated with a zero close to the imaginary axis. See the illustration given in Figure 4.2.
Figure 4.2: Responses of a biochemical reaction when $v_3$ is small.
Chapter 5

Sensor Fusion

Highlights of the year are:

- The books on sensor fusion [5] and signal processing [6].

- The magazine article [17], which summarizes 20 years experience in using wheel speed sensors for application with high demand on accuracy. It describes pre-processing to compensate for sensor imperfections, interpolation from event domain to time domain, synchronous sampling, and various automotive applications.

- The magazine article [16], which contains a tutorial on the particle filter aimed for practitioners with a background in Kalman filter applications. It overviews the connection to the point mass filter, the basic theory,
practical implementation aspects such as numerical issues, Matlab code and marginalization, and summarizes a fair amount of applications from the group.

• The scientific publications, including the journal papers [11, 23, 21, 22, 28, 10, 17, 16, 24] and the conference papers [63, 48, 67, 57, 54, 56, 47, 68, 45, 51, 50, 72, 36, 69, 53, 38, 65, 64, 35, 60, 46, 71, 39].

5.1 Book Overviews

Statistical Sensor Fusion

Sensor fusion deals with merging information from two or more sensors, where the area of statistical signal processing provides a powerful toolbox to attack both theoretical and practical problems.

The objective of this book is to explain state of the art theory and algorithms in statistical sensor fusion, covering estimation, detection and nonlinear filtering theory with applications to localization, navigation and tracking problems. The book starts with a review of the theory on linear and nonlinear estimation, with a focus on sensor network applications. Then, general nonlinear filter theory is surveyed, with a particular attention to different variants of the Kalman filter and the particle filter. Complexity and implementation issues are discussed in detail. Simultaneous localization and mapping (SLAM) is used as a challenging application area of high-dimensional nonlinear filtering problems.

The book spans the whole range from mathematical foundations provided in extensive appendices, to real-world problems covered in a part surveying standard sensors, motion models and applications in this field. All models and algorithms are available as object-oriented Matlab code with an extensive data file library, and the examples, which are richly used to illustrate the theory, are supplemented by fully reproducible Matlab code.

Signal Processing

This edition has evolved over the past twenty years, the first ten years as a compendium and then as a textbook in Swedish. It has been used in a course in Signal Processing at Linköping University by around 1500 undergraduate students from all engineering programs. Already from the start, it
distinguished itself from the large amount of textbooks on signal processing by shifting the focus from transform theory to a comprehensive treatment of classical (transform based) as well as modern (model based) signal processing aimed at applications on real data and problems. The selection of topics is guided by the topics of more than 200 external M.Sc. theses in signal processing as well as the needs from our many industrial research partners. With this first international edition, we have further increased the connection to Matlab. The general idea is that each topic should lead to an algorithm with a compact Matlab function. These Matlab functions gradually adds functionality to the reader’s versatile signal processing toolbox, where only standard Matlab is needed. However, each chapter summary also points out which functions are already available in the signal processing, control and system identification toolboxes. The presented functions are a part of Signal and Systems Lab, a toolbox tailored to the theory of this book. The lab contains a database of real signals the reader can play around with, many of these are used in the examples. All non-trivial examples of the book includes reproducible code, and all functions and examples in the book are included in the installation. There is also an accompanying book with exercises, also with a practical focus with a mix of problem solving by hand and Matlab programming. See also the publisher’s homepage.

5.2 Project Overview

Our research in sensor fusion covers the whole chain of problems, from sensors to applications, as illustrated in Figure 5.1:

- **Sensor and dynamic motion models**
  - *Sensor modeling* is focused on inertial measurement units (IMU) and using cameras as sensors. The problems involve sensor error modeling, 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 aircrafts (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, and FOCUS (VINNOVA institute excellence center) on sensor networks.

5.3 Localization, Navigation and Mapping

5.3.1 Silent Localization of Underwater Sensors

The publication [11] is about sensor localization, which is a central problem for sensor networks. If the sensor positions are uncertain, the target tracking ability of the sensor network is reduced. Sensor localization in underwater environments is traditionally addressed using acoustic range measurements involving known anchor or surface nodes. We explore the usage of triaxial magnetometers and a friendly vessel with known magnetic dipole to silently localize the sensors. The ferromagnetic field created by the dipole is measured by the magnetometers and is used to localize the sensors. The trajectory of the vessel and the sensor positions are estimated simultaneously using an extended Kalman filter. Simulations show that the sensors can be accurately positioned using magnetometers.

5.3.2 Joint Ego-Motion and Road Geometry Estimation

In the article [28] we provide a sensor fusion framework for solving the problem of joint ego-motion and road geometry estimation. More specifically we employ a sensor fusion framework to make systematic use of the measurements from a forward looking radar and camera, steering wheel angle sensor, wheel speed sensors and inertial sensors to compute good estimates of the road geometry and the motion of the ego vehicle on this road. In order to solve this problem we derive dynamic models for the ego vehicle, the road and the leading vehicles. The main difference to existing approaches is that we make use of a new dynamic model for the road. An extended Kalman filter is used to fuse data and to filter measurements from the camera in order to improve the road geometry estimate. The proposed solution has been tested and compared to existing algorithms for this problem, using measurements
from authentic traffic environments on public roads in Sweden. The results clearly indicate that the proposed method provides better estimates.

5.3.3 Random Set Based Road Mapping

The work [56] is concerned with the problem of multi-sensor multi-target tracking of stationary road side objects, i.e., guard rails and parked vehicles, in the context of automotive active safety systems. Advanced active safety applications, such as collision avoidance by steering, rely on obtaining a detailed map of the surrounding infrastructure to accurately assess the situation. Here, this map consists of the position of objects, represented by a random finite set (RFS) of multi-target states and we propose to describe the map as the spatial stationary object intensity. This intensity is the first order moment of a multi-target RFS representing the position of stationary objects and it is calculated using a Gaussian mixture probability hypothesis density (GM-PHD) filter.

