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Chapter 1

Introduction

The Division of Automatic Control at Linköping University consists of some twenty-five people. We teach thirteen undergraduate courses to more than eleven hundred students. The courses cover both traditional control topics and more recent topics in model building and signal processing.

Our research interests are focused on the following areas:

- *Nonlinear Modelling and Control*: 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.

- *System Identification and Signal Processing*: We are interested in a number of aspects ranging from applications of modern signal processing techniques in automobiles, to theoretical aspects in how to evaluate model quality in the presence of under-modelling.

- *Hybrid modelling*: This is an important and emerging field covering problems of how to deal with system with both discrete and continuous phenomena. The modelling of discrete event dynamic systems (DEDS), sequential planning control problems, and various supervision problems also belong to this area.

In the following pages the main research results obtained during the academic year 1991/92 are summarized. More details about the results can be found in the list of articles and technical reports (See Appendices G and H. Numerals within brackets refer to the items of these appendices). These reports are available free of charge. Starting this year we also offer a service where anyone interested can have direct access to them using ftp. The procedure for this is described below.

A main event during the year was that our two research assistants, Bo Wahlberg and Björn Ottersten have been appointed Professors at the Royal Institute of Technology in Stockholm in Automatic Control and Signal Processing, respectively.

During the year Mats Viberg and Mille Millnert have been appointed "docents" in Automatic Control. Furthermore Krister Forsman, Fredrik Gustafsson and Peter Nagy have defended their doctoral theses.

Finally, we thank The Swedish Board for Technical Development (NUTEK) and the Swedish technical Research Council (TFR) for funding a major part of our research.

Network Access to Reports and Software

Over the last year we have seen an increasing number of services being offered over the network[1], e.g. the news group: `sci.engr.control` and the newsletters: `Eletter` and `OpenCACSD` as well as the `SCAD database`.

We have had an anonymous ftp server in operation since the fall of 91 and this is probably a good opportunity to announce it to wider audience. The server can be reached through anonymous ftp at `joakim.isy.liu.se` or `130.236.24.1`. The services offered so far are technical reports (`~ftp/pub/reports`) and some software (`~ftp/pub/src`). Hopefully this network infrastructure will develop even further over the next couple of years and perhaps we will be able to share datasets, models and teaching material.

Below follows a sample ftp session:

[1] Internet

Ftp our server.	`unix> ftp joakim.isy.liu.se`
Use **`anonymous`** as login name and use your email address as password.	`Name (joakim.isy.liu.se:roger): anonymous` `Password:`
Change directory to **`pub/reports`**.	`ftp> cd pub/reports`
Get the **`AAREADME`** file. This file lists the reports present.	`ftp> get AAREADME`

Now suppose you have checked the **`AAREADME`** file and know what reports you want.

Set the channel type to binary, since we have compressed files. Finally get the file of interest.	`ftp> type binary` `ftp> get LiTH-ISY-I-1259.ps.Z`

Chapter 2

System Identification and Adaptive Control

System identification concerns the problem of estimating mathematical models of dynamical systems from observed input-output data. Within this general area several research problems have been investigated. These are described below.

2.1 Model Quality: The Roles of Prior Knowledge and Data Information

A model is useless without an estimate of its reliability. Any modeling, estimation or identification procedure must therefore be accompanied by a method to assess the accuracy of the delivered model. One could even say that the product delivered to the user must be a set of models, among which a useful or "true" description is (likely) to be found. If the objective is to design a regulator, it is actually the delivered set that is the input to the (robust) control synthesis.

A finite data set does not contain enough information to produce a meaningful posterior model set. This is only possible by combining data with prior information

$$\{\text{Prior Information about the system}\} \quad + \quad \text{Data} \mapsto \qquad (2.1)$$
$$\{\text{Posterior Information about the system}\}$$

Usually the prior about the system is quite vague which means that there is a lot of freedom and arbitrariness when the prior is chosen. Hence, it may be possible to obtain several posterior model sets. Provided that the priors are consistent with the data (unfalsified) one may then ask the question which one of the posteriors that should be chosen? Based on general scientific arguments it is argued in [22], [55] that one should choose the most powerful posterior, *i.e.* the one that gives the most precise information (smallest error bounds). If the model set is to be used for control design it might be useful to evaluate the sensitivity of the controller with respect to the priors; a control design that is very sensitive to a vague prior should be avoided. This idea is put forward in [46].

One part of the modelling error is the variability error or random error; when we repeat an experiment with the same input we get a different output. It is common to model these disturbances as random variables. In [11] one way to estimate the random error in parametric estimates is developed.

It is also possible to attribute this variability in the output to the system itself. It may be in some sense be ill-defined and hence respond differently at different times. Means to model, detect and estimate such variability are examined in [44] and [45].

2.2 Artificial Neural Network as a Black-Box Structure

There has been a growing interest in artificial neural networks (NN) in various applications during the past years. Many results, well-known in statistics or other scientific fields, have been rediscovered in the NN context. In our project we analyse NN in a system identification perspective, viewing NN as "just another model set". An overview of this viewpoint can be found in [146].

A characteristic feature of NN models is that the number of parameters is quite large which should raise concerns, since it is bound to give a large "variance error". Nevertheless NN's have shown good abilities for modeling different nonlinear system. This is due to regularization which can be described as

$$W_N(\theta) = V_N(\theta) + \delta \mid \theta - \theta_{\#} \mid^2 \tag{2.2}$$

being minimized instead of $V_N(\theta)$, which is the usual sum of squared errors.

In [64] it is shown how the regularization improves the variance error. Further we show, in case no explicit regularization is used but the iterative search is terminated before the true minimum is reached, then this also corresponds to a regularization, implicitly. This is illustrated in Figure 2.1. A NN is used to model a dynamical system and $V_N(\theta)$ is computed for the validation data after every iteration of the minimization procedure. When the criterion is $W_N(\theta)$, with an appropriate choice of δ, we receive the dashed line, and when $V_N(\theta)$ is minimized we end up with the solid line. In this case we clearly see how the fit becomes worse after a certain number of iterations which corresponds to a regularization which is gradually switched off.

2.3 Parameter Identifiability

A long standing problem in System Identification is that of parameter identifiability. This concerns the question whether it is possible to uniquely (globally!) determine the values of model parameters from input-output data. Solutions have existed for certain traditional linear black-box structures. However the general problem is known to be "difficult".

In [115, 37], using tools from differential algebra, we have given a constructive approach to this problem. Briefly, global parameter identifiability has been shown to be equivalent to the possibility to rearrange the original model equation to a linear regression (in the original parameters!). A constructive test which converges in a finite number of steps has been developed and implemented in Macsyma and Maple.

Figure 2.1: Solid line: no regularization; dashed line: regularized with 10^{-2}.

2.4 Adaptive Control

The activities in the adaptive control area have been concentrated to an application carried out together with the Department of Mechanical Engineering, where we have studied adaptive control strategies for a lorry crane controlled by hydraulic actuators. This system has a number of properties which make it an interesting application of adaptive control. First, the flexibility in the structure of the crane induces an oscillatory behavior when the crane is operated. The flexibility furthermore results in a steady state error in the tip position when a load is applied. Finally the system contains several nonlinearities. The dominating resonance frequency changes when the geometry of the crane changes for example.

Instead of trying to model the system in detail we have tried to use simple models that describe the principal behavior of the system. We have, for example, chosen to describe the mechanical structure as a system consisting of a mass connected to the piston via a spring and a damper. The valve is also described using a simplified model, obtained by linearizing the equations describing the relationship between valve position, pressure drop, oil flow and piston speed.

The major task for the control system is to reduce the oscillatory behavior when the crane is operated, and by applying LQG design to the state space model we obtain information concerning a suitable structure of the regulator. We have however chosen to implement simpler regulator transfer functions that have the main properties of the LQG feedback. To implement these transfer functions only a few parameters have to be identified, and this is carried out using recursive identification. The control system has also been extended by introducing a procedure to compensate for the deformation caused by loads applied to the crane. The control system has been implemented and tested on the crane with good results, and a substantial reduction of the oscillations has been obtained.

Chapter 3

Signal Processing and Tracking

3.1 General Aspects

Consider the problem to track a time varying parameter vector $\theta(t)$ in a linear regression model

$$y(t) = \varphi^T(t)\theta(t) + e(t) \tag{3.1}$$

based on measurements of $\{y(t)\}$ and $\{\varphi(t)\}$. There is quite a substantial literature dealing with algorithms and analysis of this problem. A basic algorithm is the following one

$$\hat{\theta}(t) = \hat{\theta}(t-1) + P(t)\varphi(t)(y(t) - \varphi^T(t)\hat{\theta}(t-1)) \tag{3.2}$$

The many algorithms differ primarily in the choice of $P(t)$. This in turn can be interpreted as introducing various assumptions about the variation of the true parameter $\theta(t)$. A survey over approaches to the tracking problem and analysis of tracking properties is given in [49].

An analysis result on the tracking error is developed in [12, 13, 32]. It has the basic form

$$\mid \Pi(t) - \hat{\Pi}(t) \mid \leq \sigma(\mu) \cdot \mu \tag{3.3}$$

where μ is the step size in (3.2), $\Pi(t)$ is the true tracking error

$$\Pi(t) = E(\theta(t) - \hat{\theta}(t))(\theta(t) - \hat{\theta}(t))^T$$

and $\hat{\Pi}(t)$ is the conventional, asymptotic (in $\mu \to 0$) estimate of this variance. Moreover, $\sigma(\mu)$ is a function that tends to zero as μ tends to zero.

Unlike most previous results, (3.3) is not, in itself, asymptotic in $\mu \to 0$. It applies over unbounded time intervals and also to the transient phase of the tracking.

