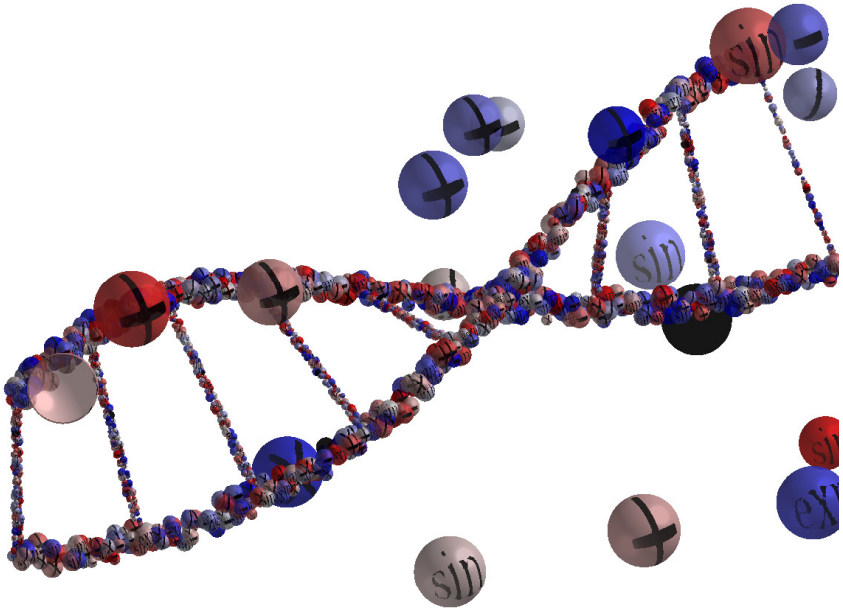
Thomas Duriez
Steven L. Brunton
Bernd R. Noack

Machine Learning Control – Taming Nonlinear Dynamics and Turbulence



May 2, 2016

Springer

Contents

Preface vii

1 Introduction 1
1.1 Feedback in engineering and living systems 1
1.2 Benefits of feedback control 3
1.3 Challenges of feedback control 6
1.4 Feedback turbulence control is a grand challenge problem 8
1.5 Nature teaches us the control design 8
1.6 Outline of the book 9
1.7 Exercises 10

2 Machine learning control (MLC) 11
2.1 Methods of machine learning 12
2.1.1 System identification as machine learning 13
2.1.2 Genetic algorithms 14
2.1.3 Genetic programming 16
2.1.4 Additional machine learning methods 18
2.2 MLC with genetic programming 19
2.2.1 Control problem 19
2.2.2 Parameterization of the control law 20
2.2.3 Genetic programming as a search algorithm 22
2.2.4 Initializing a generation 23
2.2.5 Evaluating a generation 26
2.2.6 Selecting individuals for genetic operations 26
2.2.7 Selecting genetic operations 27
2.2.8 Advancing generations and stopping criteria 31
2.3 Examples 33
2.3.1 Fitting a function through data points 34
2.3.2 MLC applied to control a dynamical system 37
2.4 Exercises 45
2.5 Suggested reading 45

2.6 Interview with Professor Marc Schoenauer 47

3 Methods of linear control theory 51
3.1 Linear systems 52
3.2 Full-state feedback 53
Linear quadratic regulator (LQR) 53
3.3 Sensor-based state estimation 55
Kalman filtering 55
3.4 Sensor-based feedback 58
Linear quadratic Gaussian (LQG) 58
3.5 System Identification and Model Reduction 60
3.5.1 System identification 61
3.5.2 Eigensystem realization algorithm (ERA) 61
3.5.3 Observer Kalman filter identification (OKID) 64
3.6 Exercises 68
3.7 Suggested reading 69

4 Benchmarking MLC against linear control 71
4.1 Comparison of MLC with LQR on a linear oscillator 72
4.2 Comparison of MLC with Kalman filter on a noisy linear oscillator . 75
4.3 Comparison of MLC with LQG for sensor-based feedback 82
4.4 Modifications for small nonlinearity 86
4.5 Exercises 89
4.6 Interview with Professor Shervin Bagheri 92

5 Taming nonlinear dynamics with MLC 95
5.1 Generalized mean-field system 96
5.2 Machine learning control 100
5.2.1 Formulation of the control problem 100
5.2.2 MLC parameters 101
5.2.3 MLC results 101
5.3 Derivation outline for the generalized mean-field model 106
5.4 Alternative control approaches 110
5.4.1 Open-loop forcing 111
5.4.2 Closed-loop forcing 113
5.4.3 Short-term forcing 115
5.5 Exercises 117
5.6 Suggested reading 118
5.7 Interview with Professor Mark N. Glauser 119

6 Taming real world flow control experiments with MLC 123
6.1 Separation control over a backward-facing step 124
6.1.1 Flow over a backward-facing step 124
6.1.2 Experimental setup at PMMH 125
6.1.3 Results 128
6.2 Separation control of turbulent boundary layers 130

