DATA-DRIVEN CONTROL

Overview of basics and latest trends

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http://aa4cc.dce.fel.cvut.cz
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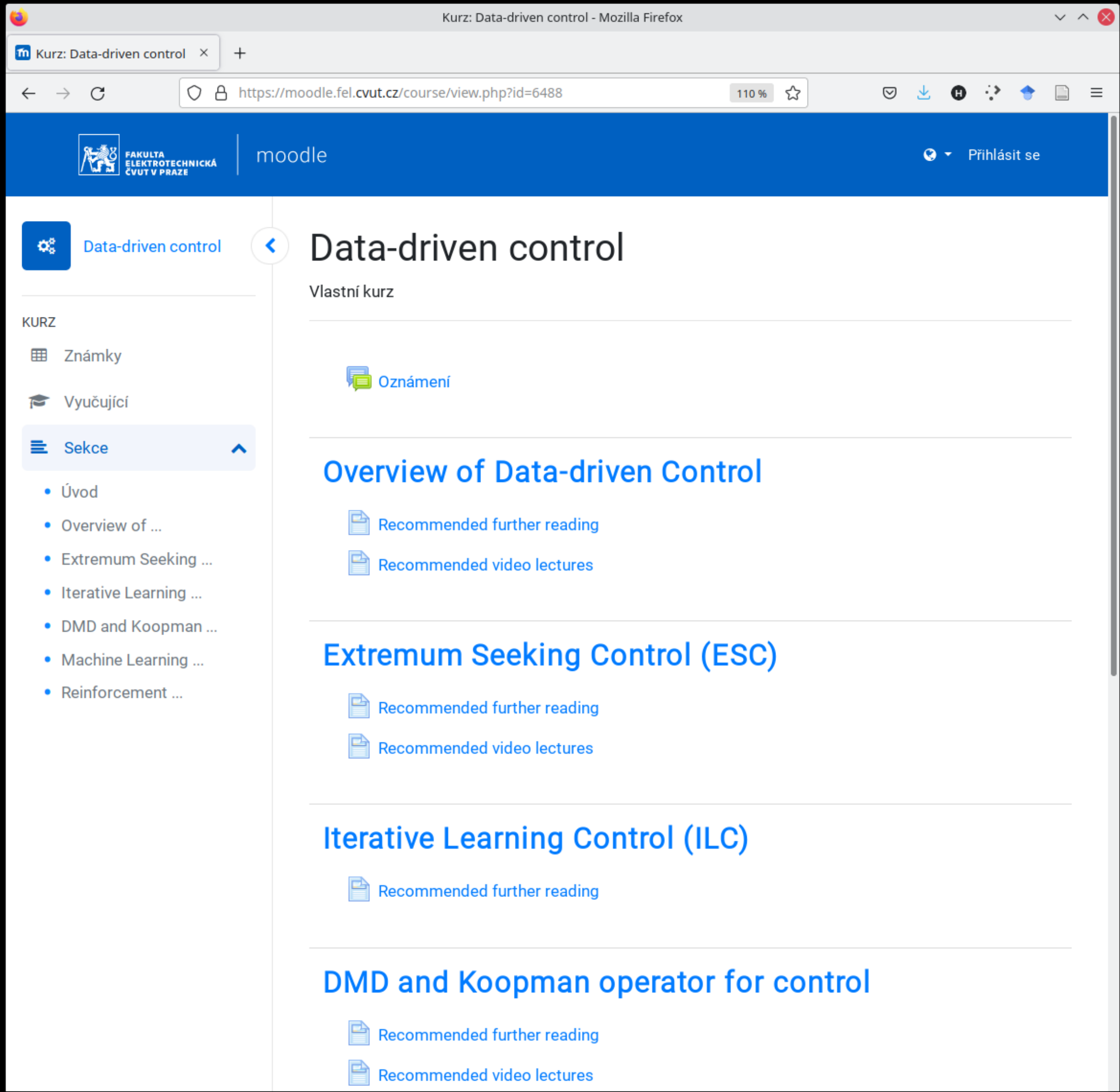