3.2 Model Quality in Recursive Identification

A basic problem when applying recursive identification is the trade-off between tracking ability and disturbance rejection. In this work the aim has been to study this problem by deriving expressions that describe the trade off in the frequency domain. The quality measure that has been used is the mean square error of the transfer function estimate

$$E \mid \hat{G}(e^{i\omega}, t) - G(e^{i\omega}, t) \mid^2$$

where $G(q, t)$ denotes the transfer operator from input to output. We have considered systems that can be described as linear regressions

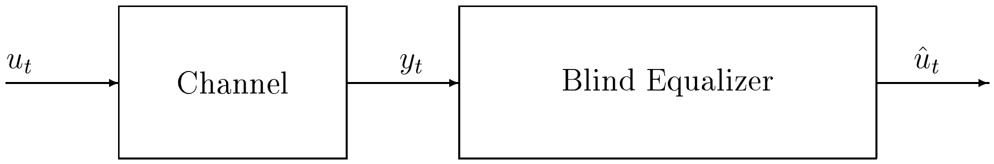
$$y(t) = \varphi^T(t)\theta(t) + v(t)$$

where different model structures can be obtained by different choices of the elements in the regression vector $\varphi(t)$. By letting $\varphi(t)$ contain delayed input signals a model with finite impulse response (FIR) is obtained, [20]. A further extension of the FIR model is obtained when the elements in the regression vector are filtered versions of the input signal. In particular we have studied the use of Laguerre filters, by which the model order needed to give a desired accuracy can be reduced, [18]. When the regression vector contains delayed input and output signals and the disturbance signal is white noise an ARX model is obtained, [19].

In the models discussed above the disturbances are described in a statistical framework and the model quality is described in terms of, for example, variance or mean square error. Another situation, which also has been considered, is when the disturbance is known to be bounded but no further assumptions are made. This type of problem can be treated by so called bounding ellipsoid algorithm in which a strict bound on the parameter error is updated in each step. We have investigated the properties of a bounding ellipsoid algorithm for a particular choice of design variables and derived asymptotic expressions for the bound on the parameter error and the transfer function error, [143], [72].

3.3 Blind Equalization

Consider the following model of a digital communication channel:



Suppose that the input is binary, $u_t = \pm 1$, and the channel can be described by a noise-free third order FIR filter. Can we then assure that the input sequence can be recovered from the observed output? This is the question of *identifiability* in *blind equalization*, which is treated in [1, 43].

For example, if the received sequence is (0.3, 0.7, 1.3, 2.3) the input sequence can be uniquely determined, while (0.3, 0.7, 1.3, 0.3) cannot. In the aforementioned papers it is shown that this question relates to the degree of persistently exciting of the input. Compared to classical identification with a known input where the FIR model can be identified if the input is persistently existing of order 3 (or the degree of the model), it is here sufficient if the input is persistently existing of order 5 (or twice the degree minus 1).

This result motivates a recursive algorithm where all permissible input sequences are examined. It is guaranteed to find the exact solution as fast as possible. An upper bound on the computional complexity of the algorithm is given. This algorithm is then generalized to cope with a time-varying IIR channel model with additive noise. The estimated sequence is an arbitrary good approximation of the *maximum a posteriori* estimate. The proposed method is evaluated on a Rayleigh fading communication channel. It shows fast convergence properties and good tracking ability.

3.4 Signal processing in cars

In a project "Support systems for active safety" the goal is to compute safety margins for cars, and as a first step supply the driver with this information.

Figure 3.1: The process with controller

A key issue is to estimate the friction between tires and road surface. For economical reasons, only standard sensors in the car are used. To implement this scenario, a Volvo 850 GLT has been hooked up to a PC with real-time software written in MATLAB.

The program uses sensor information from the ABS system, which measure all four wheel velocities separately. Also, a load signal from the injection system is used to compute the engine torque. From these five signals, the following quantities are computed as a first step:

- curve ratio,
- gearing level,
- longitudinal and lateral forces and
- wheel slip.

Figure 3.2: A typical step response when accelerating the car. (The upper curve, the lower ones show the slip for left and right driven wheels).

An example of a test drive is shown in Figure 3.2. The driven path can be determined from the curve radius and velocity. An example is shown in Figure 3.3, where several turns and a roundabout is tracked with rather high accuracy. The wheel slip is related to the friction; the larger slip the smaller friction. The second plot in Figure 3.3 shows an interesting example, where slip is shown for several lane changes on a road with one paved and one unpaved lane. The lane changes are at time 12, 22, 27, 35 and 40. From this single plot several conclusions can be drawn:

- There is a bias on either the right or left slip value. This means that one wheel (at least) has a different radius. From the bias in curve radius, it is possible to point out which wheel is abnormal, and give advise how the air pressure should be adjusted.
- It is clearly visible where the lane changes occur, and the mean slip level increases drastically indicating that the friction is lower on the unpaved road.
- It is also obvious that the noise level in the slip is larger on the unpaved lane, which depends on the uneven surface here. Thus, the quality of

Figure 3.3: Left: Driven path determined from the wheel velocities. Right: Slip values for lane changes from paved to unpaved road for right and left driven wheels.

the road can be judged from this signal.

- Finally, the time delay for the left and right wheel pair for each lane crossing is seen to be roughly one sample interval (0.5 s).

The project is a part of the Prometheus project DALTM (Driver Assistance and Local Traffic Management) in the swedish RTI (Road Transport Informatics) program. +

3.5 Segmentation

In this work the problem of abrupt changes in the dynamical properties of signals and systems is studied. The goal is to estimate the time instants when these changes occur. The proposed method is model based. The measured signal y_t is described as a linear regression,

$$y_t = \varphi_t^T \theta_t + e_t.$$

The unique feature in segmentation is that the time-varying parameter vector is assumed to be piecewise constant, in contrast to tracking problems where it is commonly modelled as a random walk. The estimate of the change instants in θ_t is found by maximizing the *maximum a posteriori* (MAP) probability or, alternatively, the likelihoods.

The parameters can either change or not change at each time instant. With t measurements there are 2^t possibilities and each *a posteriori* probability has to be considered. The inevitable problem is that each one requires one filter, and this exponential growth make a direct implementation impossible. Fortunately, some relations between the *a posteriori* probabilities have been found, so only a small number of sequences really has to be considered. The main result derived is an algorithm where this number is between 2 and t depending on the noise e_t. A remarkable result is that the lower bound of just two filters is achievable if the noise variance magnitude is small enough. The details are given in [1] and [40].

One example of segmentation is the following. Consider a vehicle moving along the path in Figure 3.4, which is sampled from a city map. See also

Figure 3.4: A sampled path and the estimated jump instants (*).

Figure 3.3 for a real application where almost the same path occur. This signal can be modelled by piecewise straight lines, so the parameter vector consists of velocities in two dimensions. The segmentation problem is to estimate the time instants for the turns of the vehicle and in this way be able to track and predict its movements. The classical approach is to use an adaptive filter, for instance RLS with forgetting factor, but it will give a long transient response after each turn. The aforementioned optimal estimates for this example are shown in the figure as stars. The smoothed parameter estimates are not shown in the figure, but they can easily be reconstructed by drawing straight lines between the stars. As seen, every turn is found and the roundabout is approximated well. For this example, with 117 measurements, the computation of the MAP estimate requires only 17 filters. This is a considerable decrease compared to 2^{117}!

An on-line implementation requires an *a priori* fixed number of filters. A discussion is given in [1] about different search strategies, which use an *a priori* known constant number of filters to get a natural appoximation of the MAP estimate.

Chapter 4

Sensor Array Processing

Sensor array processing (SAP) has been an active research area for more than 20 years. The automatic control group has performed work in this field the last six years. The projects reported in Section 4.1 include co-operation with the Information Systems Laboratory at Stanford University, Stanford, USA and Prof. Arye Nehorai at the Department of EE at Yale University, New Haven, USA. The experiments mentioned in Section 4.2 are made on data collected by the Swedish National Defence Research Institute in Stockholm (FOA 3), and the last project of Section 4.2 is conducted in co-operation with Prof. Petre Stoica at the Department of Control and Computers, Polytechnic Institute of Bucharest, Romania.

In this context, a *sensor array* consists of a group of spatially distributed sensors. Arrays of electromagnetic antennas are, for instance, used in communication and radar systems to protect a signal transmission from undesired interference and/or to localize objects of interest. Acoustic devices (hydrophones) are encountered in, e.g., underwater and seismic applications. The array receives a superposition of the waveforms from several signal sources. The problems of interest include detecting the number of signals present, estimate their parameters (*e.g.* azimuthal angle), and separate the individual signal waveforms.

Let an array of m sensors receive the wavefronts of d narrowband emitters, where $d < m$. The sensor outputs are sampled and collected in a vector $\mathbf{x}(t)$, modeled by the equation

$$\mathbf{x}(t) = \mathbf{A}(\boldsymbol{\theta})\mathbf{s}(t) + \mathbf{n}(t) \ . \tag{4.1}$$

Here, the columns of the $m \times d$ matrix $\mathbf{A}(\boldsymbol{\theta}) = [\mathbf{a}(\theta_1), \ldots, \mathbf{a}(\theta_d)]$ are the *array propagation vectors*, and $\mathbf{a}(\theta_k)$ models the array response to a narrowband signal with parameter[1] θbf. The d-vector $\mathbf{s}(t)$ represents the signal waveforms, and $\mathbf{n}(t)$ is an additive noise term. The array output, $\mathbf{x}(t)$, is measured at N time instants. Based on these observations, one wishes to estimate the number of signals and their parameters. Once these are known, it is a simple task to separate the individual signal waveforms, if desired.

4.1 Asymptotic Analysis of Subspace Fitting and ML Techniques

A major theme within this project has been performance analysis of parametric estimators assuming a large number of data samples. The most complete results are presented in [7, 8]. The algorithms under study are two different versions of the maximum likelihood technique; one based on the assumption of stochastic Gaussian signal waveforms and one that assumes deterministic signals. Compact expressions for the asymptotic estimation error variance (the Cramer-Rao bound) are derived.

The insight gained through this work has led to the development of a new methodology for estimation and detection. The technique, referred to as (weighted) *signal subspace fitting* is based on geometrical properties of the array output covariance matrix. The method is found to be a large sample approximation of the stochastic ML estimator [7]. Numerical implementation of the technique is discussed in [6], and a scheme for detecting the number of signals is presented in [6, 5]. Results from a practical experiment is included in [30].

The above mentioned results are based on the assumption that a large number of data samples is available. An alternative analysis, assuming the number of sensors in the array to be large is presented in [28].

[1] In general, θ_k can contain several unknown parameters per signal, such as azimuth and elevation angle, polarization, etc. However, some methods are only applicable when θ_k is a real scalar, in this case referred to as the k^{th} *direction-of-arrival* (DOA).

4.2 Direction Finding in the Presence of Array Uncertainties

It is widely appreciated that the array response models used in sensor array signal processing can give only approximate descriptions of the actual data collection system. Recent studies have shown that "traditional" parametric estimation techniques are quite sensitive to the array response information as well as to the covariance matrix of the background noise. The latter effect is studied in [42]. Alternative signal parameter estimators that are less susceptible to perturbations in the nominal data model have recently been considered within the present project.