5.3.4 Estimating Polynomial Structures from Radar Data

Situation awareness for vehicular safety and autonomy functions includes knowledge of the drivable area. This area is normally constrained between stationary road-side objects as guard-rails, curbs, ditches and vegetation. In [57] we consider these as extended objects modeled by polynomials along the road, and propose an algorithm to track each polynomial based on noisy range and bearing detections, typically from a radar. A straightforward Kalman filter formulation of the problem suffers from the errors-in-variables (EIV) problem in that the noise enters the system model. We propose an EIV modification of the Kalman filter and demonstrates its usefulness using radar data from public roads.

5.3.5 Fingerprinting Localization in Wireless Networks Based on RSS Measurements

Localization in wireless networks based on received-signal-strength (RSS) observations is a challenging problem. This is mainly due to the noisy characteristics of the RSS measurements which are influenced a lot by non-line-
if-sight and multi-path effects. Modeling such phenomena is very difficult using mathematical models if not impossible. Hence, maps of different RSS measurements called fingerprints collected from different points in the area of surveillance are experimentally obtained and used later for localization. Our work [10] shows how such maps can be utilized in particle filters as a form of a measurement model. The results of the proposed approaches are illustrated and compared with an example whose data were collected from a WiMAX network in a challenging urban area in Brussels, Belgium.

5.3.6 Modeling and Calibration of Inertial and Vision Sensors

The paper [51] is concerned with the problem of estimating the relative translation and orientation of an inertial measurement unit and a camera, which are rigidly connected. The key is to realize that this problem is in fact an instance of a standard problem within the area of system identification, referred to as a gray-box problem. We propose a new algorithm for estimating the relative translation and orientation, which does not require any additional hardware, except a piece of paper with a checkerboard pattern on it. The method is based on a physical model which can also be used in solving, for example, sensor fusion problems. The experimental results show that the method works well in practice, both for perspective and spherical cameras.

5.3.7 Geo-referencing for UAV Navigation using Environmental Classification

The paper [54] considers the problem of UAV navigation. In particular, we seek a GPS free navigation system that does not suffer from long term drift. A UAV navigation system relying on GPS is vulnerable to signal failure, making a drift free backup system necessary. Here, we introduce a vision based geo-referencing system that uses preexisting maps to reduce the long term drift. The system classifies an image according to its environmental content and thereafter matches it to an environmentally classified map over the operational area. This map matching provides a measurement of the absolute location of the UAV that can easily be incorporated into a sensor fusion framework. Figure 5.2 shows experimental results using data collected during a test-flight in southern Sweden. The experiments show that the geo-
Figure 5.2: True trajectory illustrated with circles and the estimated trajectories with (solid line) and without (dashed line) geo-referencing. By comparing the images from an on-board camera with an existing map of the operational environment, the long term drift in the position estimate can be reduced.

referencing system reduces the long term drift in UAV navigation, enhancing the ability of the UAV to navigate accurately over large areas without the use of GPS, see Figure 5.2.

5.3.8 Learning to Close the Loop from 3D Point Clouds

For mobile robots and autonomous vehicles, the ability to recognize previously visited places is important, especially in the Simultaneous Localisation and Mapping (SLAM) problem. Place recognition, also known as loop closure detection, has been addressed for robots equipped to acquire three dimensional laser range data, called point clouds [47]. The point clouds are given a mathematical description using more than 40 features that describe the geometric and statistical properties of the data. The features are rotation invariant, enabling loop closure detection from arbitrary direction.

Features from two point clouds are compared using an AdaBoost learned classifier. AdaBoost is an iterative machine learning algorithm which builds classifiers by concatenating simple, so called “weak”, classifiers. With the learned classifier, 63% and 53% detection rates are achieved at 0% false alarm, for outdoor and indoor data, respectively. Experiments where the classifier is learned using outdoor data and tested using indoor data from a different sensor setup show the classifiers strong generalisation capabilities. Figure 5.3 shows a two dimensional projection of the resulting SLAM map from one of the experiments.
5.3.9 Ultra-Wideband Calibration for Indoor Positioning

The main contribution of this work is a novel calibration method to determine the clock parameters of the UWB receivers as well as their 3D positions. It exclusively uses time-of-arrival measurements, thereby removing the need for the typically labor-intensive and time-consuming process of surveying the receiver positions. Experiments show that the method is capable of accurately calibrating a UWB setup within minutes.

5.3.10 Probabilistic Stand Still Detection using Foot Mounted IMU

The paper [36] is about stand still detection for indoor localization based on observations from a foot-mounted inertial measurement unit (IMU). The main contribution is a statistical framework for stand-still detection, which is a fundamental step in zero velocity update (ZUPT) to reduce the drift from cubic to linear in time. First, the observations are transformed to a test statistic having non-central $\chi^2$ distribution during zero velocity. Second, a hidden Markov model is used to describe the mode switching between stand still and moving. The resulting algorithm computes the probability of being
in each mode, and it is easily extendable to a dynamic navigation framework where map information can be included. Results of mode probability estimation are provided.

5.3.11 Simultaneous Navigation and SAR Auto-focusing

In the work [69] we present a method of using Synthetic Aperture Radar (SAR) images and focus information in these together with the navigation system. This information is combined together in a sensor fusion framework and improvement to both navigation state estimate and image focus is obtained. The method is evaluated on a representative simulated test images and the results are promising.

5.3.12 Window Based GPS Integrity Test using Tight GPS/IMU Integration

This work [71] presents integrity monitoring and integration methods for an Inertial Measurement Unit (IMU) and a GPS receiver. The methods are applied to data from a Maxus sounding rocket used for microgravity research. It is crucial to determine the rocket position during launch to ensure a safe landing location. Today, the navigation relies on IMU integration only. Involving a GPS receiver enhances the position accuracy but there is a need for protection against faulty satellite range measurements. Monitoring over a sequence of the measurements gives higher confidence to the tests.

