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Krzysztof Patan

Robust and Fault-Tolerant Control

Neural-Network-Based Solutions

 Springer

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To my family

Foreword

This monograph aims at presenting novel ideas, concepts and results in robust fault-tolerant control. Rapid developments in control technology have an impact on all the areas of the control discipline: there emerge new theories, advanced control solutions, new industrial processes, computer methods and implementations, new applications, new philosophies, and, inescapably, new challenges. Much of this development work is presented in the form of industrial reports, feasibility study papers and reports on advanced collaborative projects. Therefore, this monograph offers an opportunity for researchers, practitioners and students to gain access to an extended and clear exposition of new investigations in all the aspects of robust fault-tolerant control, intended for a rapid dissemination of the results and accessible to a wider readership.

As many technological systems are becoming increasingly complex, more widespread and integrated, the effects of system faults can potentially be devastating to the infrastructure of any modern society. Feedback control is just one important component of the total system supervision. Fault-tolerant control describes another set of components having extensive commercial, industrial and societal implications; it is imperative, however, that we are able to make use of them in a robust and inexpensive manner. The model-based approach is the usual solution of the practical fault-tolerant control design but, as the author Krzysztof Patan has highlighted in this monograph, the methodologies based on neural networks can also be successfully exploited. The search for reliable, robust and inexpensive fault-tolerant control methods has been ongoing since the early 1980s. Since 1991, the SAFEPROCESS Steering Committee, created by the International Federation of Automatic Control (IFAC), is in operation promoting research, developments and applications in the field of fault-tolerant control. The last decade has seen the formalisation of several theoretical approaches accompanied by some attempts to standardise the nomenclature in the field.

There are not many research publications within this important research area: one can point to certain monographs that can be said to provide interesting contributions to fault-tolerant control describing, however, the topic from slightly different points of view. To these, we can now add this monograph by Krzysztof

Patan. The key features of this text include a useful survey material, a description of new approaches (utilising data-driven and neural-network-based methodologies), as well as a number of experimental studies helpful in understanding the advantages and the drawbacks of the suggested strategies and tools. Different groups of readers, from industrial engineers wishing to gain insight into the applications potential of new fault-tolerant control methods relying on artificial intelligence tools, to the academic control community looking for new problems to tackle will find much to learn from this monograph.

Ferrara, Italy
October 2018

Silvio Simani

Preface

Indisputably, what is known as the robust and the fault-tolerant approaches have become important and essential subclasses of modern control theory. Nowadays, control systems designed for industrial plants have to meet the high requirements for the operation safety, stability and control performance. The notion of system robustness is made more concrete by means of the following two important notions. *Robust stability* means that the system remains stable for every plant belonging to the uncertainty set, whereas *robust performance* means that the performance specifications are satisfied for every plant belonging to the uncertainty set. Arguably, both of these are some of the most desirable features of the designed control systems. Robustness, however, is a problem that is hard to solve in the context of nonlinear systems. While robust control strategies allow a system to cope with model uncertainty, *fault-tolerant* control allows the system to cope with possible faulty situations occurring in industrial plants. The main objective of fault-tolerant control is to continue the plant operation, possibly at a reduced performance, and to preserve stability conditions in the presence of unexpected changes of system work caused by faults. There are, however, many problems encountered when designing fault-tolerant control for nonlinear systems.

Solutions of both robust control and fault-tolerant control problems can be obtained through the use of artificial neural networks. Neural networks can be effectively applied to deal with uncertainty modelling for the robust control purposes as well as to design the fault diagnosis units required by fault-tolerant control. The book proposes a number of strategies based on neural networks for nonlinear systems, e.g. model predictive control, control reconfiguration approaches and iterative learning control. Each proposed control strategy is accompanied by an example showing its applicability.

The material included in the monograph results from research that has been carried out by the author at the Institute of Control and Computation Engineering (the University of Zielona Góra, Poland) for the last eight years in the area of the modelling of nonlinear dynamic processes as well as control of industrial processes. Some of the presented results were developed with the partial support of the Ministry of Science and Higher Education in Poland under the grants N N514

678440 *Predictive fault tolerant control for nonlinear systems* (2011–2014), 2014/15/B/ST7/03208 *Improvement of the control performance using iterative learning* (2015–2018) and 2017/27/B/ST7/01874 *Learning-based methods for high-performance robust control* (2018–2021).