Perhaps, the most serious problem in practical direction finding is to obtain an accurate model of the array response ($\mathbf{a}(\theta)$ in 4.1). Often, an experimental array calibration procedure is the only tractable way of obtaining a sufficiently good model. In [27, 31], some of the practical issues that arise in generating a smooth array manifold from a finite collection of calibration vectors are addressed. The references include practical tests on hydro-acoustical data, collected in the Baltic sea.

An important drawback of most parametric estimation techniques is that the covariance matrix of the background noise must be known. In practice, this is achieved by collecting data when no signals are present. However, in many applications this procedure is not feasible; and errors in the noise model give raise to highly biased estimates. In [25], a technique that is insensitive to the spatial noise color is presented. The approach is based on the assumption that the signal waveforms are temporally correlated, whereas the noise is white. Thus, the auto-covariance matrix of the array output can be used to extract information of the signal parameters regardless of the covariance matrix of the noise.

4.3 Dimension Reduction

The interest in performance improvement for DOA estimation algorithms can result in antenna arrays composed of a large number, m, of sensor elements. Since the computational requirements are directly affected by the dimension of the collected data, the burden increases rapidly with the number of sensors. This increase is often proportional to the cube of the dimension of the Element SPace (ESP), m. This is the case, *e.g.*, for high-resolution methods based on eigendecomposition of the array covariance matrix, which requires $\mathcal{O}(m^3)$ operations. Therefore, in order to reduce the computational complexity of the algorithms it is useful to introduce some sort of mapping that reduces the dimension of the data set, from m to r ($r << m$), before performing the signal processing, see [29]. Another advantage is that if the transformation matrix is implemented using analog technology, there is a need for only r analog-to-digital converters, in contrast to the m ones needed for ESP computations. The space into which the set of full dimensional data is mapped is referred to as the Reduced Dimension BeamSpace (RDBS).

One approach to reduce the amount of computations is to employ a linear (matrix) transformation for mapping the full dimension ESP data into the lower dimensional RDBS, and then apply a signal processing algorithm to this new set of data. The main interest is then to analyze under which circumstances it is possible to retain the property of asymptotically achieving the full-dimension CRB, while significantly reducing the dimension of the data set used for the DOA estimation. Somewhat surprisingly, it is possible to obtain very simple analytical expressions for the requirements to be met by an optimal transformation matrix. These expressions rely on knowledge of the functional form of the array (calibrated array of arbitrary geometry) and the true locations of the sources present. This last condition is, however, not limiting the possibilities of using the results derived to outline a design method. If a spatial sector is specified, in which sources of interest are assumed to be located, it is possible for the locations of these sources to be (nearly) optimally estimated in the sense of the full-dimension CRB.

Moreover, an approach for asymptotic analysis is under investigation, using the reduced data vectors, that examines the estimation accuracy of several estimation methods when a large number of sensor elements is used. This analysis is valid for a fairly general transformation matrix, and the methods considered are the Weighted Subspace Fitting (WSF) and Noise Subspace Fitting (NSF) methods, including MUSIC. By employing the optimal transformation matrix, the WSF method is shown to to be efficient, *i.e.*, to attain the Cramér-Rao bound. An examination of the estimation accuracy, compared to that optimally attainable, is made for the case when the transformation matrix differs from the optimal one.

Chapter 5

New Approaches in System Identification, Modelling and Signal Processing

5.1 Numeric-Symbolic Signal Processing

The purpose of this project is to develop tools and methods which make it possible to incorporate symbolic information into the signal processing. With symbolic information we here mean the relations between "named" quantities, e.g., higher/lower concerning peaks in spectra, signals being more/less oscillatory and so forth. Symbolic information is easiest conceived as quantities and rules in a rule-based expert system. A framework for numeric/symbolic signal processing gives several advantages:

- The possibility to include heuristic information.
- The possibility to make the knowledge on which the implemented algorithms are based more explicit. (Declarative programming)
- The possibility to automate tasks where reasoning-based decisions have to be made.

In the project we have developed a software environment, MaMiC, for numeric/symbolic signal processing. The environment consists of three major components

1. MATLAB, The well-known package for numerical calculations.
2. Common-Lisp and Yaps. For implementation of the symbolic processing. Yaps is a rule-based expert system shell.
3. MACSYMA. A package for symbolic mathematics.

The MaMiC environment is described in [2]. The environment has been applied to various signal processing tasks. Among the applications we can mention the implementation of an intelligent help function to support the use of a system identification software packages. See [35, 47]. In particular we have in [47] applied the approach to integrating modelling and identification using bond-graphs.

5.2 Modelling Discrete/Continuous Systems

A relatively new research area for the group is to study modelling of more "unconventional" physical systems. By unconventional we mean, in this context, that the model cannot easily be described by differential/difference equations only. There may be a number of "ifs" and "buts" influencing the behaviour of the system.

Such systems either occur naturally, *e.g.* the tank in Figure 5.1, or appear as a consequence of introducing binary actuators, *e.g.* on/off valves, on/off motor controllers etc. A more peripheral reason for dealing with this class of systems, would be searching for qualitative descriptions. Then we might need to partition an otherwise continuous behaviour into a set of qualitative characterstic classes.

Regardless of our intentions – they may be identification, control or diagnosis to mention a few – the main issue is that of modelling the system. We will here give a brief outline of the basic ideas underlying the proposed modelling strategy.

Figure 5.1: A naturally discrete/continuous system

5.2.1 Decision Trees

Traditionally, tree chassifiers have been used to classify data such as in medical diagnosis. There are at least two potential applications of decision trees to dynamical systems modelling [48]. In either case the internal nodes of the tree carries questions on measured signals (current and delayed versions). These questions are Boolean valued for binary trees and gives the direction of traversal when searching for the leaf which contains the "decision" or class label. The simplest kind of question is based on a single signal, such as $u(t-1) < 2.37$, but more complex questions involving several signals, are of course considered as well.

The application of decision trees differs only in how the leaves of the tree are labeled. In the first alternative, which will not be elaborated on here any further, the leaves are labeled according to quantized versions of some output signal. One example would be an alarm device predicting if, for example, the water level $x_1(t) \geq h$. In the context of discrete/continuous systems, however, the concept of *Model Trees* is more interesting. Here each leaf of the tree is labeled with a continuous **model**, an *operating mode model.* Here we may use any conventional model structure like, *e.g.*, differential equations. For the water tank we have the model tree of Figure 5.2 where we have chosen to use bond graphs to represent the operating mode models. To be able to estimate trees from data online, online tree construction methods have been studied [52].

Figure 5.2: The model tree for the tank

5.2.2 Bond Graphs

A bond graph is basically a graphical representation of ordinary state space equations (not necessarily linear). Moreover, the drawing of bond graphs is restricted under a set of strict syntax rules derived from first principles of energy conservation. Thus it is in fact a “high level” *language* for modelling physical systems. The “high level” notion comes from the fact that the syntax rules supports and guides the modelling engineer in his work of deriving a mathematical model when confronting a real physical device.

In the context of discrete/continuous systems, bond graphs may be used as they were originally intended, as description of the operating mode models in the leaves of the tree; Figure 5.2 once again. However, since any non-linearity may be incorporated in bond graphs, it is possible to have a complete system description in terms of **one single** unifying bond graph [70]. The proposed bond graph for the tank is depicted in Figure 5.3. Half arrows are the energy bonds (physical level), full arrows are active bonds carrying signals (control level) and lines without arrows are connections carrying logical values (math level).

Figure 5.3: The proposed *unifying* bond graph model

5.2.3 Model-families

In the project we also try to model "non-standard" system, e.g., systems for which one single model is not sufficient. The objective is to develop methods for modelling, filtering and parameter estimation for such systems. Consider the system description

$$y(t) = H(q; \xi)u(t) + e(t) \tag{5.1}$$

where ξ is some unobservable, time-varying parameter, affecting the system behaviour. Different assumptions can be made concerning the variations of ξ. For instance it can be modelled as a Markov process or jump process. The approach in this project is to assume that ξ is a non-observable variable of low dimension, e.g., some linear combination of the system state vector. In the project we try to find methods to automatically find suitable ξ, and identify the system models corresponding to different ξ-values. The proposed method, see [14], is based on a combination of statistical techniques and methods for classification/clustering from pattern recognition. A potentially useful tool for numeric/symbolic signal processing is the use of symbolic reasoning, e.g., in the form of expert systems. An important issue is then how this type of reasoning can be merged with traditional, statistical methods. This question is addressed in [15]. Another application of signal classification and interpretation is reported in [26]. In the paper methods for automatic segmentation of laser range images are presented.

5.3 Symbolic Control

Symbolic processes are processes that allow an *exact* finite description. Some well known descriptions include: Finite State Systems, Petri Nets, Polynomial Dynamical Systems. The main applications are various forms of sequential control such as:

- Strategic control for plants which include start up, shut down and error recovery.
- Proper sequencing of events in chemical processes and work cells. In this case "proper" should include the enforcing of various constraints such as safety measures and perhaps ordering of events.

The algorithmic treatment of these processes and their controls is decidedly of a different flavour from traditional control, in that exact representations and computations are used. This is a strong departure from the approximate, numerical analysis based, paradigm usually followed. In this area this is quite natural since there is no notion of approximation anyway, i.e. the only topology is typically the trivial one of equality.

Formally all models can still be stated as state space models, i.e.

$$x(k+1) = f(x(k), u(k)), \quad y(k) = g(x(k), u(k))$$

although there can be a wide range in exactly how this state space looks[1]. At a first level one could separate these according to the size and structure of their state or memory. This yields the usual formal language based hierachy with Turing equivalent systems at the top and regular languages at the bottom. From a descriptive point of view one would of course like to work with models close to the top in this hierachy – and that is quite feasible if the only objective is to simulate. If the objective is to analyse and synthesize systems then one quickly finds that most properties are undecidable. For these reasons one would hope that finite state based systems are good enough for many real world problems.

[1] E.g. as formulas in λ-calculus, machine state in Turing machines or marking vectors in Petri Nets etc.

When concetrating on finite state based systems one immediately finds out that finite numbers can be very big. In practice this comes from the fact that one connects several subcomponents to form the complete system. If these subcomponents interact or we put constraints on these togther we will have to form the product state space, i.e. the set of all tuples with components in the respective subsystems. Having p subsystems with n states in each would then yield a combined state space of n^p states. For these reasons the focus is very much on complexity.