5.4 Particle Filtering

5.4.1 Particle Filtering — The Need for Speed

The particle filter (PF) is sometimes believed to be trivially parallelized on multi-core processors, since each core can be responsible for the operations associated with one or more particles. This is true for the most characteristic steps in the PF algorithm applied to each particle, but not for the interaction steps. Further, as is perhaps less well known, the bottleneck computation even on CPU’s is often not the particle operations but the re-sampling, and this is not obvious to parallelize.
The main steps in the PF and their complexity as a function of $N$ number of particles are discussed in [21], and are summarized in words below:

- Initialization: each particle is sampled from a given initial distribution and the weights are initialized to a constant. Parallelizable and thus $O(1)$.
- Measurement update: The likelihood of the observation is computed conditional on the particle. Parallelizable and thus $O(1)$.
- Weight normalization: The sum of the weight is needed for normalization. A hierarchical evaluation of the sum is possible, which leads to complexity $O(\log(N))$.
- Estimation: The weighted mean is computed. This requires interaction. Again, a hierarchical sum evaluation leads to complexity $O(\log(N))$.
- Re-sampling: This step first requires the weights to be sorted. Sorting is an $O(\log(N))$ operation, and it is not obvious how to parallelize it. There are other similar interaction steps.
- Prediction: Each particle is propagated through a common proposal density. Parallelizable and thus $O(1)$.
- Optional steps of Rao-Blackwellization: If the model has a linear Gaussian substructure, a part of the state vector can be updated with the Kalman filter. This is done locally for each particle, and thus $O(1)$.
- Optional step of computing marginal distribution of the state (the filter solution) rather than the state trajectory distribution. This is $O(N^2)$ on a single core processor, but parallelizable to $O(N)$. It also requires massive communication between the particles.

This suggests the following basic functions of complexity:

$$ f_1(N) = c_1 + c_2N $$

$$ f_M(N) = \frac{N}{M} \left( c_3 + c_4 \log(N) \right) $$

In the future, we might be able to use $N = M$ above. Eventually, the multi-core implementation will always be more efficient as $N \to \infty$. However, for
the value of $N$ that the application requires, the best solution depends on the constants. One can here define a break-even number

$$N_{\text{breakeven}} = \text{sol}_N c_1 + c_2 N = \frac{N}{M} \left( c_2 + c_3 \log(N) \right)$$

This number depends on the relative processing speed of the single and multi-core processors, but also on how efficient the implementation is.

It is the purpose of this contribution to discuss these important issues in more detail, with a focus on general purpose graphical processing units (GPGPU). We also provide one of the first complete GPGPU implementations of the PF, and use this example as a ground for a discussion of $N_{\text{breakeven}}$.

### 5.4.2 The Rao-Blackwellized Particle Filter — A Filter Bank Implementation

In our earlier publications, we have derived the marginalized particle filter (MPF), Rao-Blackwellized particle filter, in terms of a structured model of the form

\[
\begin{align*}
    x^{n}_{k+1} &= f^n_k(x^n_k) + F^n_k(x^n_k)x^l_k + G^n_k(x^n_k)v^n_k \\
    x^l_{k+1} &= f^l_k(x^l_k) + F^l_k(x^l_k)x^l_k + G^l_k(x^l_k)v^l_k \\
    y_k &= h_k(x^n_k) + H_k(x^n_k)x^l_k + e_k
\end{align*}
\]

The resulting algorithm is a mixture of particle filter steps and Kalman filter like steps. For the latter, the first equations above is interpreted as virtual measurement equations, and the resulting update step does not immediately fit a Kalman filter framework. The article [22] makes a more or less trivial re-formulation of the model above as

\[
\begin{align*}
    x_{k+1} &= F^n_k(x^n_k)x_k + f^n_k(x^n_k) + G^n_k(x^n_k)v_k \\
    y_k &= H_k(x^n_k)x_k + h_k(x^n_k) + e_k
\end{align*}
\]

This model is exactly on the same form as the model used in Kalman filter banks, where the non-linear part of the state vector, $x^n_k$, corresponds to the discrete mode of the system. This fact is exploited in [22], and an algorithm that has the same steps as a Kalman filter bank is presented, but where the mode pruning is replaced with stochastic re-sampling. The key advantage is that all updates are either pure Kalman filter measurement and time updates, or standard particle filter steps. This facilitates code reuse and object oriented implementations.
5.4.3 Particle Filtering with Signal Propagation Delays

An increasing trend in sensor networks is to use many cheap and low quality sensors to accomplish the tasks that were done in the past using few expensive and high-quality sensors. In such scenarios, the signal propagation delays between the target and the sensors start to become more and more important. This is especially the case when the target speed approaches the propagation speed of the signals (e.g., sound) in the propagation medium (air, in the case of sound).

A deterministic sampling based estimation algorithm was proposed from our group in the previous years in order to compensate for the unpredictable effects of propagation delays in the tracking filters. This year, the follow-up work in [63] generalizes the delay compensation framework we proposed earlier to particle filters.

5.4.4 Marginalized Particle Filters for Bayesian Estimation of Gaussian Noise

We suggest a marginalization approach for estimating the unknown parameters of process and measurement noises in general nonlinear state space models in [68]. Particle filter provides a general solution to the nonlinear filtering problem with arbitrarily accuracy. However, the curse of dimensionality prevents its application in cases where the state dimensionality is high. Furthermore, estimation of the stationary parameters is a known challenge in the particle filtering framework. The posterior densities of unknown mean and covariance of both process and measurement noises have the sufficient statistics which allows recursive analytical updating using the concept of conjugate prior distributions. The resulting marginalized particle filter improves other approaches in the literature in that it does neither require any extra states for the parameters, nor additional sampling steps. The resulting algorithm is illustrated on both a standard example and a navigation application based on odometry. The latter involves formulas for dead reckoning rotational speeds of two wheels with unknown radii.
5.4.5 Particle Filters with Dependent Noise

The theory and applications of the particle filter (PF) have developed tremendously during the past two decades. However, there appears to be no version of the PF readily applicable to the case of dependent process and measurement noises. This is in contrast to the Kalman filter, where the case of correlated noise is a standard modification. This noise dependency arises quite naturally in many practical problems of interest. Further, the fact that sampling continuous time models leads to dependent noise processes is an often neglected fact in literature. We develop a PF framework with this noise dependency in [50]. The corresponding optimal proposal distribution was derived, and the two most common approximations (prior and likelihood, respectively) were also stated. The special case of additive Gaussian noise processes was studied in detail, and the common Bootstrap/SIR PF was modified by a new prediction step.

