System Identification, Optimization and Automation

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Editor

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Preface

The first chapter presents a personal view on the development of identification theory in the control community, starting from the year 1965. We show how two laodmark papers and gave birth to two main streams of research that have dominated the development of system identification over the last fourty years. The Ho-Kalmao paper gave a first solution to state-space realization theory, which led to stochastic realization, aod much later to subspace identification. In the second chapter we discussed about a variety of techniques exist for interbody fusion of the lumbar spine. Transforaminal Lumbar Interbody Fusion (TLIF) demonstrates advantages over the anterior and bilateral posterior procedures because it requires only unilateral access to the disc via a far-lateral approach; thereby minimizing the risk of vascular and neurologic complications. Minimally invasive techniques for TLIF (MIS TLIF) have been introduced with the aim of smaller wounds, less tissue trauma, and faster recovery. However, during MIS TLIF, access to the disc and by consequence, the extension of the discectomy, can be reduced. The Mechanical control systems have become a part of our everyday life. Systems such as automobiles, robot manipulators, mobile robots, satellites, buildings with active vibration controllers and air conditioning systems, make life easier and safer, as well as help us explore the world we live in and exploit it's available resources. In this chapter, we examine a specific example of a mechanical control system; the Autonomous Underwater Vehicle (AUV). Our contribution to the advancement of AUV research is in the area of guidance and control. We present innovative techniques to design and implement control strategies that consider the optimization of time and/or energy consumption. In the forth chapter we discussed about automation is "the application of machines to tasks once performed by human beings, or increasingly, to tasks that would otherwise be impossible", Encyclopaedia Britannica. The term automation itself was coined in the 1940s at the Ford Motor Company. The idea of automating processes and systems started many years earlier than this as part of the agricultural and industrial revolutions of the late 18th and early 19th centuries. There is little disputing that England was a major contributor to the Industrial Revolution and indeed was the birth place of some prominent inventors, for example. In the fifth chapter we discussed about representative research reported in journal articles in the field of structural system identification published in journals since 1995 is presented. The chapter is divided into five sections based on the general approach used: conventional model-based, biologically-inspired, signal processing-based, chaos theory, and multi-paradigm approaches. Most of the published papers deal with small and academic problems. System identification of large real-life structures with nonlinear behavior subjected to unknown dynamic loading such as strong ground motions is challenging. It is believed a multi-paradigm approach is the most effective strategy for system identification of large structures subjected to dynamic loading. In the sixth chapter we discussed about a trend to study linear system identification with high order finite impulse response (FIR) models using the regularized least-squares approach. One key of this approach is to solve the hyper-parameter estimation problem that is usually non-convex. Our goal here is to investigate implementation of algorithms for solving the hyper-parameter estimation problem that can deal with both large data sets and possibly ill-conditioned computations. In particular, a QR factorization based matrix-inversion-free algorithm is proposed to evaluate the cost function in an efficient and accurate way. It is also shown that the gradient and Hessian of the cost function can be computed based on the same QR factorization. At first, the core ideology, advantage and principle of Software Testing Automation Framework (STAF) are presented in this paper. Several automated testing frameworks are summarized and analyzed. In addition, date driven automation test framework is given more attention. Test script is the important composing part of software test automation. Then the chapter seven introduces several technologies of script along with their characteristics. Automatic inspection is common in mass production inspections where robot manipulators are chosen to perform visual inspection to avoid inconsistency in manual inspection. The purpose of this work is to estimate the optimum workspace where a robot manipulator could perform a visual inspection tasks onto a work piece where a camera is attached to the end effector. While maneuvering through the programmed path, the robot will stop at a predefined point so that an image could be captured where the ideal parameter for the coefficient correlation (CC) template matching was computed. This we discussed in the eighth chapter. One of the most important problems in many industrial applications is the redundancy optimization problem. This latter is well known combinatorial optimization problem where the design goal is achieved by discrete choices made from elements available on the market. The natural objective function is to find the minimal cost configuration of a series-parallel system under availability constraints. This we discussed in the ninth chapter. In the tenth chapter, joint identification for structural systems, characterized by severe nonlinearities (softening) in the constitutive model, is pursued via the Sigma-Point Kalman Filter (S-PKF) and the Particle Filter (PF). Since a formal proof of the effects of softening in a stochastic structural system on the accuracy and stability of the filters is still missing, we comparatively assess the performances of S-PKF and PF. We show that the PF displays a higher convergence rate towards steady-state model calibrations and the S-PKF is less sensitive to the measurement noise. Both S-PKF and PF are robust, even if they tend to get unstable when a structural failure is triggered.