5.3.1 Simplified Action Structures (SAS)

Simplified action structures is another notation for finite state based systems. The states are given as tuples:

$$x = [x_1, x_2, \ldots, x_n]$$

and each x_i resides in some finite domain $\mathcal{S}_i$. The controls or inputs are termed *actions* and their affect on the system is described through *pre-*, *post-* and *prevail-conditions*. The pre- and post-conditions tells us the actual effect of the action and the prevail condition can detail further conditions which must be satisfied during the execution. Without further restrictions this is of course exactly the set of finite state systems.

We have focused on the *planning problem*, that is, the problem of finding a control sequence which transforms a given initial state into a desired final state. It is easy to show that without further restrictions the complexity of planning increases exponentially with the number of state variables. This is because the state space is exponential in size in terms of the number of state variables, and there are systems that force you to traverse the entire state space to reach your goal. Since a lower bound of the algorithm is derived from the size of the output it is then of course impossible to find the plan in polynomial time.

The set of problems analysed in this study basically excludes such processes as described above. The exact class studied is defined through explicit conditions on the actions and the details can be found in [10, 69, 63]. In these papers there are also algorithms for solving the planning problem under different restrictions. The algorithms are proved to be correct and complete.

They always return a minimal plan (in terms of length) if there is one. Furthermore the generated plan show maximal parallelism. The complexity of the algorithm is proved to increase polynomially with the number of state variables.

5.3.2 Polynomial Dynamical Systems over Finite Fields

This work focuses on using polynomial dynamical systems over finite fields as a system description. These systems all have the familiar form:

$$x(k+1) = f(x(k), u(k)), \quad y(k) = g(x(k), u(k))$$

where f and g are vectors of polynomials over some finite field.[2]

In terms of descriptive power these are exactly the set of finite state systems, this is easily realized through the use of Lagrange interpolating polynomials. This has the following consequences:

+ We can map all finite state based formalisms into this one. (We don't loose any of these systems.)
– We can map all finite state based formalisms into this one. (We also get all the hard systems.)

Since we are dealing with polynomial systems one of course immediately thinks of commutatative algebra and/or ideal theory as a means of describing computations. However to do this one also need to know something about the structure in these polynomial rings, this has been investigated in [90], where all ideals are characterized and an extension to Hilberts Nullstellensatz is given for the rings in question. This mode of computing is also very similar to logic, and one can in fact emulate propositional logic proofsystems. In [100] and [109] new completeness theorems are given for propositional and multivalued logic. These proofs are all based on the extension of Nullstellensatz above. From a control theory point of view these logic merely represent

[2]One could of course drop the assumption about *finite* fields above and thus obtain general polynomial dynamical systems, these are described elsewhere in this report.

static systems, the study [133] shows how one may analyse dynamic systems in this context. In this study various forms of reachability/controllability are analysed and whether or not certain properties can be guaranteed to hold in a system. It is worthwhile to note that the Ramadge/Wonham based notion of discrete control entails analysing a controllability concept.

Chapter 6

Differential Algebra and Nonlinear Systems.

When modelling a nonlinear system one might get a large collection of dynamic and static relationships between the physical variables. To get a useful model one has to extract a small number of reasonably simple relationships that give physical insight and/or can be used for numeric simulation. Recently it has become apparent that the framework of differential algebra can be used to make this process systematic.

6.1 Input Output Relations

In previous work it has been shown how differential algebra can give insight into the structure of the system. The concept of an autoreduced set can be used to determine the number of necessary input variables. Also input output relations can be computed, see [53]. The observability of the system is another property that can be determined. A particularly interesting situation occurs when a certain physical variable is unobservable from a particular output. In this case the output variable satisfies a differential equation of reduced order. In [62] some of these ideas are applied to an estimation problem. The task of estimating the primary current from the secondary in a transformer with possible saturation is considered. This can be regarded

(a) (b)

Figure 6.1: (a) (b) The true primary currents and their estimates from an iterative algorithm, and the secondary currents used for the estimation

as either an observability problem or an inversion problem.

Some practical approaches of reconstructing the primary current from distorted secondary current were proposed, see [62]. Figure 6.1(a)(b) are the simulation results from one of the methods.

6.2 Nonlinear Regulators.

A simple problem formulation for nonlinear regulators is the following. Let the system dynamics be given by

$$F(u, \dot{u}, \ldots, y, \dot{y}, \ddot{y}, \ldots) = 0$$

and let the desired behavior with a reference input r be given by

$$G(r, \dot{r}, \ldots, y, \dot{y}, \ddot{y}, \ldots) = 0$$

Now try to find a feedback law where u is computed from r and y in such a way that the desired performance is achieved.

In [17] it is shown that this is achieved by the controller

$$R(u, \dot{u}, \ldots, y, \dot{y}, \ldots, r, \dot{r}, \ldots) = 0$$

where R is the remainder of G with respect to F in the differential algebraic sense. It is also shown that the zero dynamics of the system, i.e., the dynamics corresponding to identically zero output

$$F(u, \dot{u}, \ldots, 0, 0, 0, \ldots) = 0$$

plays a key role. If the zero dynamics is unstable the procedure is unsuitable.

A simple example of the method is given by

$$F = \dot{y} - y^3 - u, \quad G = \ddot{y} + 2\dot{y} + y - r$$

where the regulator is

$$R = 3y^5 + 2y^3 + 3uy^2 + y + \dot{u} + 2u - r$$

If the system and desired dynamics are

$$F = \ddot{y} - \dot{u} + u^2, \quad G = y^{(3)} + 2\ddot{y} + 2\dot{y} + y - r$$

the regulator is given by

$$R = \ddot{u} + 2(1-u)\dot{u} - 2u^2 - r + y + 2\dot{y}$$

which has the realization (state space description)

$$\dot{x}_1 = x_2 - 2y, \quad \dot{x}_2 = -2(1-x_1)(x_2 - 2y) + 2x_1^2 + r - y, \quad u = x_1$$

However, the zero dynamics is highly unstable:

$$\dot{u} = u^2$$

with a finite escape time.

The computational aspects of this design method are treated in [74]. Implementation issues are covered in [73].

6.3 Mathematical Tools and Software for Analysis and Design of Nonlinear Control Systems

The mathematical tools for nonlinear control systems have developed rapidly during the last years. However, in order to make use of the comprehensive theory in practice, we need efficient and powerful software tools as well. Since most computations related to nonlinear control theory will involve a lot of symbolic manipulations, the natural tool to use is a computer algebra system. Therefore, algorithms for symbolic computations is being developed and a package of computer algebra routines for analysis and design of nonlinear control systems is being implemented.

We are also studying theoretical questions of practical importance, related to two areas of nonlinear control theory — Volterra series expansions and exact linearization.

A Volterra series expansion is an input-output description which can be quite demanding to compute, and to use it the analysis. We thus investigate structural questions which makes it possible to draw conclusions from the structure of the system or the series, without having to make a lot of computations. We also study how the structure of the system can be used to simplify the computations.

Exact linearization is a design method which can be used if the nonlinear system satisfies certain conditions. The method requires a good model for the system but since we cannot always obtain that in practice, we are investigating some robustness issues related to this method.

The results of this research was presented in Tommy Svensson's Ph.D. thesis, which was defended in September, 1992.

6.4 Commutative Algebra and Algebraic Geometry

Today the most common mathematical tool in the study of nonlinear systems is probably differential geometry. However, if we consider the subclass of nonlinear systems where all nonlinearities are polynomial it seems more natural to employ methods from commutative algebra or, as above, differential algebra. It can be hoped that "nonlinear algebra" will be to polynomial systems what linear algebra has been to linear systems. For this to happen we must have access to efficient computational tools, though.

In the past 20 years, algebraists have begun to seriously study a method in elimination theory called Gröbner bases, GB. In some sense Gröbner bases are the analogue of Gaussian elimination for systems of polynomial equations. Algorithms for computing Gröbner bases are available for instance in the symbolic algebra programs Maple, Macsyma and Reduce.

In [3] some applications of Gröbner bases to nonlinear systems are considered. For example, the problem of determining critical levels of local Lyapunov functions can be tackled with constructive algebra. If V is a local Lyapunov function for a system $\dot{x} = f(x)$ we may consider the system of $n+2$ equations in $n+2$ variables

$$V - d = 0, \quad V_x f = 0, \quad \nabla_x V - \lambda \nabla_x (V_x f) = 0 \tag{6.1}$$

where d is a positive parameter and λ a Lagrange multiplier. Now we can use Gröbner bases to eliminate all variables except d so that we get a polynomial, p say, in d only, which is in the ideal generated by (6.1). The critical value of d now has to be a root of p.

The above ideas can also be used to analyse robustness against structured uncertainty of nonlinear systems. In this case we fix d and let some uncertain parameters η vary, and use elimination theory to determine for which values of η that the region $\{x \mid V(x) < \delta\}$ is stable for a given δ. This approach is studied in [50].

In nonlinear state space theory Gröbner bases can be of great help. In [3] it showed how they can be used to find the input-output relation for a system in state space form when all nonlinearities are polynomials. Furthermore some questions relating to observability and state space transformations can be handled in this framework.

A Maple package called Polycon has been written for state space analysis of polynomial and rational systems using Gröbner bases. Polycon is available by anonymous ftp, and is included in the Maple share library.

The classical problem of realizing a nonlinear input-output differential equation has been investigated. In [59] it is shown that given a polynomial differential equation in y the question of determining if this d.e. can be realized in rational state space form is strictly harder than a famous unsolved problem in algebraic geometry, namely the one of determining whether a given affine variety is unirational or not.