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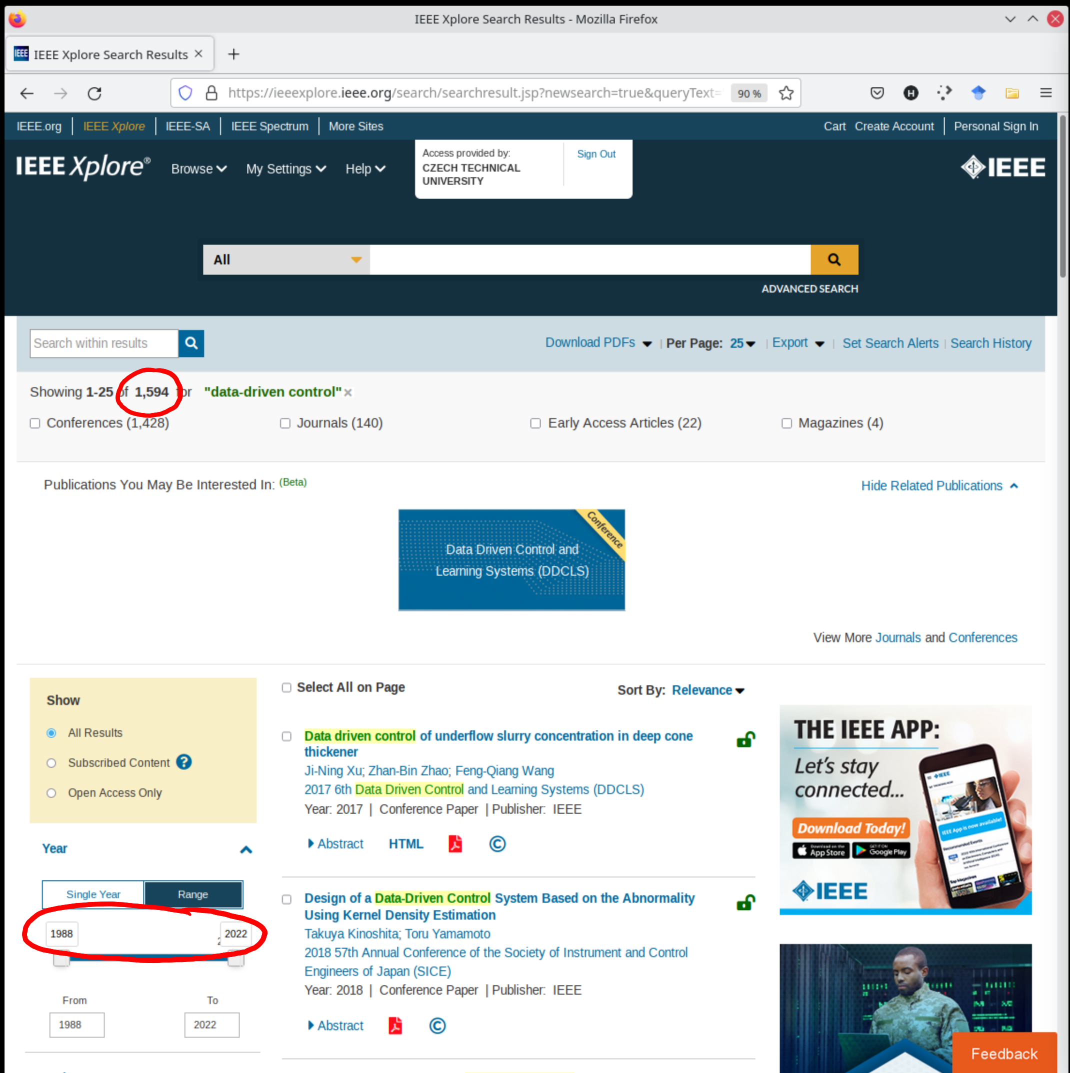
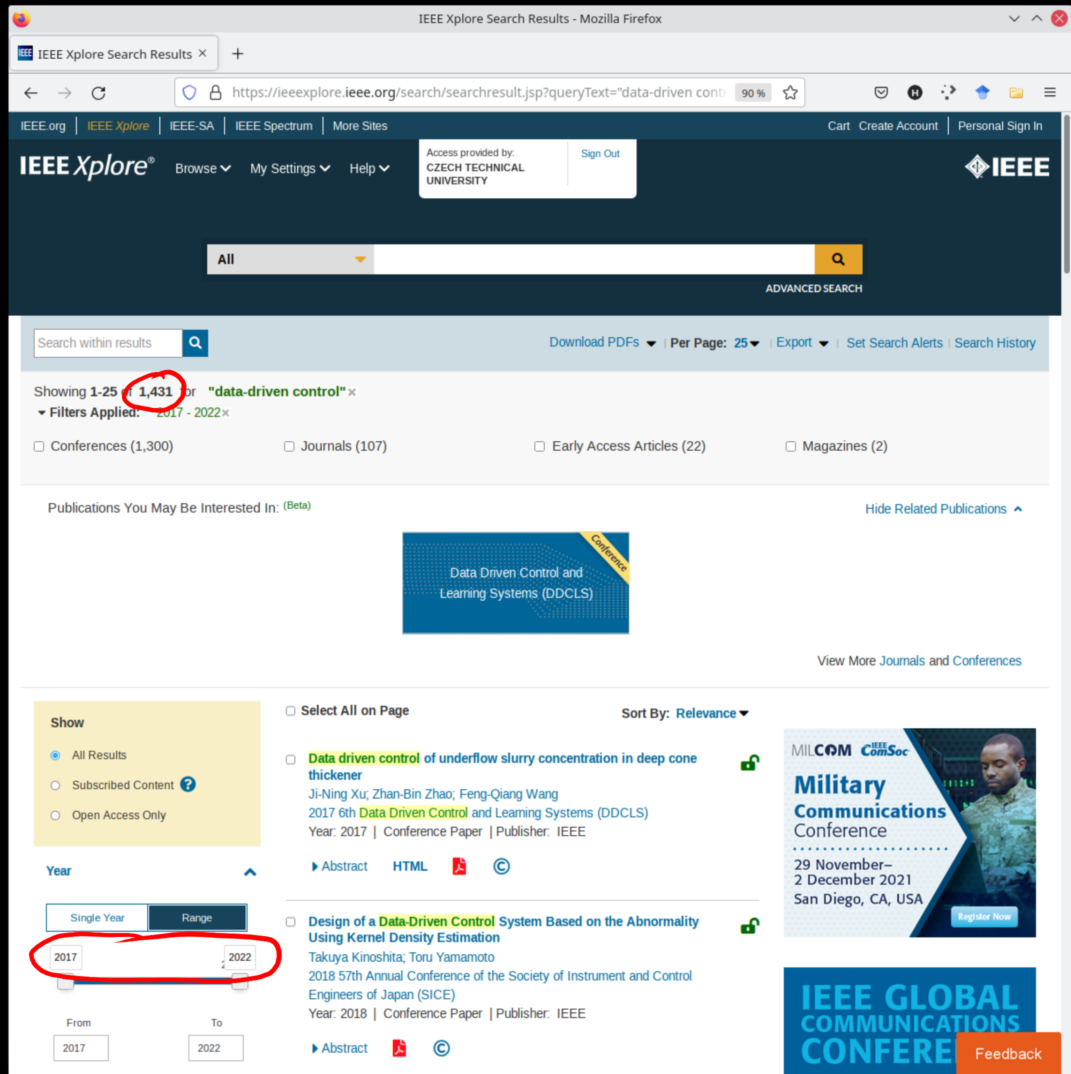