5.4.6 Decentralization of Particle Filters

In the work [38], a new PF which we refer to as the decentralized PF (DPF) is proposed. By first decomposing the state into two parts, the DPF splits the filtering problem into two nested sub-problems and then handles the two nested sub-problems using PFs. The DPF has an advantage over the regular PF that the DPF can increase the level of parallelism of the PF. In particular, part of the resampling in the DPF bears a parallel structure and thus can be implemented in parallel. The parallel structure of the DPF is created by decomposing the state space, differing from the parallel structure of the distributed PFs which is created by dividing the sample space. This difference results in a couple of unique features of the DPF in contrast with the existing distributed PFs.

5.5 Target Tracking

5.5.1 A GM-PHD Filter for Extended Target Tracking

In classic target tracking, it is often assumed that each target causes at most one measurement per time step. However, with many modern sensors, e.g., cameras, laser range sensors, and automotive radar, the single measurement assumption does not apply. Instead, the targets occupy multiple resolution
cells of the sensor, and thus cause multiple measurements per time step. Such targets are called extended targets.

Finite set statistics (FISST) provides a rigorous framework for multiple target tracking. Using FISST, the probability hypothesis density (PHD) filter can be derived, giving a framework for propagation of the first order moment of a random set. An implementation of a Gaussian Mixture PHD filter for extended target tracking was presented in [48]. The implemented filter requires a summation over all possible partitions of the measurement set, an operation which quickly becomes intractable as the size of the measurement set grows. To remedy the problem, a partitioning function is proposed that reduces the number of partitions that have to be considered by several orders of magnitude. The implemented extended target tracking framework can efficiently track multiple targets that each produce a Poisson distributed number of measurements. In cluttered sets of measurements the target cardinality (i.e., the number of targets) is correctly estimated, with the exception of when targets are spatially very close.

### 5.5.2 Magnetometers for Tracking Metallic Targets

Tracking and classification of vehicles are primary concerns in intelligent transportation and security systems. During the spring, the use of magnetometers for such applications was investigated in the master’s thesis [152]. Early results from that work resulted in a conference contribution [72].

### 5.5.3 Combined PMF and PF for Target Tracking

The paper [65] presents a combined point mass filter (PMF) and particle filter (PF), which utilizes the support of the PMF and the high particle density in the PF close to the current estimate. The result is a filter robust to unexpected process events but still with low error covariance. This filter is especially useful for target tracking applications, where target maneuvers suddenly can change unpredictably.

### 5.5.4 Multiple Target Tracking with Acoustic Power Measurements

Multiple target tracking using acoustic power measurements obtained from an acoustic sensor network poses problems that are quite unconventional for
target tracking. Since the sensors are superpositional, the classical notion of data association becomes irrelevant. In the work [64] we show how one can achieve an acceptable multiple target tracking performance for this problem using a novel concept called emitted power density (EPD) which is an aggregate information state that holds the emitted power distribution of all targets in the scene over the target state space. We propose a Gaussian process based representation for estimating the EPDs using Kalman filter formulas, which results in a recursive EPD-filter that is based on the discretization of the position component of the target state space. The results are illustrated on a real data scenario, where experiments are done with two targets constrained to a road segment.
Chapter 6

Robotics

6.1 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.

6.2 Modeling, Identification, and 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. Due to a desire to reduce cost and weight, each new robot generation offers new challenges since the robots contain more of mechanical elasticities. The PhD thesis by Stig Moberg, [1], addresses the entire chain from physical modeling and parameter estimation to feedforward control and robust feedback.

The thesis deals with different aspects of modeling and control of flexible, i.e., elastic, manipulators. For an accurate description of a modern industrial manipulator, this thesis shows that the traditional flexible joint model, described in literature, is not sufficient. An improved model where the elasticity is described by a number of localized multidimensional spring-damper pairs is therefore proposed. This model is called the extended flexible joint
model. An example of such a model structure with eight degrees of freedom is shown in Figure 6.1.

The main contributions of the work are the design and analysis of identification methods, and of inverse dynamics control methods, for the extended flexible joint model. The proposed identification method is a frequency-domain non-linear gray-box method, which is evaluated by the identification of a modern six-axes robot manipulator. The identified model gives a good description of the global behavior of this robot. The inverse dynamics problem is discussed, and a solution methodology is proposed. This methodology is based on the solution of a differential algebraic equation (DAE). The inverse dynamics solution is then used for feedforward control of both a simulated manipulator and of a real robot manipulator. The last part of the work concerns feedback control. First, a model-based nonlinear feedback control (feedback linearization) is evaluated and compared to a model-based feedforward control algorithm. Finally, two benchmark problems for robust feedback control of a flexible manipulator are presented and some proposed solutions are analyzed.
6.3 Trajectory Generation and Time Optimal Control

To maximize the productivity in modern production plants, the cycle time in the robot cells is often a limiting factor. Therefore time-optimal motion planning applied to robotic manipulators is of significant importance in real applications. For an optimization method to be useful there are a number of requirements that have to be met. Firstly the solution, the time optimal trajectory, must be possible to compute in a short time, preferably in real time. Secondly, the optimization problem formulation must have a high degree of flexibility, which means that it must be easy to add new constraints and the constraints must be possible to parameterize in a general way. Of equal importance is that the optimization uses realistic constraints, considering both the user’s demands on the tool velocity, as well as the internal robot constraints. In [77] previous results in literature on time optimal convex optimization for a predefined path are extended to cover speed dependent constraints, such as viscous friction in the model. In Figure 6.2 an example is shown to illustrate the difference in the torque utilization, using constant torque constraint, and speed dependent torque constraint. The speed dependent constraint makes it possible to get higher torque at lower speed and, at the same time, increase the maximum speed compared to the constant torque constraint approach. In [77] it is shown how the speed dependent constraints should be added in order to keep the convexity of the overall problem. A method to, conservatively, approximate the linear speed dependent constraints by a convex constraint is also proposed. A numerical example is provided where the resulting performance difference is illustrated in terms of decreased cycle time.