Appendix A

Personnel

Lennart Ljung is professor and head of the control group since 1976. He was born in 1946 and has his Ph.D. in Automatic Control from Lund Institute of Technology. He is currently a Vice President of the International Federation of Automatic Control (IFAC), and an associate editor of several journals.
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Torkel Glad was born in Lund, Sweden in 1947. He received his M.S. degree in engineering physics in 1970 and the Ph.D. degree in automatic control in 1976, both from the Lund Institute of Technology, Lund, Sweden. Since 1988 he is Professor of Nonlinear Control systems in the department. His research interests include Nonlinear Systems, algebraic aspects of System Theory and Optimal Control.
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Mille Millnert is a Lecturer in the department. He was born in 1952 and received his M.S. in 1977 and his Ph.D. in Automatic Control 1982 from Linköping Institute of Technology. His research interests are Model Based Signal Processing, Parameter Estimation and the Combination of Numerical and Symbolical techniques in Signal Processing and Control.
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Bo Wahlberg was born in Norrköping, Sweden, in 1959. He received his M.S. degree in 1983, the Licentiate's degree of Technology in 1985 and the Ph.D. in 1987, all from Linköping Institute of Technology. He received the Hugo Schuck Best Paper Award of 1986 American Control Conference. Dr. Wahlberg is an Associate Editor of *Automatica*. His research interests include System Identification, Time Series Analysis and Signal Processing. Since January 1, 1992 he is Professor of Automatic Control at the Royal Institute of Technology in Stockholm.
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Svante Gunnarsson was born in 1959. He received his M.S. in 1983, his Licentiate's degree in 1986 and his Ph.D. in 1988 all from Linköping Institute of Technology. Since 1989 he is Lecturer at the department, and his research interests are system identification and adaptive control.
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Alf Isaksson was born in 1959. He is Lecturer in the department. He received his M.S. in 1983 and his Licentiate's degree in 1986 and Ph.D. in 1988, all from Linköping Institute of Technology. His research interests are System Identification and Signal Processing. He spent the academic year 91/92 at the Centre for Industrial Control Science, The University of Newcastle, Australia where he, amongst other duties, acted as a so-called Foreign Examiner for a PhD Thesis at the Department of Chemical Engineering, The University of Queensland, Brisbane.
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Mats Viberg was born in 1961. He is a Research Associate at the department. He received his M.S. in 1985, his Licentiate's degree in 1987 and his Ph.D. in 1989, all from Linköping Institute of Technology. His research interests include Sensor Array Processing, Adaptive Signal Processing and Parameter Estimation.
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Björn Ottersten was born in 1961. He received his M.S. degree in electrical engineering and applied physics in 1986 from Linköping University and the Ph.D. degree in electrical engineering in 1989 from Stanford University, USA. His research interests include stochastic signal processing, sensor array processing and parameter estimation. Since January 1992 he is Professor of Signal Processing at the Royal Institute of Technology in Stockholm.
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Peter A J Nagy was born in 1961. He received his M.S. in 1986 and his Licentiate's degree in 1988 and his Ph.D. in 1992, all from Linköping Institute of Technology. His research interests are in Artificial Intelligence, expecially Expert Systems and their use in control theory and signal processing. Since June 1, 1992, he is with the National Defense Research Laboratory in Linköping.
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Tommy Svensson was born in 1963. He received his M.S. degree in Applied Physics and Electrical Engineering from Linköping Institute of Technology in 1986. His research interest is nonlinear systems.
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Inger Klein was born in 1964. She received her M.S. in 1987 and her Licentiate's degree in 1990, all from Linköping Institute of Technology. Her research interest Discrete Event Systems and Sequential Control.
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Krister Forsman was born in Stockholm in 1963. He got his M.S. in Applied Physics and Electrical Engineering in 1987 and his Ph.D. in 1991, both from Linköping University. He is currently a research associate at the department. His research interests include algebraic and algebro-geometric aspects of nonlinear systems theory.
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Ke Wang Chen was born in 1960 and came from Shanghai, China in September 1986. She graturated from East China Normal University with B.S. in Mathematics in 1982. She received her Licentiate's degree in 1991 from Linköping Institute of Technology. She spent the 1991/92 academic year at University of California, Berkeley as Visiting Scholar. Her research interests include applications of differential algebra to nonlinear systems and transformer saturation problems.
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Fredrik Gustafsson was born in 1964. He received his M.S. degree in electrical engineering in 1988, his Licentiate's degree in 1990 and his Ph.D. in 1992. He is currently a Research Associate at the department. His research interests include segmentation, blind equalization, model strucure selection and aspects on estimation of discrete parameters in linear systems.
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Sören Andersson was born in 1964. He received his M.S. degree in Electrical Engineering in 1988 and the Licentiate's degree in 1990, both from Linköping University. His research interests are in array processing and parameter estimation.
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Håkan Hjalmarsson was born in 1962. He received his M.S. degree in Electrical Engineering in 1988 and his Licentiate's degree in 1990. He spent the academic year 1991/92 at California Institute of Technology, Pasadena, USA. Topics from system identification, especially when oriented towards control design, are included among his research interests.
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Jan-Erik Strömberg was born in the deep dark forests of Dalarna, the forest called Gagnef, in 1963. His hobbies are dogs, flying objects and coffee. He received his M.S. in Computer Science from Linköping Institute of Technology in 1988. Trees and dogs still play an important role in his life, since they form an integral part of his research in nonconventional system identification and modelling. He is a bit fuzzy and frugal.
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Roger Germundsson was born in 1965. He received his M.S. degree in electrical engineering and technical physics in 1988 at Linköping University. He spent 1988/89 at Stanford University at the Information Systems Laboratory. He is currently a PhD candidate at Linköping University. His research interests include areas where symbolic computation can be expected to have an impact such as nonlinear polynomial dynamical systems, polynomial dynamical systems over finite fields, sequential control.
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Jonas Sjöberg was born in 1964. He received his M.S. in 1989 from Uppsala University. His current research interest is in the field of nonlinear identification with neural networks.
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Torbjörn Andersson was born in 1967. He received his M.S. in 1990 from Linköping Institute of Technology. His current research interest is in the field of identification.
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Predrag Pucar was born in 1965. He received his M.S. degree in electrical engineering and technical physics in 1990 at Linköping University. He is currently a PhD student and his research interests are signal and image segmentation.
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Håkan Fortell was born in 1967, and he received his M.Sc. degree in Applied Physics and Electrical Engineering at Linköping Institutute of Technology in 1991. His current research interest is nonlinear systems.
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Tomas McKelvey was born in 1966. He received his M.Sc. degree in Electrical Engineering at Lund Institute of Technology in 1991. His current research interests are in System Identification.
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Anna Soffia Hauksdottir was born in the vicinity of the hot springs of Iceland. She spent the autumn of 1991 at our department as a guest researcher.

Qinghua Zhang was born in Shenyang, China, in 1963. He graduated from the University of Sciences and Technologies of China in 1986, and received the diploma of E.E.A. from Universite de Lille I, France, in 1988. From 1988 to 1991 he made his study on industrial process monitoring at IRISA, France, and received the degree of "docteur de l'Universite de Rennes I" in 1991. His current research interests are failure detection and neural networks.

Sten Granath was born in 1951. He received his M.S. in 1975 from Linköping University, Department of Applied Mathematics.

Kent Hartman was born in 1951. He received his M. S. in 1975 from Linköping University, Department of Applied Mathematics.

Patrik Lägermo was born in 1965. He received his M.S. in 1989 from Linköping University, Department of Electrical Engineering. As a research engineer he is responsible for the computer network and the laboratory equipment.
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Ingegerd Stenlund and Ulla Salaneck are secretaries for the control group. Like everybody else in the department they were born. Their interests are Stochastic Error Processing and Optimal Fuzzy Control. They are responsible for this publication and you can imagine the hard work to get all the loose ends together.
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Appendix B

Courses

B.1 Undergraduate Courses

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

Automatic Control M (Reglerteknik M) Basic course for the Mechanical Engineering Program. 120 participants. Lecturer: Svante Gunnarsson.

Control Theory I (Reglerteori I) Advanced course for the Industrial Economy Program. Sampled data systems, stochastic control, system identification. 55 Participants. Lecturer: Svante Gunnarsson.

Control Project Laboratory (Reglerteknisk projektkurs) For the Electrical Engineering and Computer Engineering Programs. Modelling and identification of laboratory processes. Controller design and implementation. 22 Participants. Lecturer: Svante Gunnarsson.

Automatic Control, advanced course (Reglerteknik, fortsättningskurs M). For the Mechanical Engineering Program. Sampled data systems, Nonlinear systems, Signal processing. 24 participants. Lecturer: Torkel Glad

Modelling and Simulation (Modellbygge och Simulering). For the Electrical Engineering program. Physical system modelling, Bond graphs, Identification methods, Simulation. 102 participants. Lecturer: Torkel Glad.

Digital Signal Processing (Digital Signalbehandling). For the Electrical Engineering and Computer Engineering Programs. Spectral analysis, Filtering, Signal Modelling, Wiener and Kalman filtering, Adaptive filters. 150 participants. Lecturer: Mille Millnert.

Automatic Control Y (Reglerteknik Y). Basic course for the Electrical Engineering Program. 180 participants. Lecturer: Mille Millnert.

Modelling of Industrial Systems (Modellering av Industriella System). For the Computer Engineering Program. Physical system modelling, Bond Graphs, Identification, Simulation. 25 participants. Lecturer: Mats Viberg

Control Theory Y (Reglerteori Y). Advanced course for the Electrical Engineering and Computer Science Programs. Sampled data systems, stochastic control, LQG-control with LTR, nonlinear systems. 125 participants. Lecturer: Lennart Ljung

Automatic Control I (Reglerteknik I). Basic course for the Industrial Economy Program. 45 participants. Lecturer: Peter Nagy.

Digital Control (Digital Styrning). For the Electrical Engineering, Computer Science and Industrial Economy Programs. Numerical control, binary control and PLCS, process computers and applications of digital process control. 180 participants. Lecturer: Lars Nielsen

B.2 Graduate Courses

Nonlinear Optimization. Lecturer: T. Glad. Literature: J. E. Dennis, jr, R. B. Schnabel *Numerical methods for unconstrained optimization and nonlinear equations*, Prentice Hall, 1983

Optimal Control. Lecturer: T. Glad. Literature: G. Leitmann *The calculus of variations and optimal control*, Plenum Press 1981.

Identification. Lecturer: L. Ljung. Literature: L. Ljung *System Identifica-*

tion: Theory for the User, Prentice-Hall, 1987

Nonlinear systems. Lecturer: T. Glad. Literature: T. Glad *Lecture Notes*

Appendix C

Computers and Laboratory Equipment

The automatic control group uses an Ethernet based computer network with Sun Microsystems workstations and QMS laser printers in their daily work. In the laboratory, mainly used by students in the different courses, there are a lot of different processes and some 10 Intel-based computers for measurement and control.

Comments and questions on the equipment can be directed to Patrik Lägermo.

The computer network consists of the following components.

- A computer network with a Sun SPARCsystem 300 server
- 1 Sun 386i
- 1 Sun SPARCstation 1+
- 5 SPARCstation 2
- 1 SPARCstation ELC
- 19 SPARCstation SLC.