6.2.1 Separating boundary layers 130
6.2.2 Experimental setups at LML and PRISME 131
6.2.3 Results 134
6.3 Control of mixing layer growth 136
6.3.1 Mixing layer flows 136
6.3.2 Experimental setup of the TUCOROM wind tunnel 138
6.3.3 Results 140
6.4 Alternative model-based control approaches 142
6.5 Implementation of MLC in experiments 144
6.5.1 Real-time control loop - from sensors to actuators 145
6.5.2 MLC implementation in the PMMH flow over a backward-facing step 146
6.5.3 MLC implementation in the LML and PRISME experiments 147
6.5.4 MLC implementation in the TUCOROM experiment 147
6.6 Suggested reading 149
6.7 Interview with Professor David Williams 151

7 MLC tactics and strategy 155
7.1 The ideal flow control experiment 155
7.2 Desiderata of the control problem — from the definition to hardware choices 156
7.2.1 Cost function 157
7.2.2 Actuators 158
7.2.3 Sensors 158
7.2.4 Search space for control laws 159
7.3 Time scales of MLC 160
7.3.1 Controller 160
7.3.2 Response time of the plant 162
7.3.3 Learning time for MLC 163
7.4 MLC parameters and convergence 164
7.4.1 Convergence process and its diagnostics 164
7.4.2 Parameters 166
7.4.3 Pre-evaluation 168
7.5 The imperfect experiment 169
7.5.1 Noise 169
7.5.2 Drift 169
7.5.3 Monitoring 170

8 Future developments 171
8.1 Methodological advances of MLC 172
8.2 System-reduction techniques for MLC — Coping with high-dimensional input and output 176
8.3 Future applications of MLC 178
8.4 Exercises 184
8.5 Interview with Professor Belinda Batten 186

Glossary 191

Symbols 199

Abbreviations 203

Matlab® Code: `OpenMLC` 205

Bibliography 207

Index 219

Preface

This book is an introduction to machine learning control (MLC), a surprisingly simple model-free methodology to tame complex nonlinear systems. These systems are assumed to be manipulated by a finite number of actuators (inputs) and monitored by a finite number of sensors (outputs). The control logic is chosen to minimize a well-defined cost functional.

MLC brings together three well-established disciplines: the theory of closed-loop feedback control, machine learning and regression, and the nonlinear dynamical systems that are characteristic of turbulent fluid flows. Over the past decades, control theory has developed into a mature discipline with a beautiful theoretical foundation and powerful associated numerical algorithms. Important advances have been made to enable robust linear control of systems with sensor noise, external disturbances, and model uncertainty. Modern methods from control theory now pervade the engineering sciences and have transformed the industrial landscape. However, challenges remain for the control of systems with strongly nonlinear dynamics leading to broadband frequency spectra, a high-dimensional state space, and large time delays. MLC begins to address these challenges using advanced methods from machine learning to *discover* effective control laws.

Many turbulence control problems are not adequately described by linear models, have exceedingly large state spaces, and suffer from time delays from actuators to sensors via nonlinear convective fluid dynamic effects. Take for instance the aerodynamic drag minimization of a car with actuators at the back side, pressure sensors distributed over the car, and a smart feedback control logic. Numerical simulation of the underlying dynamics given by the Navier-Stokes equations requires days or weeks, while the control system requires actuation decisions on the order of milliseconds. Reduced-order models that incorporate nonlinearities, multi scale phenomena, and actuation effects have eluded many serious efforts and will likely remain elusive for many years to come. In short, there may not even be a viable model for robust control design. Nevertheless, the literature contains many studies on turbulence control, with the majority either employing open-loop forcing such as periodic blowing, slowly adapting a working open-loop strategy, or stabilizing an underlying laminar solution such as a laminar boundary layer on an aircraft wing.

Feedback control responding to dominant flow structures in real time may be found in numerical studies but is rarely found in real-world experiments with turbulent flows. Indeed, turbulence control is a grand challenge problem in engineering, with far reaching potential scientific, industrial, and societal impact.

Yet, just looking at the flight maneuvers of a bird, bat or insect, it is clear that nature has found impressive feedback flow control solutions without employing advanced mathematical models. An eagle, for instance, can land gently on a rocky surface under gusty wind conditions and in rain by moving its wings and feathers to expertly manipulate fluid forces. More than 50 years ago, Ingo Rechenberg and Hans-Peter Schwefel have emulated nature's evolutionary way to optimize flow properties at the former Hermann-Föttinger-Institut of the Berlin Institute of Technology, Germany. Their pioneering evolutionary strategies started evolutionary computations. Subsequent innovations include evolutionary programming (Fogel, Owens & Walsh, 1966), genetic algorithms (Holland 1975) and genetic programming (Koza 1992). These evolutionary computations constitute an important pillar of machine learning. In a visionary publication in 1959, the artificial intelligence pioneer Arthur Samuel defined machine learning as a 'field of study that gives computers the ability to learn without being explicitly programmed.' Machine learning is a rapidly evolving discipline of computer science that is benefiting from the current explosion of big data. It has successfully improved an immense range of technologies – from the smart phone to the autopilot in Tesla's Sedan and to large-scale factory processes. In academia, nearly all scientific disciplines are profiting from machine learning.