Figure 6.2: Resulting torque constraints when considering constant torque (left), and speed dependent torque (right).
6.4 Sensor Fusion

One consequence of the increased mechanical flexibility of modern industrial robots is a need to develop methods to estimate the position, orientation, speed, etc., of the robot tool. It is therefore natural to apply sensor fusion methods to industrial robots, and this is for several reasons a very challenging task. First, the dynamic model of an industrial robot is very complex, and that will make sensor fusion algorithms very computationally demanding, and second, the models will contain a large number of model parameters, which unavoidably are subject to uncertainty. These aspects lead to the problem of designing and tuning sensor fusion algorithms of realistic complexity that are able to generate estimates of sufficient accuracy. One aspect of the tuning problem is studied in [78], where a variant of the expectation maximization (EM) algorithm is used and iteratively estimates the unobserved state sequence and $Q$ based on the observations of the process. The extended Kalman smoother (EKS) is the instrument to find the unobserved state sequence. The contribution fills a gap in literature, where previously only the linear Kalman smoother and particle smoother have been applied. The algorithm will be important for future industrial robots with more flexible structures, where the particle smoother cannot be applied due to the high state dimension. The proposed method is compared to two alternative methods on a simulated robot.

6.5 Iterative Learning Control

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 large 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.
One approach to handle this problem is to estimate the position and orientation of the tool and use the estimated variables in the ILC algorithm. This idea has been implemented and evaluated in simulation examples in previous publications, and it has now been generalized by formulating a framework for observer-based ILC, presented in [73]. The framework can be used to analyze the control performance using different types of ILC algorithms and different ways to estimate the controlled variables, also including additional sensors. ILC using estimated signals has also been implemented and evaluated in experiments using the so called Gantry-Tau parallel kinematic robot structure. The experiments, presented in [122], show that there is a large potential in using estimated variables in ILC.

By definition an ILC algorithm operates over finite time intervals, and since it often involves non causal filtering operations it is important to handle the boundary effects in an appropriate way when implementing the algorithm. In [123] some alternative ways to handle boundary effects are presented, and it is found that they can have a large impact on the algorithm performance and even affect the stability properties.

6.6 Robot Diagnosis

Industrial robots are often used in large and complex production systems where productivity and reliability is of extreme importance. It is therefore critical to be able to detect if the performance of the components of the production system, in this case the industrial robot, starts to deteriorate and if there is risk for mechanical failures. The gearboxes are critical components for the performance of a robot and it is hence important to monitor their performance. The performance and condition of a gearbox can in many cases be related to friction, and it is of interest to be able to model the friction. Based on extensive experiments and data collection, an extended friction model has been derived. Details concerning the modeling procedure are given in [37] and it results in a model with the structure

\[
\tau_f(\dot{\varphi}_m, \tau_m, T) = (F_c,0 + F_c,\tau_m | \tau_m |) + F_s,\tau_m | \tau_m | e^{-|\dot{\varphi}_m,\tau_m|^{1.3}} \\
+ (F_s,0 + F_s,T) | \tau_m | e^{-|\dot{\varphi}_m,0+\dot{\varphi}_s,T^{T}|^{1.3}} + (F_v,0 + F_v,T e^{T\tau_0})\dot{\varphi}_m
\]
where $\tau_m$ and $T$ denote load torque and temperature respectively. Figure 6.3 shows how the friction torque depends on the angular velocity and the load torque for one particular temperature. A number of other aspects of the problem are discussed in [37].

In [85] a statistical method is developed for estimation of wear in the gearbox, using the extended friction model above. In practice the temperature is not measured and in the method this is handled by assuming a statistical distribution of the temperature.
The research in optimization for control is currently focused on optimization algorithms for robust control, model predictive control, and model reduction.

7.1 Optimization Algorithms for Robust Control

In this project we study how to efficiently solve optimization problems for robust control.

7.1.1 Structure Exploitation in Semidefinite Programming for Control

In the Licentiate thesis by Rikard Falkeborn, [3], two ways to exploit structure in semidefinite programming for control is investigated.

One is related to semi-definite programs (SDPs) derived from the Kalman-Yakubovich-Popov (KYP) lemma. There are several applications for such SDPs in control and signal processing, e.g., filter design, robust control analysis, Lyapunov function search, etc. In industrial applications the optimization problems often get so large that standard SDP solvers cannot handle them. It is shown that dual decomposition can be useful for certain applications. One such application that is considered in more detail in the thesis is mixed $H_2/H_\infty$-design.

The second approach exploits the fact that many SDPs in control theory involve matrix variables, i.e., the decision variables in the optimization prob-
lem enter in a very particular manner. By using this fact, the compilation of the linear system to determine the search direction in an SDP solver can be sped up significantly. The method is implemented as an add-on to the public SDP solver SDPT3, is completely transparent to the user, and has shown gains of up to an order of magnitude on standard problems in control [43].

7.1.2 Robust Finite-Frequency $H_2$-Analysis

Finite frequency $H_2$ analysis is relevant to a number of problems in which a prior information is available on the frequency domain of interest. This work addresses the problem of analysing robust frequency $H_2$ performance of systems with structured uncertainties. An upper bound on this measure is provided by exploiting convex optimization tools for robustness analysis and the notion of finite-frequency Gramians. An application to a comfort analysis problem for an aircraft aeroelastic model is also investigated in [107, 58].