- 2 QMS-PS 800 laser printers
- 1 QMS-PS 810 laser printer

In the laboratory the following processes and computers are used:

- 11 AC and DC servo systems, Feedback MS150
- 5 hot air processes, Feedback PT326
- 9 simple tank processes
- 5 double tank processes
- 6 modular systems with simulated processes, PID-Lead/lag compensation, and time discrete controllers
- 1 air-driven generator plant
- 1 air-driven steam generator
- 1 hot water heating process
- 1 coupled tanks process (level control by Tecquipment)
- 1 "ball and beam" process by Tecquipment
- 1 "ball and hoop" process by Tecquipment
- 3 Lego processes for sequential control
- 1 helicopter-like process
- 2 wind meter processes from Chalmers Institute of Technology
- 8 LED 386 computers with Metrabyte Dash 16 interfaces (A/D, D/A and digital I/O).
- 8 Ericsson AT computers
- 1 Ericsson AT computer with AT&T DSP32C signal processor.
- 1 Compaq Deskpro 386 computer with the SattLine software.

Appendix D

Seminars

Identification of a helicopter model. Dr Guillermo Peretti, ETH, Zurich, Switzerland, August 15, 1991.

On adaptive algorithms. Professor C. R. Johnson, Jr, Cornell University, Ithaca, USA, September 19, 1991.

Performance related adaptive friction compensation for uncertain systems. Dr Per-Olof Gutman, Faculty of Agricultural Engineering, Haifa, Israel. September 27, 1991.

A decoupling controller design of a ferrosilicium furnace. Professor Anna Soffia Hauksdottir, Dept of Engineering and the Engineering Research Institute, University of Iceland. October 3, 1991.

Some optimization problems within the agriculture area. Dr Per Molander, ESO, Ministry of Finance, Stockholm, Sweden. October 10, 1991.

SIMULAB a new system for dynamical simulations and Coming up next - MATLAB V4.0. Sparse technique. Dr John Little and Dr. Cleve Moler, The MathWorks Inc., October 17, 1991.

Anti-reset windup for PID controllers. Dr Lars Rundquist, SAAB Flygdivisionen, Linköping, Sweden. November 7, 1991.

Generic model control - theory and applications. Dr Peter Lee, Department of Chemical Engineering, University of Queensland, Australia. November 21, 1991.

Hypermedia, possibilities, applications and problems. Roland Hjerpe, LIBLAB, IDA, Linköping Institute of Technology, Linköping, Sweden. November 28, 1991.

Adaptive stabilization of trajectory motion. The implicit reference model approach and A gradient algorithm of fast adaptation. Dr Vladimir O. Nikiforov, St. Petersburg Institute of Fine Mechanics and Optics, St Petersburg, Russia. December 4, 1991.

Språkteknologisk forskning inom området Interpreting Telephony vid ATR i Kyoto. Dr Dieter Huber, Chalmers Institute of Technology, Gothenburg, Sweden, December 5, 1991.

Optimal state sequence detection of given complexity. Dr Tor Aulin, Chalmers Institute of Technology, Gothenburg, Sweden. December 12, 1991.

Symmetry and extremality. Professor Michiel Hazewinkel, Centrum voor Wiskunde en Informatica, Amsterdam, The Netherlands. December 19, 1991.

Parametric uncertainty in linear control systems. Dr Anders Rantzer, Royal Institute of Technology, Stockholm, Sweden. February 6, 1992.

A regulator design method for linear discrete time systems. Anders Malmgren, Department of Automatic Control and Systems Analysis, Uppsala University, Uppsala, Sweden. February 20, 1992.

About chaos, simulators and why it is about time. Magnus Sterky, Eurosim AB, Vattenfall, Sweden. February 27, 1992.

Robust and adaptive control. Dr Michael Lundh, Department of Automatic Control, Lund Institute of Technology, Lund, Sweden. March 5, 1992.

Identification for high performance control design. Dr. Ruud Schrama, Delft University of Technology, Department of Mechanical Engineering and Marine Technology, Delft, The Netherlands. March 12, 1992.

The local approach to change detection and its robustness properties. Wavelet Networks. Dr Qinghua Zhang. March 12, 1992.

*μ-tools: A toolbox for H^∞ and μ design*Anders Helmersson, SAAB Space, Linköping, Sweden, March 26, 1992.

A frequency domain method for low order controller design. Dr Mats Lilja, Technical Institute, Hässleholm, Sweden. April 10, 1992.

Statistical change detection: Likelihood and non-likelihood based algorithms and performances. Professor M. Basseville, IRISA, Rennes, France, April 14, 1992.

Adaptive changes in state space models: Statistical and geometrical points of view. Professor M. Basseville, IRISA, Rennes, France, April 16, 1992.

Nonlinear synthesis problem: From linearity to nonlinearity. Professor Henri Huijberts, Eindhoven, The Netherlands, April 21, 1992.

On the analysis of routing methods for array processing. Hamid Krim, LSS-ESE, France. April 23, 1992.

Control of error and convergence in ODE solvers. Kjell Gustafsson, Lund Institute of Technology, Lund, Sweden. May 14, 1992.

Statistical process modelling and optimization for quality control in power semiconductor device manufacturing. Dr Andres Kiitam, Control Engineering Laboratory at Tallinn Technical University, Tallinn, Estonia. May 21, 1992.

Active sonar and "stealth" submarines. Lars Götherström, LG Marinakustik AB, Linköping, Sweden. June 9, 1992.

Process identification. Professor Sten Bay Jorgensen, Denmark Institute of Technology, Lyngby, Denmark. June 11, 1992.

Path constrained robot control. Dr Ola Dahl, Dept of Automatic Control, Lund Institute of Technology, Lund, Sweden. June 15, 1992.

Appendix E

Lectures by the staff

K. Forsman: *Applications of Gröbner Bases to Nonlinear Systems*, First European Control Conference, Grenoble, France, July 2, 1991

J.E. Strömberg: *Trees as black box model structures for dynamical systems*, First European Control Conference, Grenoble, France, July 3, 1991

H. Hjalmarsson: *Estimation of the Variability of Time-Varying Systems.* IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

M. Viberg: *Effects of Unknown Noise Covariance on Parametric Array Processing Algorithms*, IFAC Symp. on Syst. Param. Est., Budapest, Hungary, July 1991.

L. Ljung: *An Exact Formula for the Tracking Ability of Adaptive Algorithms: Implications for the General Case.* IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

B. Wahlberg: *Estimation of noise models by means of discrete Laguerre/Kautz filters.* IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

B. Wahlberg:*On Sampling and Reconstruction of Continuous Time Stochastic Systems*. IFAC Symposium on System Identification and System Parameter Estimation, Budapest Hungary, July 1991.

P. Nagy: *Computer-aided Model Structure Selection*. IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

P. Nagy: *Estimating time-delays via state-space identification methods*. IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

L. Ljung: *Testing Global Identifiability for Arbitrary Model Parameterizations*. IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

P. Nagy: *System Identification Using Bond Graphs*. European Control Conference, Grenoble, France, July 1991.

L. Ljung: *Optimal and Ad Hoc Adaptation Mechanisms*. European Control Conference, Grenoble, France, July 1991.

L. Ljung: *On the Dead-zone in System Identification*. IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

L. Ljung: *Identifying State-space Models with Mathwork's System Identification Toolbox*. IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

F. Gustafsson: *Optimal Segmentation of Linear Regression Parameters*. IFAC Symposium on System Identification and System Parameter Estimation, Budapest, Hungary, July 1991.

L. Ljung: *On the Estimation of Transfer Function Error Bounds*. European Control Conference, Grenoble, France, July 1991.

L. Ljung: *An Introduction to System Identification Concepts*. Course on "Theory and Control of Dynamic Systems", Södertörns Sommaruniversitet, Huddinge, Sweden, August 8, 1991.

I. Klein: *Parallel Non-Binary Planning in Polynomial Time*, 12th International Joint Conference on Artificial Intelligence, Sydney, Australia, 24-30 August 1991.

J.E. Strömberg: *Physical systems modelling – an interdisciplinary matter*, C.S.I.R.O., Division of Information Technology, Sydney, Australia, September 2, 1991

L. Ljung: *A (simple) perspective on adaptation and performance of adaptation mechanisms.* Conference on Stochastic Control, University of Kansas, Lawrence, KA, USA, September 27, 1991.

K. W. Chen:*Observability and Invertibility of Nonlinear Systems*, University of California at Berkeley, October 28 1991

M. Viberg: *Performance Analysis of a Subspace Based Method for State Space System Identification*, Uppsala University, Sweden, Oct. 1992.

S.Andersson:*Optimal Dimension Reduction for Sensor Array Signal Processing*, Asilomar Conference on Signals, Systems and Computers, Monterey, California, November 4-6 1991

M. Viberg: *Estimation Accuracy of Maximum Likelihood Direction Finding Using Large Arrays*, 25^{th} Asilomar Conf. Sig., Syst.,Comput., Monterey, CA, USA, Nov. 1991.

M. Viberg: *Local Modeling and Robust Estimation for High-Resolution Direction Finding*, 25^{th} Asilomar Conf. Sig., Syst.,Comput., Monterey, CA, USA, Nov. 1991.

J.E. Strömberg: *Processmodeller för reglering, prediktering och övervakning*, ABBA, Göteborg, Sweden, November 8, 1991.

J.E. Strömberg: *Huru modellera ingenjörssystem på ett systematiskt sätt*, FOA, Linköping, Sweden, November 28, 1991.

K. W. Chen: *Estimation of Primary Current in a Saturated Transformer*, 30th Conference on Decision and Control, Brighton, England, 11-13 December 1991.

I. Klein: *On the planning problem in sequential control*, 30th Conference on Decision and Control, Brighton, England, 11-13 December 1991.

K. Forsman: *Construction of Lyapunov Functions Using Gröbner Bases*, 30th Conf. on Decision and Control, Brighton, UK, December 11, 1991.

L. Ljung: *Model Quality: The Role of Prior Knowledge and Data Information.* 30th Conference on Decision and Control, Brighton, England, December 1991.

J.E. Strömberg: *On recursive construction of trees as model structure for dynamical systems*, 30th Conf. on Decision and Control, Brighton, UK, December 12, 1991.

K. Forsman: *An Algorithm for Finding Periodic Solutions to Systems of Nonlinear Difference Equations*, 30th Conf. on Decision and Control, Brighton, UK, December 13, 1991.