Not surprisingly, machine learning methods may augment or replace control design in myriad applications. Robots learn to walk with dynamic programming. Genetic algorithms are used to optimize the coefficients in proportional-integral-derivate (PID) controllers. The groups of N. Benard and E. Moreau employ genetic algorithms to optimize linear sensor feedback in a flow-control experiment. Reinforcement learning has been successfully applied to stabilize chaotic dynamics, and has recently also reduced cavity noise in an experiment operated by F. Lusseyran, L. Pastur and L. Mathelin. The authors of this book have pushed the first applications of genetic programming in feedback control of nonlinear dynamics, direct Navier-Stokes simulations and experimental turbulent shear flows. This book focusses on arguably one of the simplest, most versatile and yet very powerful version of machine learning control: Optimal nonlinear control laws are identified with genetic programming. Some corresponding success stories are described throughout this book.

The authors have taught material from this book in several university courses. These courses focus on basic principles using simple examples, and the content requires anywhere from 15-30 hours to cover. Our students have had backgrounds in computer science, control theory, nonlinear dynamics or fluid mechanics. The prospective reader is not expected to have hands-on expertise in any of these fields but should come with the ambition to control a complex system. The book is organized as follows. In Chapter 1, the reader is introduced to feedback control and its challenges for complex real-world problems. Chapter 2 constitutes the core of the book. This chapter formulates feedback control as a regression problem and

employs genetic programming as a powerful regression technique to identify the best feedback law. Chapter 3 reviews classical methods of control theory against which MLC is benchmarked in Chapter 4 for linear and weakly nonlinear dynamics. These chapters provide context for feedback control, but they are not required to implement the MLC methods in Chapter 2. The hurried reader may jump to Chapter 5 if she/he is interested in strongly nonlinear dynamics applications or to Chapter 6 if she/he is interested in experimental implementations of feedback flow control. Chapter 7 distills good practices for real-world experiments that need to be taken into account in any MLC implementation. In Chapter 8 we provide an outlook on future methodological advances, which are expected to drastically amplify the applicability and performance of MLC. In addition, we list a number of future MLC applications with epic proportions.

We have profited tremendously from interactions with many colleagues on machine learning control. First, we highly appreciate André Thess for his continual encouragement to write a book about turbulence control for this Springer series. He has nurtured the idea for years before we decided to write this book. We highly appreciate the insightful and inspiring interviews with leading scholars of the field: Shervin Bagheri, Belinda Batten, Mark Glauser, Marc Schoenauer and David Williams. These additions provide valuable perspectives for past progress and future work. Eurika Kaiser has provided continual exquisite feedback on our chapters and also contributed with her illuminating visualizations in Chapter 7 showing the performance of MLC.

We have also benefited greatly from our mentors throughout our careers. BRN is deeply indebted to his turbulence control mentors Andrzej Banaszuk, Andreas Dillmann, Helmut Eckelmann, Rudibert King and William K. George who shared and fueled the passion for the field. SLB would like to gratefully acknowledge and thank Nathan Kutz, Naomi Leonard, Richard Murray, Clancy Rowley, and Rob Stengel, who each found unique ways to make dynamics and control theory come to life. TD would like to acknowledge Eduardo Jose Wesfreid, Jean-Luc Aider, Guillermo Artana, Luc Pastur, François Lusseyran and Bernd R. Noack who each have had a profound (and most beneficial) impact on his perception of the different fields he has been in contact with. This book would not have been possible without our many colleagues, collaborators, and co-authors who have shared our early enthusiasm for MLC and have dedicated significant energy to developing it: Markus Abel, Jean-Luc Aider, Zhe Bai, Diogo Barros, Jean-Paul Bonnet, Jacques Borée, Bing Brunton, Juan Martin Cabaleiro, Camila Chevot, Tom Daniel, Antoine Debien, Laurent Cordier, Christophe Cuvier, Joël Delville (d), Caroline Fourment (d), Hiroaki Fukumoto, Nicolas Gautier, Fabien Harambat, Eurika Kaiser, Laurent Keirsbulck, Azeddine Kourta, Kai von Krbek, Nathan Kutz, Jean-Charles Laurentie, Ruiying (Cecile) Li, François Lusseyran, Robert Martinuzzi, Lionel Mathelin, Nicolas Mazellier, Marek Morzyński, Christian Nayeri, Robert Niven, Akira Oyama, Vladimir Parezanović, Oliver Paschereit, Luc Pastur, Brian Polagye, Josh Proctor, Bartosz Protas, Rolf Radespiel, Cedric Raibaudo, Jim Riley, Tony Ruiz, Michael Schlegel, Peter Scholz, Marc Segond, Richard Semaan, Tamir Shaqarin, Andreas Spohn, Michel Stanislas, Ben Strom, and Sam Taira. Many of our co-authors have applied the nascent MLC

methodology in their own experiments early on, when success was far from certain. We thank our students for visiting our courses in Argentina, France, Germany and the USA and contributing with many good questions, new ideas and encouraging project results. Anneke Pot from Springer Publisher has dependably supported us in critical decisions about book contents and the production procedure.

Thomas Duriez
Steven Brunton
Bernd Noack
Seattle, March 2016