7.1.3 Polytopic Differential Inclusions

Polytopic differential inclusions is a common way to represent uncertainty in dynamical systems. These type of systems can be analysed with SDPs. One way to solve these SDPs in an efficient way is to use an infeasible interior point method where the search directions are not computed exactly, see [20].

7.2 Model Predictive Control

Model predictive control (MPC) is based on solving optimization problems on-line in order to perform the best possible action on controlled systems. For some systems, it is not tractable to run a full-fledged optimization algorithm in real-time, typically due to computational resources. Explicit MPC is a recent popular approach to overcome this by computing the optimal control policy off-line, using multiparametric programming. The optimal policy is in the case of piecewise affine systems a piecewise affine control law, which thus should be used on-line. Unfortunately, this piecewise affine function can easily become very complex, thus rendering also the explicit MPC approach intractable. In [52], it is shown how the complex piecewise affine control law can be approximated using low-complexity polynomial expressions. The approximation is efficiently derived using linear programming.
MPC can be applied to linear as well as to nonlinear systems. A special case of nonlinear systems that has received an increased attention in the MPC community the past 10 years is hybrid systems. Hybrid systems are systems where continuous dynamics interact with logic. Due to the logic in the system, the MPC optimization problem becomes significantly more challenging compared to MPC for linear systems. In order to solve these optimization problems a branch and bound method is used. In this method upper and lower bounds of the optimal objective function value are computed. The performance of the algorithm is highly dependent on how close these upper and lower bounds are compared to the true optimal objective function value and, of course, how fast these computations can be performed. In [7] semidefinite programming (SDP) relaxations are investigated as means for computing the lower bounds (relaxation). In that work, different relaxations applicable to the hybrid MPC application are compared and it is studied how these can be computed efficiently.

7.2.1 Applications

In [70] an application of MPC to speed tracking of a linear induction motor is presented. The key to an efficient implementation is to carry out the optimization for the finite alphabet controller by enumeration.

7.3 Model Reduction

Model reduction focuses on how to find lower-order models or controllers for more complex systems. These kind of problems are normally nonconvex and various optimization techniques can be used.

In [75] an approach to low order $H_{\infty}$ control is presented that is based on formulating the constraint on the maximum order of the system as a polynomial or rational criterion. By using the fact that this function is non-negative on the feasible set, the problem is reformulated as an optimization problem where the nonconvex criterion function is minimized over a convex set defined by linear matrix inequalities (LMIs). To solve this optimization problem, a method based on a primal-dual framework is proposed. The method has been evaluated on several problems and compared with a well-known method found in the literature. These results are also presented in [33]. In [76], numerical results from a modified version of the method discussed in [75] is
presented.

In the Licentiate thesis by Daniel Petersson, [4], methods for identifying linear parameter-varying (LPV) state-space models and for finding low-order LPV controllers for LPV state-space models that are based on model reduction techniques are presented. Results can also be found in [113, 114]. The emphasis is on derivation of computationally efficient schemes to optimize system-relevant performance measures of the approximation quality. Problem specific regularization terms are derived to make the solutions more robust to uncertainties in data, see [66].
Appendix A

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Michael Roth is a Ph.D. student at the Division of Automatic Control since November 2010. He received his academic degree (Diplom-Ingenieur) in Electrical Engineering with a focus on automatic control from Technische Universität Berlin, Germany. In 2009, he visited the Scottish Centre for Innovation in Spinal Cord Injury where he was working on the application of system identification algorithms in spinal cord research.
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Sören Hansson is employed as Research Engineer at the Division of Automatic Control on a part time basis, where he is responsible for the laboratory equipment.
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Visitors

Michel Verhaegen  Delft University of Technology, Netherlands, visited the division on April 14-15.

Shankar Sastry  University of California at Berkeley, USA, visited the division on April 27.

Roy S. Smith  University of California, Santa Barbara, USA, visited the division on May 5.

Claire J. Tomlin  Stanford University, USA, visited the division on May 25.

George Theodorakopoulos  EPFL, Lausanne, Switzerland, visited the division on June 15.
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. 100 participants. Lecturer: Johan Löfberg.

  Y, D Applied Physics and Electrical Engineering and Computer Engineering. 130 participants. Lecturer: Torkel Glad.

  I Industrial Engineering and Management. 130 participants. Lecturer: Svante Gunnarsson.

TB, KB Engineering Biology and Chemical Biology Programs. 45 participants. Lecturer: Thomas Schön.

IT Information Technology. 20 participants. Lecturer: Martin Enqvist.

• **Automatic Control M, advanced course** (Reglerteknik, fortsättningskurs M). For the Mechanical Engineering Program. Multivariable systems, Nonlinear systems. 30 participants. Lecturer: Svante Gunnarsson.


• **Sensor Fusion** (Sensorfusion). For the Applied Physics and Electrical Engineering and Computer Science and Engineering Programs. Estimation and detection theory, Sensor networks, Linear and non-linear filters, SLAM. 40 participants. Lecturer: Fredrik Gustafsson.


• **Modelling and Simulation** (Modellbygge och simulering). For the Applied Physics and Electrical Engineering program. Physical system modelling, Bond graphs, Identification methods, Simulation. 60 participants. Lecturer: Torkel Glad.

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

• **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, Sensor fusion. 45 Participants. Lecturer: David Törnqvist.
• *Introduction to MATLAB* (Introduktionskurs i MATLAB). Available for several engineering programs. 300 participants. Lecturer: Johan Löfberg

• *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. 90 participants. Lecturer: Ragnar Wallin.

• *Automatic Control*. Sequential control and logic controllers, A typical industrial control system. 45 participants. Lecturer: Ragnar Wallin.

**B.2 Graduate Courses**

• *Dynamic Programming* Lecturer: Anders Hansson.