Editor

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Chapter 1

SYSTEM IDENTIFICATION WITHOUT LENNART LJUNG: WHAT WOULD HAVE BEEN DIFFERENT?

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ABSTRACT

This chapter presents a personal view on the development of identification theory in the control community, starting from the year 1965. We show how two laodmark papers, (Ho and Kalmao, 1965) aod (Astrom aod Bohlin, 1965), gave birth to two main streams of research that have dominated the development of system identification over the last fourty years. The Ho-Kalmao paper gave a first solution to state-space realization theory, which led to stochastic realization, aod much later to subspace identification. The Astrom-Bohlin paper laid the foundations for the highly successful Prediction Error methods based on parametric input-output models. The chapter highlights the key inlluence of Lennart Ljung on the development of Prediction Error Identification; it shows how his seminal contributions have profoundly chaoged the community's view on identification from a search for the elusive "true system" to a goaloriented design problem.

INTRODUCTION

The development of identification theory in the control literature followed on the heels of the development of model-based control design around 1960. Up until the late 1950's, much of control design relied on Bode, Nyquist and Nichols charts, or on step response aoalyses. These techniques were limited to control design for single-input single-output (SISO) systems. Around 1960, Kalmao introduced the state-space representation aod laid the foundations for state-space based optimal filtering aod optimal control theory, with Linear Quadratic (LQ) optimal control as a cornerstone for model-based control design.

The availability of these model-based control design techniques put pressure on the scientific community to extend the fields of application of "modern" control design beyond the realm of mechanical, electrical aod aerospace applications, for which reliable models were easily available. Thus the need arose to develop data-based techniques that would allow one to develop dynamical models for such diverse fields as process control, environmental systems, biological aod biomedical systems, traosportation systems, etc.

Much of the early work on identification was developed by the statistics, econometrics and time series communities. Even though the statistical theory of parameter estimstion has its roots in the work of Gauss (1809) and Fisher (1912), most of the theory of stationary stochastic processes was developed during the period 1920 to 1970. We shall not describe this work here, because we want to focus on the engineering views and developments of system identification. An excellent review of the history of system identification and time series analysis in the statistics community can be found in Deistler (2002).

Although a lot of results had already been established in the statistics and econometrics literature, one can view 1965 as the birthyear for identification theory in the control community, with the publication of two seminal papers, Ho and Kalman (1965) and Astrom and Bohliu (1965). These two papers paved the way for the development of the two mainstream identification techniques that still dominate the field today: subspace identification and prediction error identification.

The former is based on projection techniques in Euclidean space, the latter is based on the minimization of a parameter dependent criterion.

The Ho-Kalman paper provided the first solution to the determination of a minimal state-space representation from impulse response data. The solution of this deterministic realization problem was later extended by Akaike (1974) and others to stochastic realization, where a Markovian model is obtained for a purely random process on the basis of covariance data. 1bis technology, based on canonical correlation analysis, was extended in the early nineties to processes that also contain a measurable (control) input, and was then rebaptized as subspace state-space identification.

The Astrom-Bohliu paper introduced into the control community the Maximum Likelihood framework that had been developed by time series analysts for the estimation of the parameters of difference equation models. These were koown in the statistical literature by such esoteric names as ARMA (AutoRegressive Moving Average) or ARMAX model (AutoRegressive Moving Average with eXogeneous inputs). These models, and the Maximum Likelihood framework, were there to stay, since they gave rise to the immensely successful Prediction Error Identification framework.

In 1970, Box and Jenkins published their book "Time series analysis, forecasting and control", Box and Jenkins (1970), which gave a major impetus to applications of identification. Indeed, the book gave a rather complete recipe for identification, all the way from initial data analysis to the estimation of a model.

In the spirit of the time series analysis methods of the time, it relied on correlation analysis for the determination of model structure. For about 15 years, it remained the major high quality reference book on system identification. Other important references of the time were the survey paper Astrom and Eykhoff (1971) and the special issue on system identification and time series analysis published by the IEEE Transactiona on Automatic Control in December 1974. The Astriim and Eykhoff survey was to be used by many young researchers of the time as a stepping stone for future work. It explained the state of the art as much as it displayed some of the important open questions of the time. One of these was the identification of closed-loop systems, for which the Hankel-based projection methods (based on cross-correlation information) had been shown to fail.