The monograph is divided into seven chapters. Chapter 1 introduces the subject matter. Chapter 2 is a survey of artificial neural networks that have possible applications to modelling and control. Some space is also devoted to the important problems of model training and the development of robust models. Chapter 3 describes the notion of control systems synthesis, focusing on the role of neural networks in that context. We also highlight the notions of robust and fault-tolerant control. Chapter 4 presents the model of predictive control based on neural networks. Fault tolerance as well as robustness of the proposed nonlinear predictive schemes are also discussed there. Chapter 5 presents the fault accommodation and control reconfiguration approach where neural networks are used in the following ways: (1) to process modelling; (2) to design what is known as a nonlinear observer and (3) to aid in uncertainty modelling. Chapter 6 discusses a number of methods that make use of neural networks in the context of iterative learning control with an emphasis on the problems of convergence and stability. Finally, Chap. 7 presents our contribution to the area of control in the context of industrial processes.

At this point, I would like to express my sincere thanks to all the colleagues from the Institute of Control and Computation Engineering at the University of Zielona Góra for many stimulating discussions and a friendly atmosphere, which was a big factor in my success in writing up this monograph. In particular, I would like to thank my former Ph.D. student Andrzej Czajkowski for his contribution to Chap. 5, my brother Maciek for his contribution to Chap. 6, and Wojtek Paszke who pointed my attention to the area of iterative learning control. Finally, I would like to express my gratitude to Dr. Adam Trybus for proofreading the text and providing linguistic advice.

Zielona Góra, Poland
September 2018

Krzysztof Patan

Acknowledgements

The ideas on robust and fault-tolerant control presented in this monograph were developed over the last few years and have previously appeared in a number of publications. However, the purpose of the book is to provide a unified presentation of these solutions and bring them together in a single publication. In order to achieve this objective, it has been necessary at times to reuse some material that we published in earlier works. In spite of the fact that such material has been modified, expanded and rewritten for the monograph, permission from the following publishers is acknowledged.

Springer, Berlin is acknowledged for permission to reuse portions of the following chapters.

Krzysztof Patan, *Locally Recurrent Neural Networks of Artificial Neural Networks for the Modelling and Fault Diagnosis of Technical Processes*, vol. 377 in the series *Lecture Notes in Control and Information Sciences*, Springer-Verlag, Berlin, 2008.

Acknowledgement is given to the Institute of Electrical and Electronic Engineers for permission to reproduce parts of the following papers.

Krzysztof Patan, *Neural Network-Based Model Predictive Control: Fault Tolerance and Stability*, *IEEE Transactions on Control Systems Technology*, vol. 23, no. 3, pp. 1147–1155, 2015.

Krzysztof Patan, Maciej Patan, Damian Kowalów, *Optimum training design for neural network in synthesis of robust model predictive control*, in *Proceedings of 55th IEEE Conference on Decision and Control*, Las Vegas, USA, pp. 3401–3406, 2016.

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Andrzej Czajkowski, Krzysztof Patan, Mirosław Szymański, Application of the state-space neural network to the fault-tolerant control system of the PLC-controlled laboratory stand, *Engineering Applications of Artificial Intelligence*, vol. 30, pp. 168–178, 2014.

Krzysztof Patan, Two stage neural network modelling for robust model predictive control, *ISA Transactions*, vol. 72, pp. 56–65, 2018.

Zielona Góra, Poland
October 2018

Krzysztof Patan

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Notation

Symbols

\mathbb{R}	Set of real numbers
\mathbb{N}	Set of nonnegative integers
t, k	Continuous and discrete-time indexes
p	Trial index
$y(\cdot), \hat{y}(\cdot)$	System output and estimated system output
$u(\cdot), \hat{u}(\cdot)$	System input and estimated system input
$x(\cdot), \hat{x}(\cdot), \bar{x}(\cdot)$	State vector, estimated state and nominal state
$u(\cdot)$	Input vector
$y(\cdot)$	Output vector
$\sigma(\cdot), \sigma(\cdot)$	Activation function and vector-valued activation function
J	Cost function
A	State matrix
W	Weight matrix
C	Output matrix
B	Input (control) matrix
D	Transfer matrix
$\mathcal{N}(m, \sigma)$	Normally distributed random number with the expectation value m and the standard deviation σ
α	Significance level
t_α	Tabulated value assigned to the significance level α
C^1	Class of continuously differentiable mappings
N_p, N_u, N_c, N_y	Prediction horizon, control horizon, constraint horizon and output constraint horizon
T_s	Sampling time
I	Identity matrix
0	Zero matrix