R. Germundsson: *A Constructive Approach to Algebraic Observability*, 30th IEEE Conference on Decision and Control, Brighton, UK, 11-13 December 1991.

S. Gunnarsson: *On the performance of the recursive least squares method in the presence of bounded disturbances*, 30th Conference on Decision and Control, Brighton, England, 11-13 December 1991.

M. Viberg: *A Statistical Perspective on State-Space Modeling Using Subspace Methods*, 30^{th} IEEE Conf. on Decision & Control, Brighton, England, Dec. 1991.

M. Viberg: *Accurate Source Localization – Theoretical and Experimental Results*, Sonar Signal Processing Conference, Loughborough, England, Dec. 1991.

K. Forsman: *Input Output Representations from Characteristic Sets.* 30th IEEE Conference on Decision and Control, Brighton, England, December 1991.

L. Ljung: *A Simple Start-up Procedure for Canonical Form State Space Identification, Based on Subspace Approximation.* 30th IEEE Conference on

Decision and Control, Brighton, England, December 1991.

L. Ljung: *System Identification.* 8 lectures held at a course at the Technical University of Denmark, DTH, Lyngby, Denmark, January 27-28, 1992.

K. Forsman: *Rational Varieties, Tame Automorphisms and the Jacobian Conjecture - Fun Problems in Algebraic Geometry*, Linköping University, Dept. of Mathematics., Linköping, Sweden, February 11, 1992.

J.E. Strömberg: *Introduction to classification and regression trees*, Linköping University, Dept. of Mechanical Engineering., Linköping, Sweden, February 12, 1992.

T. Glad: *Exact linearization*, Chalmers Institute of Technology, Göteborg, Sweden, 21 February 1992.

I. Klein: *On the planning problem in sequential control Part 1 and 2*, McGill University, Montreal, Canada, 21 February 1992.

J. Sjöberg: *An Introduction to Artificial Neural Networks.* Department of Quality Technology, University of Linköping, Sweden, February.

M. Viberg: *How to use Sensor Arrays for Locating Submarines or Increasing the Number of Mobile Telephones*, Docentföreläsning, Linköping University, Sweden, Feb. 1992.

F Gustafsson: *Blind equalization by direct examination of the input sequences.* International Conference on Acoustics, Speech and Signal Processing, San Francisco, March 92.

M. Viberg: *Robust Source Localization Based on Local Array Response Modeling*, ICASSP 92, San Francisco, CA, USA, March 1992.

M. Viberg: *An Instrumental Variable Approach to Array Processing in Spatially Correlated Noise Fields*, ICASSP 92, San Francisco, CA, USA, March 1992.

L. Ljung: *Identification Based on Physical Insight.* STFI, Stockholm, Sweden, April 21, 1992.

H. Hjalmarsson: *Estimation of Model Errors Due to Stationary Time-Variations*, UCLA, California, April 21, 1992.

H. Hjalmarsson: *Principles of System Identification*, Caltech, California, April 23, 1992.

H. Hjalmarsson: *Model Uncertainty Estimation*, Caltech, California, April 30, 1992.

K. Forsman: *Constructive Algebraic Geometry - A Tool For Nonlinear Control Systems*, Royal Institute of Technology, Dept. of Mathematics, Stockholm, Sweden, April 10, 1992.

M. Viberg: *How to use Sensor Arrays for Locating Submarines or Increasing the Number of Mobile Telephones*, Uppsala University, Sweden, April 1992.

M. Viberg: *Direction Finding in the Presence of Model Uncertainties*, Uppsala University, Sweden, April 1992.

L. Ljung: *Parameter Identifiability*. System Center University of Maryland, USA, April 27, 1992.

L. Ljung: *Process Identification, Theory and Practice*, Plenary lecture. DYCORD, University of Maryland, USA, April 28, 1992.

L. Ljung: *Quality of Estimated Models*. Rutgers Center for Systems and Control, Rutgers University, NJ, USA, April 29, 1992.

L. Ljung: *On Global Identifiability of Arbitrary Model Parameterizations*. Rutgers Center for Systems and Control, Rutgers University, NJ. USA, April 30, 1992.

T. Glad and L. Ljung: *Control Theory after Kalman*. SAAB-MISSILES, Linköping, Sweden, May 8, 1992.

S.Andersson: *Optimal Dimension-Reduction for Array Processing*, Ramprogrammöte i Digital Kommunikation, Uppsala, May 8, 1991.

K. Forsman & J.E. Strömberg: *Fuzzy Control for the Irritated Control The-*

orist, Linköping University, Dept. of Electrical Engineering, Linköping, Sweden, May 7 and May 21, 1992.

J.E. Strömberg: *Introduction to bond graphs*, Stockholm University, Dept. of Automatic Control, Stockholm, Sweden, May 8, 1992.

J.E. Strömberg: *Fuzzy Control for the Irritated Control Theorist*, Linköping University, Dept. of Electrical Engineering, Linköping, Sweden, May 21, 1992.

L. Ljung: *System Identification.* Dutch Graduate Summer School, Zeist, The Netherlands, June 1-3, 1992.

F. Gustafsson: *Segmentation.* Chalmers University of Technology, June 92.

A. Isaksson: *Model Reduction for PID Control.* Australian National University, Canberra, Australia, June 11, 1992.

A. Isaksson: *Model Reduction for PID Control.* The University of Newcastle, Australia, June 15, 1992.

H. Hjalmarsson: *Model Set Estimation: An Overview.* Workshop on the Modeling of Uncertainty in Control Systems, Santa Barbara, June 19, 1992.

J. Sjöberg: *Regularization as a Substitute for Pre-Processing of Data in Neural Network Training.* IFAC/IFIP/IMACS International Symposium on Artificial Intelligence in Real-Time Control, Delft, the Netherlands, June, 1992.

J. Sjöberg: *Overtraining, Regularization, and Searching for Minimum in Neural Networks.* ABB Corporate Research, Baden, Switzerland, June, 1992.

J. Sjöberg: *Overtraining, Regularization, and Searching for Minimum in Neural Networks.* ETH-Zentrum, Zürich, Switzerland, June, 1992.

T. McKelvey: *Neural networks applied to optimal flight control.* IFAC/IFIP/IMACS International Symposium on Artificial Intelligence in Real-Time Control, Delft, The Netherlands, June 92.

K. Forsman: *On Rational State Space Realizations*, NOLCOS'92, Bordeaux, France, June 24, 1992.

T. Glad: *Generalized state space descriptions and digital implementation*, Nonlinear Control Systems Design Symposium, Bordeaux, France, June 25.

T. Glad: *Implementing Ritt's algorithm of differential algebra*, Nonlinear Control Systems Design Symposium, Bordeaux, France, June 26.

M. Viberg: *Direction Finding in the Presence of Model Uncertainties*, Swedish National Defense Research Institute (FOA 3), Sweden, June 1992.

Appendix F

Travel and Conferences

Lennart Ljung visited the European Control Conference in Grenoble July 1-5. Hen then took part in the IFAC Symposium on Identification in Budapest the following week and after that he participated in the IFAC Council related meetings in Swansea. September 25-29 he participated in the Workshop on Stochastic Control and Adaptive Systems at The University of Kansas, Lawrence. December 11-13 he participated in the IEEE Conference on Decision and Control in Brighton, and in the IFAC Presidents' meeting April 8-12. The last week of April, he was at the IFAC Conference DYCORD in Maryland and also visited the Systems Centre at Maryland, Rutgers University and Princeton University. May 18 he visited Vrie Universiteit in Brussels as a thesis examiner, and after that he took part in the IFAC Council and related meetings in Malaga, Spain. June 1-3 he lectured at the Dutch summer school on System Identification in Zeist, The Netherlands.

Torkel Glad attended IFAC's Nonlinear Control Systems Design Symposium (NOLCOS'92), Bordeaux, France, June 24–26.

Mille Millnert attended the Digital Communication Workshop in Uppsala, May 8.

Svante Gunnarsson attended the 30th IEEE Conference on Decision and Control in Brighton, December 11-13.

Alf Isaksson spent the academic year 91/92 at the Centre for Industrial Control Science, The University of Newcastle, Newcastle, Australia. During the year he visited other Australian Universities, such as Australian National University, Canberra, Monash University, Melbourne, Univeristy of New South Wales, Sydney, Melbourne University, Sydney University and University of Queensland, Brisbane. Furthermore he visited BHP Research, Newcastle, and the power stations at Eraring and Bayswater.

Jan Erik Strömberg attended the first European Control Conference, Grenoble, France, July 2-5. August 24-30 he attended the 12th International Conference on Artificial Intelligence, Sydney, Australia. December 11-13 he participated in the 30th IEEE Conference on Decision and Control in Brighton, England. He attended the project meeting "Driftutvecklingssystem för processindustrin" March 12.

Inger Klein attended the 12th International Conference on Artificial Intelligence, Sydney, Australia, 24-30 August. December 11-13 she participated in the 30th IEEE Conference on Decision and Control in Brighton, England. She visited McGill University, Montreal, Canada February 18 - March 3. She attended the project meeting "Driftutvecklingssystem för processindustrin" March 12.

Ke Wang Chen participated in the 30th IEEE Conference on Decision and Control in Brighton, England in December 91. In June 91 she visited ABB Relays, Västerås, Sweden. She visited University of California at Berkeley during August 1991 - July 1992 and held a position there as Visiting Scholar.

Roger Germundsson participated in the 30th IEEE Conference on Decision and Control in Brighton, England in December 91. He also visited Stanford University in January 91. In March 91 he visited SAAB Military Aircraft and in May 91 he visited Nobel Tech. In June he attend the Summer school in Computer Algebra at RISC Linz, Austria and in August he attended the WODES'92 workshop in Prag, Tjeckoslovakia. Finally he also attended the *Mathematica* conference in Rotterdam, Netherlands in August 91.

Krister Forsman participated in the First European Control Conference - (ECC '91) in Grenoble, France in July 1991. July 15–17 he attended ISSAC '91 (International Symposium on Symbolic and Algebraic Computation) in Bonn, Germany. He also participated in the 30th IEEE CDC in Brighton, UK, in December 1991. On January 30 1992 he visited ABB Carbon in Finspång and in April 1992 he attended the conference MEGA 92 (Effective Methods in Algebraic Geometry) in Nice, France. He also visited the Dept. of Mathematics of the Royal Institute of Technology (KTH), Stockholm, in April '92. Furthermore he participated in IFAC's Nonlinear Control Systems Design Symposium (NOLCOS'92), Bordeaux, France, June 24–26. He also visited the Dept. of Mathematics at Stockholm University on some occasions.