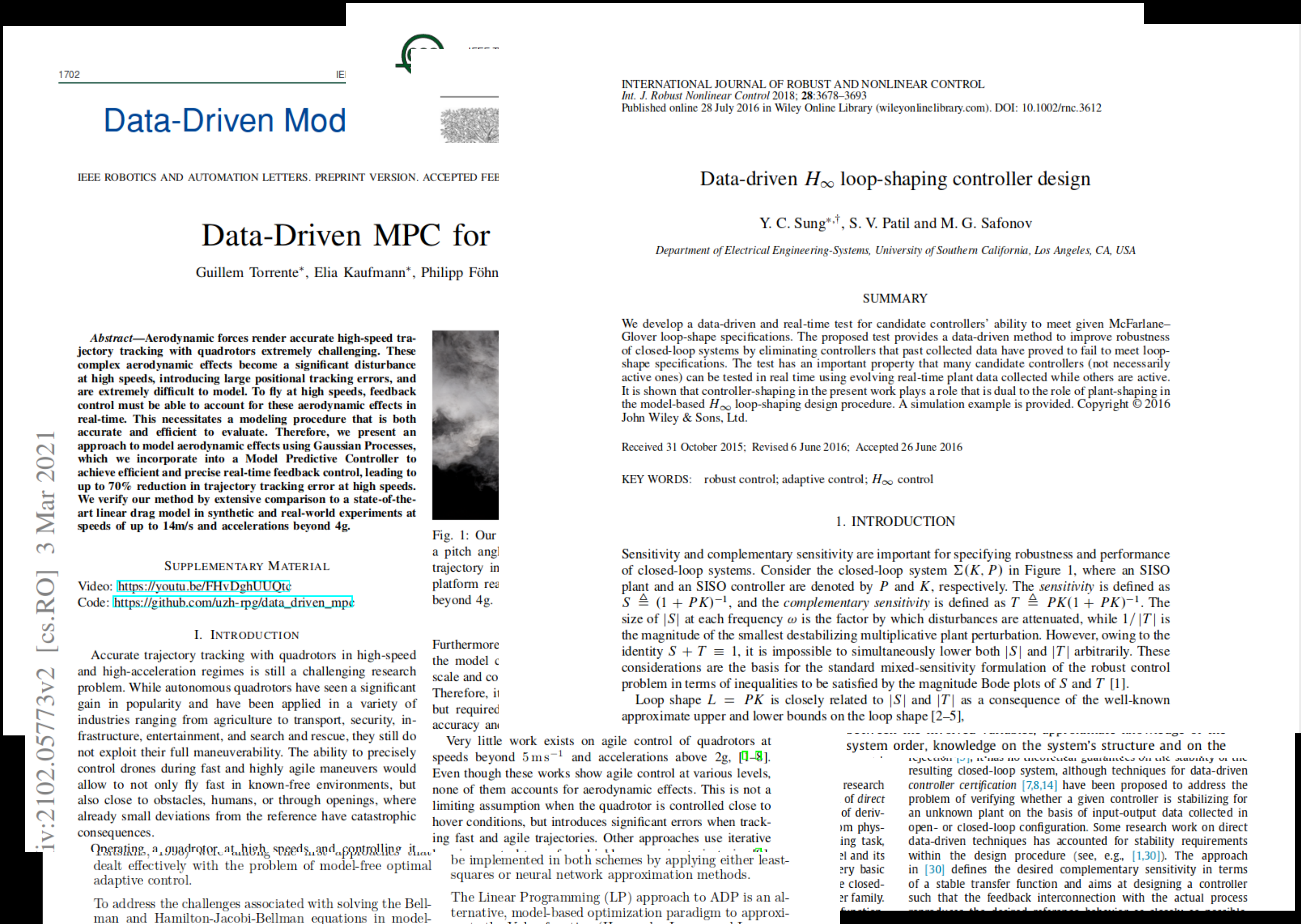
According to IEEE Xplore