$\varphi(\cdot), \phi(\cdot)$	Regression vectors
L	Lipschitz constant
$e(\cdot)$	Tracking error

Operators

∇	Gradient
∂	Partial derivative
\top	Matrix transposition
\sup	Least upper bound (supremum)
\inf	Greatest lower bound (infimum)
\max	Maximum
\min	Minimum
$\arg \max$	Argument of a maximum value
$\arg \min$	Argument of a minimum value
$\text{rank}(\mathbf{A})$	Rank of a matrix \mathbf{A}
$\det(\mathbf{A})$	Determinant of a matrix \mathbf{A}
$\text{trace}(\mathbf{A})$	Trace of a matrix \mathbf{A}
$\ \mathbf{w}\ $	Vector norm
$\ \mathbf{W}\ $	Matrix norm
\mathbf{W}^{-}	Matrix pseudoinverse

Abbreviations

ANN	Artificial Neural Network
ARX	Auto-Regressive with eXogenous input
BDM	Binary Diagnostic Matrix
BP	Back-Propagation
BPTT	Back-Propagation Through Time
CMPC	Constrained Model Predictive Control
CRHPC	Constrained Receding Horizon Predictive Control
DBN	Deep Belief Network
DFT	Discrete Fourier Transform
ESN	Echo State Network
FD	Fault Diagnosis
FDI	Fault Detection and Isolation
FIM	Fisher Information Matrix
FIR	Finite Impulse Response
FPE	Final Prediction Error
FSS	Feasible System Set
FTC	Fault-Tolerant Control

GMDH	Group Method and Data Handling
GPC	Generalised Predictive Control
IF	Integrate and Fire
IIR	Infinite Impulse Response
ILC	Iterative Learning Control
IMC	Internal Model Control
KKT	Karush–Kuhn–Tucker
LM	Levenberg–Marquardt
LMI	Linear Matrix Inequality
LQ	Linear Quadratic
LRGF	Locally Recurrent Globally Feed-forward
LSTM	Long Short-Term Memory
LVQ	Learning Vector Quantization
MDM	Multivalued Diagnostic Matrix
MEM	Model Error Modelling
MPC	Model Predictive Control
MPCD	Model Predictive Control with Disturbance model
MRAC	Model Reference Adaptive Control
MSE	Mean Square Error
NAR	Nonlinear Auto-Regressive
NARMAX	Nonlinear Auto-Regressive Moving Average with eXogenous input
NARX	Nonlinear Auto-Regressive with eXogenous input
NFIR	Nonlinear Finite Impulse Response
NIIR	Nonlinear Infinite Impulse Response
NLARX	NonLinear wavelet Autoregressive Regressive with eXogenous input
NOE	Nonlinear Output Error
OED	Optimum Experimental Design
PCNN	Pulse-Coupled Neural Network
PD	Proportional Derivative
PI	Proportional Integral
PID	Proportional Integral Derivative
PNN	Probabilistic Neural Network
RBF	Radial Basis Function
RBM	Restricted Boltzmann Machine
RMLP	Recurrent Multi-Layer Perceptron
RMPC	Robust Model Predictive Control
RNN	Recurrent Neural Network
RTRL	Real-Time Recurrent Learning
RTRN	Real-Time Recurrent Network
SGPC	Stable Generalised Predictive Control
SM	Set Membership
SNN	Spiking Neural Networks
SOM	Self-Organising Map
SSE	Sum of Squared Errors

SSIF	State-Space Innovation Form
SSNN	State-Space Neural Network
TDL	Tapped Delay Line
TDNN	Time Delay Neural Network
TDRBP	Time-Dependent Recurrent Back-Propagation

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