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Grzegorz Mzyk

Combined Parametric- Nonparametric Identification of Block-Oriented Systems

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To my wife Jana, and my children – Adam and Hanna

Preface

Should we trust the prior knowledge of the system before processing observations? It is one of fundamental questions in system identification. Correct parametric assumptions imposed on the form of input output relation obviously give chances for obtaining relatively accurate model, using only several measurements. On the other hand, if the taken assumptions were false we would risk the non-zero approximation error, which could not be avoided even for large number of measurements.

The main purpose of this book is to provide a set of flexible identification tools, which allow to work under partial or uncertain prior knowledge, support making decision of the model structure and improve accuracy of the model for small number of measurements.

The presented ideas combine methods of two different philosophies – traditional (parametric) and recent (nonparametric), trying to take advantages of both of them. The term ‘parametric’ means that the assumed class of model consists of *finite* and *known* number of parameters and we look for optimal parameters in the finite dimensional space, using observations (e.g. by the least squares method, proposed by Gauss in 1809). Nonparametric estimates ([50], [100]) use only observations to build the model, and the model becomes more and more complex, when the number of data increases.

Combined identification schemes, proposed in this book, can be divided into two groups:

- *mixed parametric-nonparametric*, in which, nonparametric algorithm is first applied for estimation of interaction signals in complex system, or generation of instrumental variables, and then, the results are used (plugged-in) in parameter stage; these methods are recommended when the prior knowledge of the system is partial,
- *semiparametric*, in which, parametric model is firstly computed in traditional way, and the nonparametric correction is added when the number of measurements grows large; these methods allow to reduce the error for small number of data.

In Chapter 1 we briefly present foundations of the identification of single-element objects (linear dynamic or static nonlinear). As regards the parameter estimation, we focus on the least squares and instrumental variables methods, which play the key role in the book. Also nonparametric techniques, i.e., kernel regression and orthogonal series expansion are shortly reminded. We start our considerations in Chapter 2, from the Hammerstein system (i.e. the simplest N-L tandem connection), with FIR dynamics, linear-in-the-parameters static characteristics, and i.i.d. excitation. Next, the assumptions are generalized for the IIR subsystem, hard nonlinearity and correlated input case. Similar analysis is made for a Wiener system (reverse connection) in Chapter 3. Chapters 4-6 are devoted to identification of systems with more complex structures, i.e. Wiener-Hammerstein (L-N-L sandwich) system, the additive NARMAX system, and the system with general structure of interconnections. The model selection problem is considered in Chapter 7, and the time-varying block-oriented systems are identified in Chapter 8. Proofs of theorems, and technical lemmas can be found in two Appendices at the end.

Some results of the book were presented at the following conferences: *IFAC World Congress 2008*, Seoul, Korea, *SYSID 2009*, Saint-Malo, France, *ALCOSP 2010*, Antalya, Turkey, *SYSID 2012*, Brussels, Belgium, *ICINCO 2012*, Rome, Italy, *ECT 2012*, Kaunas, Lithuania, and *ICCC 2012*, Kosice, Slovakia.

I would like to thank my co-workers from the Department of Control and Optimization, Wrocław University of Technology, in which I have pleasure to work. Special thanks go to prof. Zygmunt Hasiewicz and prof. Włodzimierz Greblicki, my teachers in control theory and system identification, for arranging comfortable conditions, which helped me to write this book. I would also like to thank colleagues from the room – Dr. Przemysław Śliwiński and Dr. Paweł Wachel for scientific atmosphere, discussions, and numerous suggestions.

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Abstract

This book considers a problem of block-oriented nonlinear dynamic system identification in the presence of random disturbances. The class of systems includes various interconnections of linear dynamic blocks and static nonlinear elements, e.g., Hammerstein system, Wiener system, Wiener-Hammerstein ("sandwich") system and additive NARMAX systems with feedback. Interconnecting signals are not accessible for measurement. The combined parametric-nonparametric algorithms, proposed in the book, can be selected dependently on the prior knowledge of the system and signals. Most of them is based on the decomposition of the complex system identification task into simpler local subproblems by using nonparametric (kernel or orthogonal) regression estimation. In the parametric stage, the generalized least squares or the instrumental variables technique is commonly applied to cope with correlated excitations. Limit properties of the algorithms have been shown analytically and illustrated in simple experiments.

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