• *Applied Control and Sensor Fusion*. Course coordinators: Martin Enqvist, David Törnqvist.


Appendix C

Seminars


- **Collaborating Swarms, Multi-network Topologies and Constrained Coalitional Games.** JOHN S. BARAS, University of Maryland College Park. January 20, 2010.


- **Topics in Particle Filtering/Smoothing.** SAIKAT SAHA, Automatic Control, ISY, Linköping University. February 4, 2010.


• Optimal Experiment Design for Open and Closed-loop Identification, cont’. 
  Michel Gevers, Université Catholique de Louvain, Belgium. May 21, 2010.

• Dirty Radio — a Smorgasbord with Modeling, Measurements, Pre- and Post-distortion. 


• Stable Throughput, Rate Control, and Delay in Multi-access Channels. Anthony Ephremides, University of Maryland. September 28, 2010.


Appendix D

Travels and Conferences


Tohid Ardeshiri participated in a course on distributed optimization at the Royal Institute of Technology, Stockholm, February 8–12.

Daniel Axehill participated in the OPTEC Workshop on Large Scale Convex Quadratic Programming – Algorithms, Software, and Applications in Leuven, Belgium, November 25–26. He also participated in the 49th IEEE Conference on Decision and Control, in Atlanta, USA, December 13–18.

Patrik Axelsson participated in Reglermöte 2010, Lund, June 7–9.


André Carvalho Bittencourt participated in Reglermöte 2010 in Lund, June 7–9. He attended the IV International Summer School on Fault Diagnosis of Complex Systems in Girona, Spain, July 5–9, and the IEEE/RSJ International Conference on Intelligent Robots and Systems in Taipei, Taiwan, October 18–22.

Tianshi Chen participated in the 19th ERNSI Workshop on System Identification, Cambridge, UK, September 26–29, and the 49th IEEE Con-
ference on Decision and Control, in Atlanta, USA, December 13–18.

**Martin Enqvist** participated in the 5th International workshop on Analysis of Dynamic Measurements, SP Technical Research Institute of Sweden, Borås, Sweden, June 1, Reglermöte 2010, Lund, June 7–9, and the 19th ERNSI Workshop on System Identification, Cambridge, UK, September 26–29.


**Torkel Glad** participated in Reglermöte 2010 in Lund, June 7–9.


**Svante Gunnarsson** participated in Reglermöte 2010, Lund, June 7–9, the 6th International CDIO Conference, Montreal, Canada, June 16–17, International Crossroads at Telecom SudParis, Evry, France, May 6–7, and the CDIO Nordic Regional Meeting, Umeå, October 5–6. In January he participated in a delegation from Linköping University visiting a number of universities in Japan, including Tokyo University, Kyoto University, Osaka University, and Kyushu University.

**Fredrik Gustafsson** participated in Ph.D. committees in Zürich, Trondheim, and Brussels. He participated in Reglermöte 2010, Lund, June 7–9 and the International Conference on Information Fusion, Edinburgh, UK, July 26–29.

Ylva Jung participated in Reglermöte 2010, Lund, June 7–9 and the 19th ERNSI Workshop on System Identification held at Cambridge, UK, September 26–29.


Fredrik Lindsten participated in the 2010 IEEE International Conference on Robotics and Automation, Anchorage, USA, May 3–8 and in Reglermöte 2010, Lund, June 7–9. He visited Lund University as a guest researcher for two weeks during September. He also participated in the 19th ERNSI Workshop on System Identification held at Cambridge, UK, September 26–29 and in the 49th IEEE Conference on Decision and Control, in Atlanta, USA, December 13–18.

Lennart Ljung participated in the micro-workshop on System Identification at VUB in Brussels, Feb 24–25, and was a member of the committee that evaluated NTU in Singapore, March 1–7. He participated in the LCCC workshop in Lund, April 21–23, and in Reglermöte 2010, Lund June 7–9. He visited the Academy of Mathematics and Systems Science in Beijing on July 28, and took part in the 29th Chinese Control Conference in Beijing, July 29–31. He spent part of the fall at Lund Institute of Technology, and participated in the workshop celebrating Michel Gevers’s 65th birthday in Louvain-la-Neuve, October 27–29. December 6–10 he took part in the IEEM conference in Macao, and December 13–18 he participated in the 49th IEEE Conference on Decision and Control, in Atlanta, USA.


Johan Löfberg participated in Reglermöte 2010, Lund, June 7–9 and the 2010 IEEE Multi-Conference on Systems and Control, Yokohama,
Japan, September 8–10. He visited the Automatic Control Laboratory at ETH Zürich, Switzerland, March 15–20.

Mikael Norrlöf participated in Reglermöte 2010, Lund, June 8, and in the ELLIIT workshop, Linköping, November 11.

Henrik Ohlsson participated in the LCCC workshop in Lund, April 21–23 and in Reglermöte 2010, Lund, June 7–9. He also participated in the European Research Network on System Identification workshop held at Cambridge, UK, 26–29 of September and in the 49th IEEE Conference on Decision and Control, in Atlanta, USA, December 13–18.

Umut Orguner participated in the kick-off meeting of the McImpulse project (EU FP7 Marie Curie Initial Training Network) at Thales Nederland B.V. in Hengelo, The Netherlands, during January 18–20. He also attended the 13th International Conference on Information Fusion, Edinburgh, UK, July 26–29.


Peter Rosander participated in the SSF Conference — New tools for improved profitability in the Process industry, Stockholm, April 21, and in Reglermöte 2010, Lund, June 7–9.