Sören Andersson participated in the 25 Asilomar Conference on Signals, Systems and Computers, Monterey, California, November 1991 and the meeting "Digital Kommunikation" in Uppsala, May 8.

Håkan Hjalmarsson participated in the 9th IFAC/IFORS Symposium on Identification and System Parameter Estimation '91, Budapest, July 8-12. September 1991- August 1992 he visited California Institute of Technology and held a position as Lecturer/Visiting Associate. In November 1991 he attended a workshop on Generalized Predictive Control at UCSB, Santa Barbara, California. In April 92 he visited UCLA and June 18-20, 1992, he participated in the Workshop on the Modeling of Uncertainty in Control Systems, Santa Barbara, California.

Fredrik Gustafsson participated in the 9th IFAC/IFORS Symposium on Identification and System Paramater Estimation '91, Budapest, and in ICASSP '92 in San Francisco. He took part in two TRFM (tire road friction monitoring) meetings in Stuttgart, March 4, and Wolfsburg, June 2. He attended the project meeting "Digital Kommunikation" in Uppsala in May 24-25. He gave a seminar at Chalmers in May 8. For the project DALTM, he visited Volvo in Gothenburg January 15, April 24, May 7, June 3, June 26 and SAAB in Trollhättan March 3. He also visited Nobeltech in Järfälla in June 16.

Jonas Sjöberg visited Universidad Nacional de Ingeniería, Managua, Nicaragua, in January. He participat red in IFAC/IFIP/IMACS International Symposium on Artificial Intelligence in Real-Time Control, Delft, the Netherlands, June, 1992. In June he visited ABB Corporate Research, Baden, Switzerland and ETH-Zentrum, Zürich, Switzerland.

Tomas McKelvey participated in the IFAC/IFIP/IMACS International Symposium on Artificial Intelligence in Real-Time Control, Delft, The Netherlands, June 92.

Ingegerd Stenlund and Ulla Salaneck never get a chance to travel or to attend any conference. They are stuck with the loads of work in the office and all the demanding research students.

Appendix G

Publications

Ph.D. Theses

[1] F. Gustafsson, *Estimation of discrete parameters in linear systems*, Linköping Studies in Science and Technology, Diss. No 271, ISBN 91-7870-876-1, April 1992.

Abstract

Linear models are the by far most commonly used approach for describing physical signals and systems. As a result, the theory of linear models is quite extensive in areas like control theory and signal processing. However, in many applications a linear model is adequate only if some information of discrete nature is available. This thesis addresses the problem of how to treat and estimate this discrete information.

Several applications on the problem of estimating discrete parameters in linear systems from measurements of its output are covered in the literature. Typically, the problem is treated separately in each context without overlapping. One objective of the present work is to discuss this problem in a general framework, relating proposed methods at a higher level of abstraction for revealing the main ideas. There are fundamental differences between estimating continuous and discrete parameters. Among all applicable statistical estimation techniques examined here, there are no simple examples where explicit expressions for the estimators exist. This is in clear contrast to the case of continuous parameters. On the contrary, estimators for discrete parameters are quite complex to compute, due to the fact that essentially every possible value of the discrete parameter has to be examined separately. The key question in applications is to find feasible expressions for the estimators, either exact or approximate.

Besides the general discussion of the problem, the thesis contains more detailed treatments of four applications: *model structure selection, detection, segmentation* and *blind equalization*. The main topics covered in the applications consider the computation of optimal estimates, analysis and practical recursive schemes. Several statistical optimality criteria are examined, and a number of efficient computation schemes are presented. In the analysis, questions such as *detectability*, *identifiability* and *efficiency* are addressed. It is also investigated how different prior assumptions influence the estimates, and how their effects can be reduced by giving as non-informative priors as possible. This leads to estimation algorithms which contain almost no design variables.

[2] P. A. J. Nagy, *Tools for Knowledge-Based Signal Processing with Applications to System Identification*, Linköping Studies in Science and Technology, Diss. No 280, June 1992.

Abstract

This thesis contains three parts: firstly there is an introduction to the field of knowledge-based signal processing - which denotes a combination of symbolic and numeric software capable of implementing algorithms of both algorithmic and heuristic character. Secondly suitable tools for knowledge-based signal processing are discussed - this includes the tools developed in our research. Finally we present our applications of knowledge-based signal processing.

The research in computer science and especially in the area of artificial intelligence (AI) has provided useful techniques and tools - e.g. expert systems - for "impmlementing" heuristic knowledge. This is hard to express in conventional programming languages like Fortran, Pascal and C.

To make it easy to implement knowledge-based signal processing applications, tools integrating numerical and symbolical computations (including logic inference) are needed: The tools developed in the undertaken research contains integrated building blocks: Common Lisp with YAPS (or Scheme) - the main programming language of the developed tool extended with an expert system shell, MATLAB - standard numeric software, and MACSYMA - a computer algebra system.

The applications are directed toward intelligent support system for system identification software. Two different help systems are discussed

and implemented, one for help in black-box modeling, and one for help with physical modeling. The latter system uses bond graphs to describe systems. Bond graphs give a graphical description of physical systems which allow for modeling multiple domains in a form which makes a good compromise between a high level description of physical systems and easy computation of the underlying differential equations.

[3] K. Forsman, *Constructive Commutative Algebra in Nonlinear Control Theory*, Linköping Studies in Science and Technology, Diss. No 261, December 1991.

Abstract

Linear models are the by far most commonly used approach for describing physical signals and systems. As a result, the theory of linear models is quite extensive in areas like control theory and signal processing. However, in many applications a linear model is adequate only if some information of discrete nature is available. This thesis addresses the problem of how to treat and estimate this discrete information.

Several applications on the problem of estimating discrete parameters in linear systems from measurements of its output are covered in the literature. Typically, the problem is treated separately in each context without overlapping. One objective of the present work is to discuss this problem in a general framework, relating proposed methods at a higher level of abstraction for revealing the main ideas. There are fundamental differences between estimating continuous and discrete parameters. Among all applicable statistical estimation techniques examined here, there are no simple examples where explicit expressions for the estimators exist. This is in clear contrast to the case of continuous parameters. On the contrary, estimators for discrete parameters are quite complex to compute, due to the fact that essentially every possible value of the discrete parameter has to be examined separately. The key question in applications is to find feasible expressions for the estimators, either exact or approximate.

Besides the general discussion of the problem, the thesis contains more detailed treatments of four applications: *model structure selection, detection, segmentation* and *blind equalization*. The main topics covered in the applications consider the computation of optimal estimates, analysis and practical recursive schemes. Several statistical optimality criteria are examined, and a number of efficient computation schemes are presented. In the analysis, questions such as *detectability*, *identifiability* and *efficiency* are addressed. It is also investigated how different

prior assumptions influence the estimates, and how their effects can be reduced by giving as non-informative priors as possible. This leads to estimation algorithms which contain almost no design variables.

Books

[4] L. Ljung, G. Pflug, and A. Walk, *Stochastic Approximation and Optimization of Random Systems*, volume Band 17 of *DMW Seminar*, Birkhäuser, 1992.

Journal Papers

[5] M. Viberg, B. Ottersten, and T. Kailath, Subspace based detection for linear structural relations, *J. of Combinatorics, Information & System Sciences*, **16**, 1991.

[6] M. Viberg, B. Ottersten, and T. Kailath, Detection and estimation of sensor arrays using weighted subspace fitting, *IEEE Trans. SP*, **SP-39**, 1991.

[7] B. Ottersten, M. Viberg, and T. Kailath, "Analysis of Subspace Fitting and ML Techniques for Parameter Estimation from Sensor Array Data", *IEEE Trans. on SP*, **SP-40**:590–600, March 1992.

[8] B. Ottersten, M. Viberg, P. Stoica, and A. Nehorai, Exact and large sample ML techniques for parameter estimation and detection in array processing, *Radar Array Signal Processing*, 1992.

[9] S. Andersson, M. Millnert, M. Viberg, and B. Wahlberg, An adaptive array for mobile communication systems, *IEEE Transactions on Vehicular Technology*, **40**(1):230–236, 1991.

[10] C. Bäckström and I. Klein, Planning in polynomial time: the SAS-PUBS class, *Computational Intelligence*, **7**:181–197, August 1991.

[11] H. Hjalmarsson and L. Ljung, "Estimating Model Variance in the Case of Undermodeling", *IEEE Trans. Automatic Control*, **37**:1004–1008, July 1992.

[12] L. Ljung and P. Priouret, A result on the mean square error obtained using general tracking algorithms, *Int. Journal of Adaptive Control and Signal Processing*, **5**(4):231–250, July-August 1991.

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[18] S. Gunnarsson and B. Wahlberg, Some asymptotic results in recursive identification using Laguerre models, *Int. J. on Adaptive Control and Signal Processing*, **5**:313–333, 1991.

[19] S. Gunnarsson, Frequency domain accuracy of recursively identified ARX models, *International Journal of Control*, **54**:465–480, 1991.

[20] S. Gunnarsson, On the quality of recursively identified fir models, *IEEE Transactions on Signal Processing*, **40**:679–682, 1992.

[21] B. Wahlberg and E. J. Hannan, Parametric signal modelling using Laguerre filters, *Annals of Applied Probability*, 1992.

[22] B. Wahlberg and L. Ljung, Hard frequency-domain model error bounds from least-squares like identification techniques, *IEEE Trans. on Automatic Control*, **AC-37**:900–912, 1992.

[23] M. Viberg, B. Ottersten, and B. Wahlberg, On the relation between subspace based estimation and maximum likelihood, *SIAM Journal on Matrix Analysis and Applications*, 1991.

[24] L. Ljung and B. Wahlberg, Asymptotic properties of the least-squares method for estimating transferfunctions and disturbance spectra, *Adv. Appl. Prob.*, **24**:412–440, 1992.

Conference Papers

[25] P. Stoica, B. Ottersten, and M. Viberg, An instrumental variable approach to array processing in spatially correlated noise fields, In *In Proc. ICASSP 92*, San Francisco, California, 1992.

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[27] B. Ottersten and M. Viberg, Local modeling and robust estimation for high-resolution direction finding, In *Proc. 25th Asilomar Conference on Sign. System. Comput.*, pages 1005–1009, Monterey, California, 1991.

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