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Data-Driven Mod

IEEE ROBOTICS AND AUTOMATION LETTERS. PREPRINT VERSION. ACCEPTED FEE

Data-Driven MPC for

Guillem Torrente*, Elia Kaufmann*, Philipp Föhn

Abstract—**Aerodynamic forces render accurate high-speed trajectory tracking with quadrotors extremely challenging. These complex aerodynamic effects become a significant disturbance at high speeds, introducing large positional tracking errors, and are extremely difficult to model. To fly at high speeds, feedback control must be able to account for these aerodynamic effects in real-time. This necessitates a modeling procedure that is both accurate and efficient to evaluate. Therefore, we present an approach to model aerodynamic effects using Gaussian Processes, which we incorporate into a Model Predictive Controller to achieve efficient and precise real-time feedback control, leading to up to 70% reduction in trajectory tracking error at high speeds. We verify our method by extensive comparison to a state-of-the-art linear drag model in synthetic and real-world experiments at speeds of up to 14m/s and accelerations beyond 4g.**

Fig. 1: Our a pitch angl trajectory in platform rea beyond 4g.

SUPPLEMENTARY MATERIAL

Video: https://youtu.be/FHvDghUUQtc
Code: https://github.com/uzh-rpg/data_driven_mpc

I. INTRODUCTION

Accurate trajectory tracking with quadrotors in high-speed and high-acceleration regimes is still a challenging research problem. While autonomous quadrotors have seen a significant gain in popularity and have been applied in a variety of industries ranging from agriculture to transport, security, infrastructure, entertainment, and search and rescue, they still do not exploit their full maneuverability. The ability to precisely control drones during fast and highly agile maneuvers would allow to not only fly fast in known-free environments, but also close to obstacles, humans, or through openings, where already small deviations from the reference have catastrophic consequences.

Furthermore the model c scale and co Therefore, i but required accuracy an

Very little work exists on agile control of quadrotors at speeds beyond $5\,\mathrm{m\,s^{-1}}$ and accelerations above 2g, [1–8]. Even though these works show agile control at various levels, none of them accounts for aerodynamic effects. This is not a limiting assumption when the quadrotor is controlled close to hover conditions, but introduces significant errors when tracking fast and agile trajectories. Other approaches use iterative

ariv:2102.05773v2 [cs.RO] 3 Mar 2021

dealt effectively with the problem of model-free optimal adaptive control.

To address the challenges associated with solving the Bellman and Hamilton-Jacobi-Bellman equations in model-

be implemented in both schemes by applying either least-squares or neural network approximation methods.

The Linear Programming (LP) approach to ADP is an alternative, model-based optimization paradigm to approxi-

INTERNATIONAL JOURNAL OF ROBUST AND NONLINEAR CONTROL
Int. J. Robust Nonlinear Control 2018; **28**:3678–3693
Published online 28 July 2016 in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/rnc.3612

Data-driven H_∞ loop-shaping controller design

Y. C. Sung*,†, S. V. Patil and M. G. Safonov

Department of Electrical Engineering-Systems, University of Southern California, Los Angeles, CA, USA

SUMMARY

We develop a data-driven and real-time test for candidate controllers' ability to meet given McFarlane–Glover loop-shape specifications. The proposed test provides a data-driven method to improve robustness of closed-loop systems by eliminating controllers that past collected data have proved to fail to meet loop-shape specifications. The test has an important property that many candidate controllers (not necessarily active ones) can be tested in real time using evolving real-time plant data collected while others are active. It is shown that controller-shaping in the present work plays a role that is dual to the role of plant-shaping in the model-based H_∞ loop-shaping design procedure. A simulation example is provided. Copyright © 2016 John Wiley & Sons, Ltd.

Received 31 October 2015; Revised 6 June 2016; Accepted 26 June 2016

KEY WORDS: robust control; adaptive control; H_∞ control

1. INTRODUCTION

Sensitivity and complementary sensitivity are important for specifying robustness and performance of closed-loop systems. Consider the closed-loop system $\Sigma(K,P)$ in Figure 1, where an SISO plant and an SISO controller are denoted by P and K, respectively. The *sensitivity* is defined as $S \triangleq (1+PK)^{-1}$, and the *complementary sensitivity* is defined as $T \triangleq PK(1+PK)^{-1}$. The size of $|S|$ at each frequency ω is the factor by which disturbances are attenuated, while $1/|T|$ is the magnitude of the smallest destabilizing multiplicative plant perturbation. However, owing to the identity $S+T \equiv 1$, it is impossible to simultaneously lower both $|S|$ and $|T|$ arbitrarily. These considerations are the basis for the standard mixed-sensitivity formulation of the robust control problem in terms of inequalities to be satisfied by the magnitude Bode plots of S and T [1].