Thomas Schön visited Thales Nederland B.V. in Hengelo, The Netherlands, during January 21–22. He participated in the kick-off meeting for the ELLIIT project on navigation held at Lund University on February 4. He participated in the Workshop on Swedish robotics research: Trends, applications and challenges, Royal Institute of Technology in Stockholm, Sweden on April 19. He visited The Department of Signals and Systems at Chalmers University of Technology in Göteborg, Sweden on April 23 and May 19. He visited the Swedish Defence Research
Agency in Linköping, Sweden on June 3. He participated in Reglermöte 2010, Lund, June 7–9. He also participated in the Workshop on Indoor Navigation at the Royal Institute of Technology in Stockholm, Sweden on August 19. During the time August 24 – September 30 he visited the School of Electrical Engineering and Computer Science at the University of Newcastle, Newcastle, Australia. He visited the Pacific Northwest National Laboratory in Richland, USA on November 15, and on November 17 he visited Rutgers University, New Brunswick, USA. He also visited the Science and Technology Directorate at the U.S. Department of Homeland Security, Washington DC, USA on November 18–19. He participated in the 49th IEEE Conference on Decision and Control in Atlanta, USA, December 15–17.


Per Skoglar participated in the IEEE Aerospace Conference, Big Sky, March 6–13, and in Reglermöte 2010, Lund, June 7–9, and in the TAMSEC symposium, Linköping, October 27–28. He also visited C3UV at the University of California, Berkeley, March 15–19.

Martin Skoglund participated in Reglermöte 2010, Lund, June 7–9.

David Törnqvist participated in the kick-off meeting for the ELLIIT project on navigation held at Lund University on February 4. He participated in the IEEE Aerospace Conference, Big Sky, March 6–13, and in Reglermöte 2010, Lund, June 7–9, and in the TAMSEC symposium, Linköping, October 27–28. He also visited C3UV at the University of California, Berkeley, March 15–19. He also participated in the Workshop on Indoor Navigation at the Royal Institute of Technology in Stockholm, Sweden on August 19. He participated in a workshop organized by the Swedish National Space Technology Research Programme at the Royal Institute of Technology, Stockholm, Sweden, November 1.

Niklas Wahlström participated in the International Conference on Information Fusion, Edinburgh, UK, July 26–29 and visited Luleå University of Technology, Luleå, on October 18–20.
Johanna Wallén participated in Reglermöte 2010, Lund, June 7–9. She regularly visited the Department of Automatic Control in Lund during the spring 2010. She also attended the LINK-SIC workshop in Linköping, November 8, and the ELLIIT workshop in Linköping, November 11–12.

Emre Özkan participated in the kick-off meeting of the McImpulse project (EU FP7 Marie Curie Initial Training Network) at Thales Nederland B.V. in Hengelo, The Netherlands, during January 18–20. He also attended the 13th International Conference on Information Fusion, Edinburgh, UK, July 26–29.
Appendix E

Lectures by the Staff


- Jonas Callmer: *Foot Mounted INS Activities at LiU*, Workshop on Indoor Navigation at Linköping University, August 27.


• Karl Granström: *Learning to Close the Loop from 3D Point Clouds*, IEEE/RSJ International Conference on Robots and Intelligent Systems, Taipei, Taiwan, October 20.


• Svante Gunnarsson: *IUAE Matrices Revisited — Current Activities at Linköping University*, CDIO Nordic Regional Meeting, Umeå, October 6.

• Svante Gunnarsson: *Using CDIO Standards 2.0 for Program Evaluation — Some Experiences*, CDIO Nordic Regional Meeting, Umeå, October 6.


• Fredrik Gustafsson: *Fusion in Sensor Networks*, ETH, Switzerland, May 6.


• Fredrik Gustafsson: *Sensor Networks for the Sake of Security*, Cambridge University, UK, July 22.


- Lennart Ljung: *Semi-Supervised Regression and System Identification*, the LCCC Symposium, Lund, April 22.


- Johan Löfberg: *Automatic Robust Convex Programming*, ETH Zürich, Switzerland, March 15.


• Daniel Petersson: *Nonlinear Optimization Approaches to $H_2$-Norm Based LPV Modelling and Control*, Techn.Lic. presentation at Linköping University, Sweden, November 24.


• Thomas Schön: *Some Ongoing Research — Application Oriented*, Workshop on Swedish robotics research: Trends, applications and challenges, Royal Institute of Technology, Stockholm, Sweden, April 19.

• Thomas Schön: *System Identification of Nonlinear State-space Models*, Department of Signals and Systems, Chalmers University of Technology, Göteborg, Sweden, May 19.


• Thomas Schön: *Bilar utan förare i trafiken — livsfarligt eller säkert?*, Teknikfestival, Norrköping, December 1.

• Thomas Schön: *Estimating State-Space Models in Innovations Form using the Expectation Maximisation Algorithm*, 49th IEEE Conference on Decision and Control, Atlanta, USA, December 17.
• Thomas Schön: *Estimation of General Nonlinear State-Space Models*, 49th IEEE Conference on Decision and Control, Atlanta, USA, December 17.


• Per Skoglar: *Autonoma funktioner för stöd till UAV-operatörer*, Saab, Linköping, Sweden, February 26.

• Per Skoglar: *Combined Point-Mass and Particle Filter for Target Tracking*, IEEE Aerospace Conference, Big Sky, USA, March 10.

• Per Skoglar: *Particle Filtering with Propagation Delayed Measurements*, IEEE Aerospace Conference, Big Sky, USA, March 10.


• Niklas Wahlström: *Magnetometers for Tracking Metallic Targets*, Luleå University of Technology, Luleå, October 20.
Appendix F

Publications

Phd Theses


Licentiate Theses


Books


Journal Papers and Book Chapters


**Conference Papers**


[34] P. Axelsson, M. Norrlöf, E. Wernholt, and F. Gustafsson. Extended Kalman filter applied to industrial manipulators. In *Proceedings of Regl-


[40] J. Dong, M. Verhaegen, and F. Gustafsson. Data driven fault detection with robustness to uncertain parameters identified in closed loop.


Appendix G

Technical Reports


Appendix H

Master’s Theses


[139] R. Hedberg. Tree species classification using support vector machine on hyperspectral images. Master’s thesis no LiTH-ISY-EX-4214, Department of Electrical Engineering, Linköping Univer-