From about the mid-seventies, the Prediction Error (PE) framework completely dominated identification theory and, perhaps more importantly, identification applications. Just about all of the activity at that time was focused on the search for the "true system", i.e. it dealt with questions of identifiability, convergence to the "true parameters", and asymptotic normality of the estimated parameters. Much of that activity dealt with identifiability problems for multivariable systems and for closed-loop systems.

Around 1976 the first attempts were made to view system identification as an approximation problem, in which one searches for the best possible approximation of the "true system" within some model class: Ljung (1976); Anderson eta!. (1978); Ljung and Caines (1979). The prevailing view changed consequently from a search for the "true system" to a search for and characterization of the "best approximation". Hence, the characterization of the model errors (bias error and variance error) became the focal point of research. For control engineers, the object of primary interest is the model, in particular the transfer function model, rather than the parameters which are just a vehicle for the description of this model. As it turns out, the research on bias and variance error moved remarkably swiftly from the characterization of parameter errors to that of transfer function errors, thanks to some remarkable analysis of Ljung based on the idea of lening the model order go to infinity: Ljung (1985); Wahlberg and Ljung (1986).

The work on bias and variance analysis of identified models of the eighties then led, almost natorally, to a new perspective in which identification became viewed as a "design problem". With an understanding of the effect of the experimental conditions, the choice of model structure, and the choice of criterion on the quality of the identified model, one can tune these design variables towards the objective for which the model is being identified: Gevers and Ljung (1986).

The book "System identification: Theory for the user", Ljung (1987), has had a profound impact on the engineering community of system identifiers. It squarely put forward the view of system identification as a design problem, in which the model use plays a central role. This viewpoint clearly distingnishes the field from the statisticalliteratore on system identification and time series analysis, where the prevailing view is that the model must "explain" the data as best as possible.

The observation that the model quality can be tuned, through the choice of appropriate design variables, towards the eventual objective for which the model is being built opened the way to a flood of new activity that took place in the nineties and continues up to this dsy. The major application of this new paradigm is the situation where a model is built with the view of designing a model-based controller. Thus, identification for control has blossomed, since around 1990. Because that topic embraces many aspects of identification and robust control theory, it has also opened or reopened new research interest in areas such as experiment design, closed-loop identification, frequency domain identification, uncertainty estimation, and data-based robust control analysis and design.

The present chapter attempts to exhibit both the continuity and the motivation for the developments that took place in system identification in the last fourty years, and also the significant new departures and insights that came as the result of some important breakthroughs. In doing so, this chapter will show how Leunart Ljung was responsible for several of these breakthroughs.

THE MILESTONE PAPERS

Deterministic realization theory

In 1965, Ho and Kalman (1965) provided a first solution to a challenging system theoretical problem that became known as the state-space realization problem. It can be stated as follows.

Construct a minimal state-space realization

$$\begin{cases} x_{t+1} &= Ax_t + Bu_t \\ y_t &= Cx_t \end{cases}$$

for an input-output model described by its impulse response matrices (also called

Markov parameters) $H_k \in \mathbb{R}^{p\times m}$

$$y_t = \sum_{k=1}^{\infty} H_k u_{t-k}.$$

The problem is thus to replace the infinite description

$$H(z) = \sum_{k=1}^{\infty} H_k z^{-k}$$

by a finite description with A E lRnxn,B E Rnxm,c E Rpxn, such that

$$H(z) = C(zI - A)^{-1}B$$

with dim(*A)* minimal. This problem can be split up into two parts: (i) find the McMillan degree of *H(z),* which is then the minimal dimension of *A;* (ii) compute the matrices *A, B, C.* The key tool for the solution of this problem is the Hankel matrix, and its factorization into the product of an infinite observability matrix times an infinite controllability matrix:

$$\mathcal{H} = \begin{bmatrix} H_1 & H_2 & H_3 & H_4 & \cdots \\ H_2 & H_3 & H_4 & H_5 & \cdots \\ H_3 & H_4 & H_5 & H_6 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \end{bmatrix} = \begin{bmatrix} C \\ CA \\ CA^2 \\ \vdots \end{bmatrix} [B \quad AB \quad A^2B \quad \ldots]$$

If the McMillan degree of *H (z)* is *n,* then

1. rank $\mathcal{H} = n$
2. $\exists\, A \in \mathbb{R}^{n\times n}, B \in R^{n\times m}, C \in \mathbb{R}^{p\times n}$ such that $H_k = CA^{k-1}B$.