Loop shape $L = PK$ is closely related to $|S|$ and $|T|$ as a consequence of the well-known approximate upper and lower bounds on the loop shape [2–5],

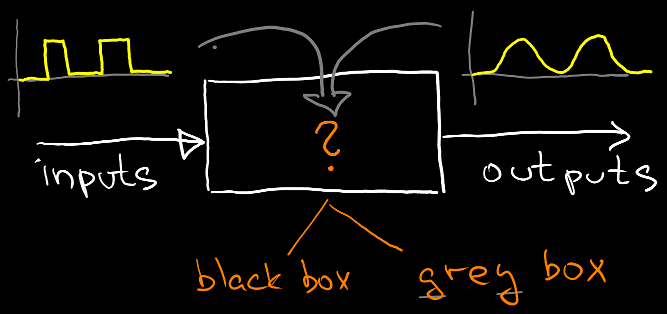
system order, knowledge on the system's structure and on the

resulting closed-loop system, although techniques for data-driven *controller certification* [7,8,14] have been proposed to address the problem of verifying whether a given controller is stabilizing for an unknown plant on the basis of input-output data collected in open- or closed-loop configuration. Some research work on direct data-driven techniques has accounted for stability requirements within the design procedure (see, e.g., [1,30]). The approach in [30] defines the desired complementary sensitivity in terms of a stable transfer function and aims at designing a controller such that the feedback interconnection with the actual process

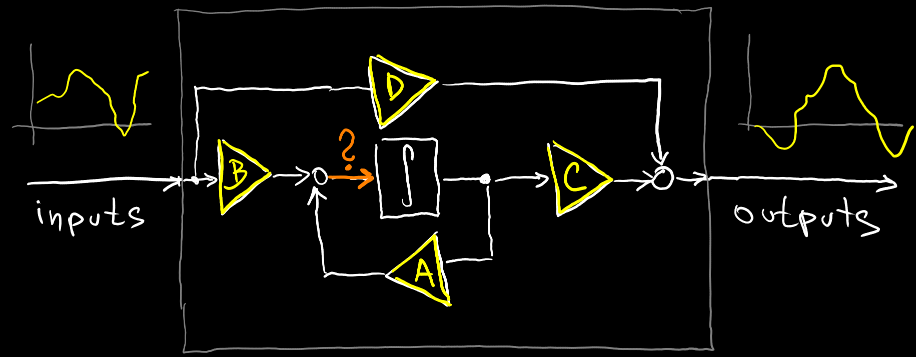
Just a buzzword? Or just a hype? Or a trend?

Control has always been driven by data:

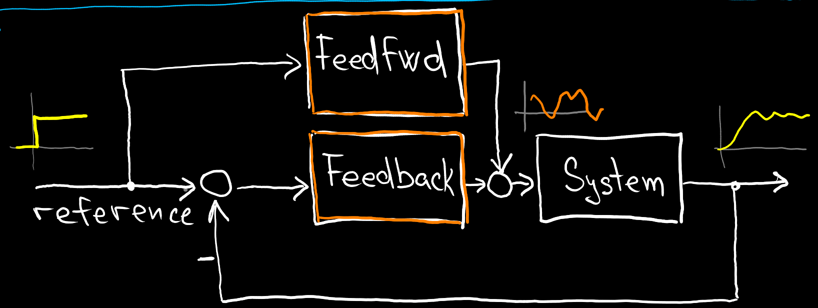
(Control-oriented) system identification