It took years of research to go from the theoretical results described in Ho and Kalman (1965) to a numerically reliable reali2ation algorithm. However, all the key insights were present in the 1965 paper, and they were to bave a profound impact on linear system theory, and on realization and identification theory.

THE MAXIMUM LIKELIHOOD FRAMEWORK

-In complete contrast to the state-space formulation of Ho and Kalman, the landmark paper Astrom and Bohlin (1965) introduced the Maximum Likelihood method for estimating the parameters of input-output models in ARMAX form:

$$A(z^{-1})y_t = B(z^{-1})u_t + \lambda C(z^{-1})e_t$$

where {e,} is a sequence of independent identically distributed Normal (0, 1) random varisbles. The Maximum Likelihood (ML) method was well known and bad been widely studied in mathematical statistics and time series analysis. However, what is remarkable about the Astrom-Bohlin paper is that the authors not only gave a complete algorithntic derivation of the ML identification method for ARMAX models, but also presented all analysis results that were available at that time, such as the consistency, asymptotic efficiency and asymptotic normality of the parameter estimates, the persistence of excitation conditions on the input signal in connection with the order of the model, the model order validation on the basis of the whiteness of the residuals, etc.

The concepts and nolations introduced by Astrom and Bohlin in 1965 have been with us for almost 40 years now. Indeed, the following household nolations of the identification community can all be found in this ntilestone paper:

- the residuals $C(z^{-1})\epsilon_t = A(z^{-1})y_t - B(z^{-1})u_t$
- the cost criterion $V(\theta) = \frac{1}{2}\sum_{t=1}^{N} \epsilon_t^2$
- the parameter estimate $\hat{\theta} = \arg\min V(\theta)$
- the white noise variance estimate $\hat{\lambda}^2 = \frac{2}{N}V(\hat{\theta})$.

The publication of Ast:rom and Boblin (1965) gave rise to a flurry of activity in parametric identification. It also established the basis for the adoption of the Prediction Error framework. The step from Maximum Likelihood to Prediction Error essentially consists of observing that, under an assumption of white Gaussian noise in the ARMAX model, the maximization of the likelihood function of the observations is equivalent to the minimization of the sum of the prediction errors. The Prediction Error framework then consists of adopting the mjnjmjzati. on of a norm of the prediction errors as a reasonable criterion for parameter estimation, even in the absence of any koown probability distribution for the observations. Such suggestion had already been made by Mr. Gauss himself, Gauss (1809), as observed in the fascinating paper Astrom (1980).

FROM DETERMINISTIC TO STOCHASTIC REALIZATION

The combination of the deterministic reali2ation theory based on the factorization of the Hankel matrix, and of the theory of Markovian and inoovations representations gave rise to the stochastic theory of minimal realizations. The stochastic realization problem can be stated as follows.

Given the covariance sequence {Rk, k = 1, 2, ... , oo} *of a zero-mean stochastic*

process {y$_{t'}$}, *where* $R_k \triangleq E\{y_t y_{t-k}^T\}$ *.Lfind a minimal Markovian representation*

for the process {Y_t }, *of the form*

$$\begin{cases} x_{t+1} = Ax_t + Gw_t \\ y_t = Cx_t + v_t \end{cases} \tag{1}$$

Where $\begin{pmatrix} w_t \\ v_t \end{pmatrix}$ *is a zero-mean white noise sequence with covariance matrix*

$$W = E\left\{\begin{pmatrix} w_t \\ v_t \end{pmatrix}\begin{pmatrix} w_t \\ v_t \end{pmatrix}^T\right\} = \begin{pmatrix} Q & S \\ S^T & R \end{pmatrix}$$

This problem amounts to finding state-space matrices {A, G, C} with n ~ dim(A) minimal. and the elements Q, S, R of the covariance matrix W such that the covariance of the output of (1) is exactly R,.

Observe that the covariance of the output of the Markovian representation (1) is given by $R_{k'} \sim CA^{k-l} N$ with $N = A\pi C^T + GS$ for $k >$ 0, and $R_0 = C\pi C^T + R$, where π is the state covariance: $\Pi \triangleq E\{x_t x_t^T\}$.

The stochastic realization problem was studied very intensively during the early seventies in connection with innovations theory and spectral factorization theory: Akaike (1974); Gevers and Kailath