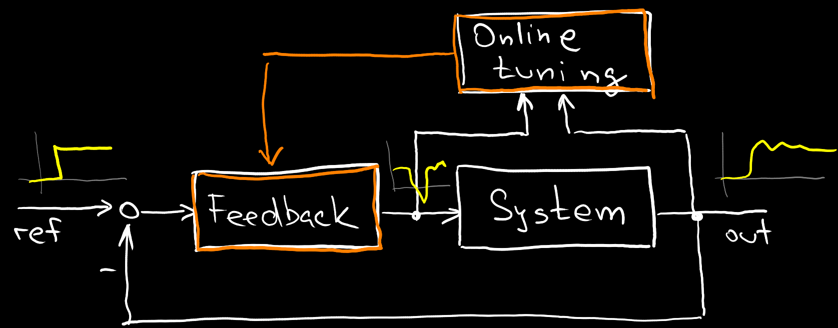
State estimation



Feedback & feedforward control

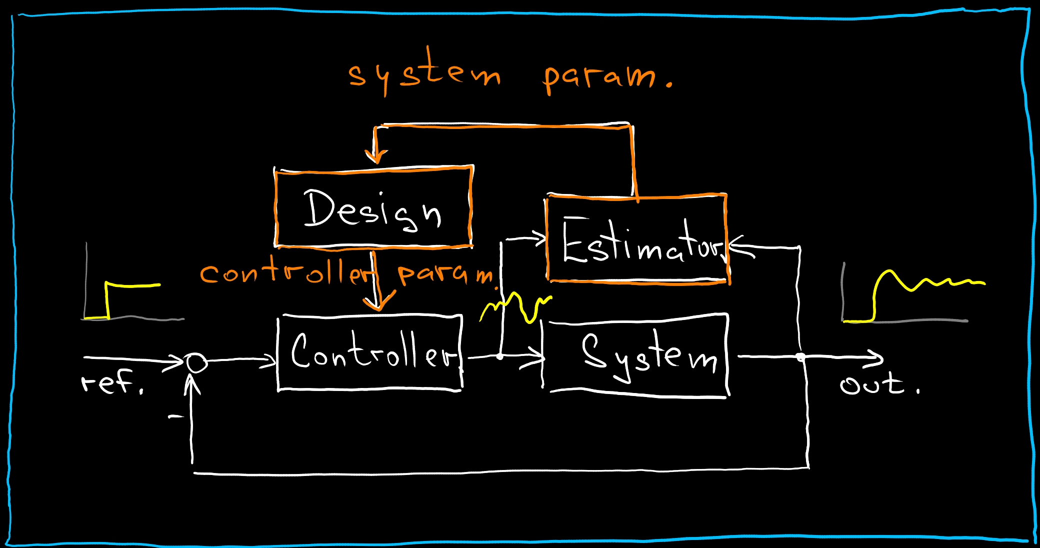


Adaptive control

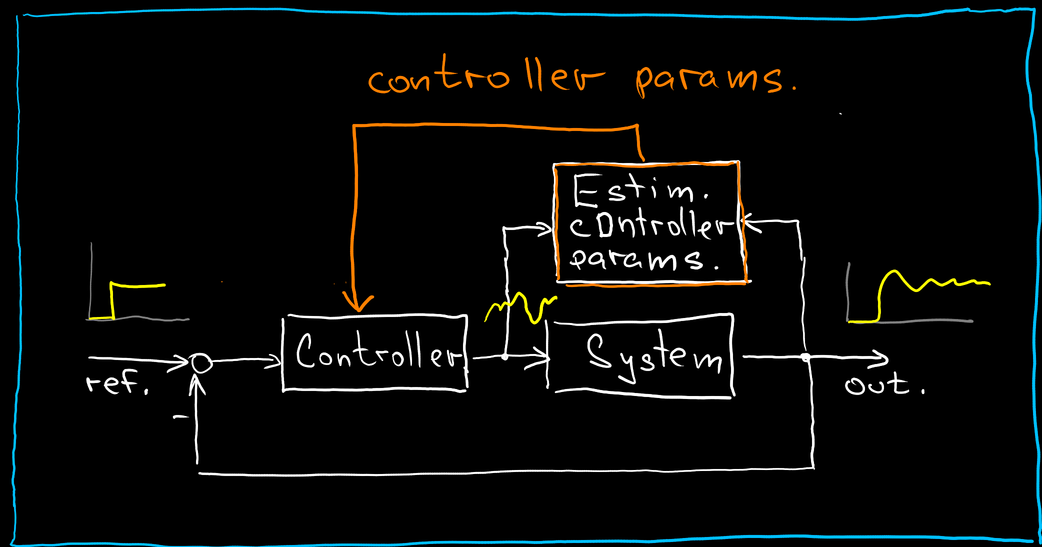


Adaptive control

Indirect adaptive control

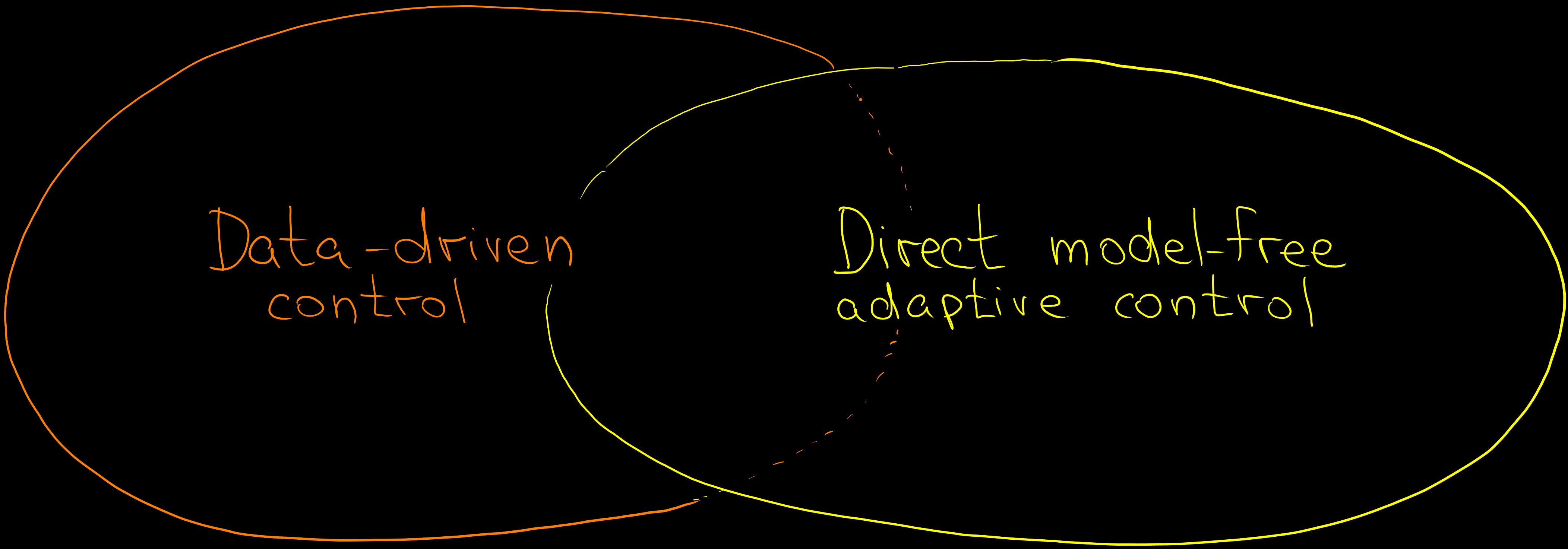


Direct adaptive control



Can be
- model-based
- model-free

But Model-free also
- online
- offline
  - using experimental data
  - using simulation data



Rise and fall of adaptive control:

Fatal accident of NASA X-15-3 on November 15, 1967
(MH-96 adaptive controller)

Dydek, Zachary T., Anuradha M. Annaswamy, and Eugene Lavretsky.
“Adaptive Control and the NASA X-15-3 Flight Revisited.”
IEEE Control Systems Magazine 30, no. 3 (June 2010): 32–48.
https://doi.org/10.1109/MCS.2010.936292.

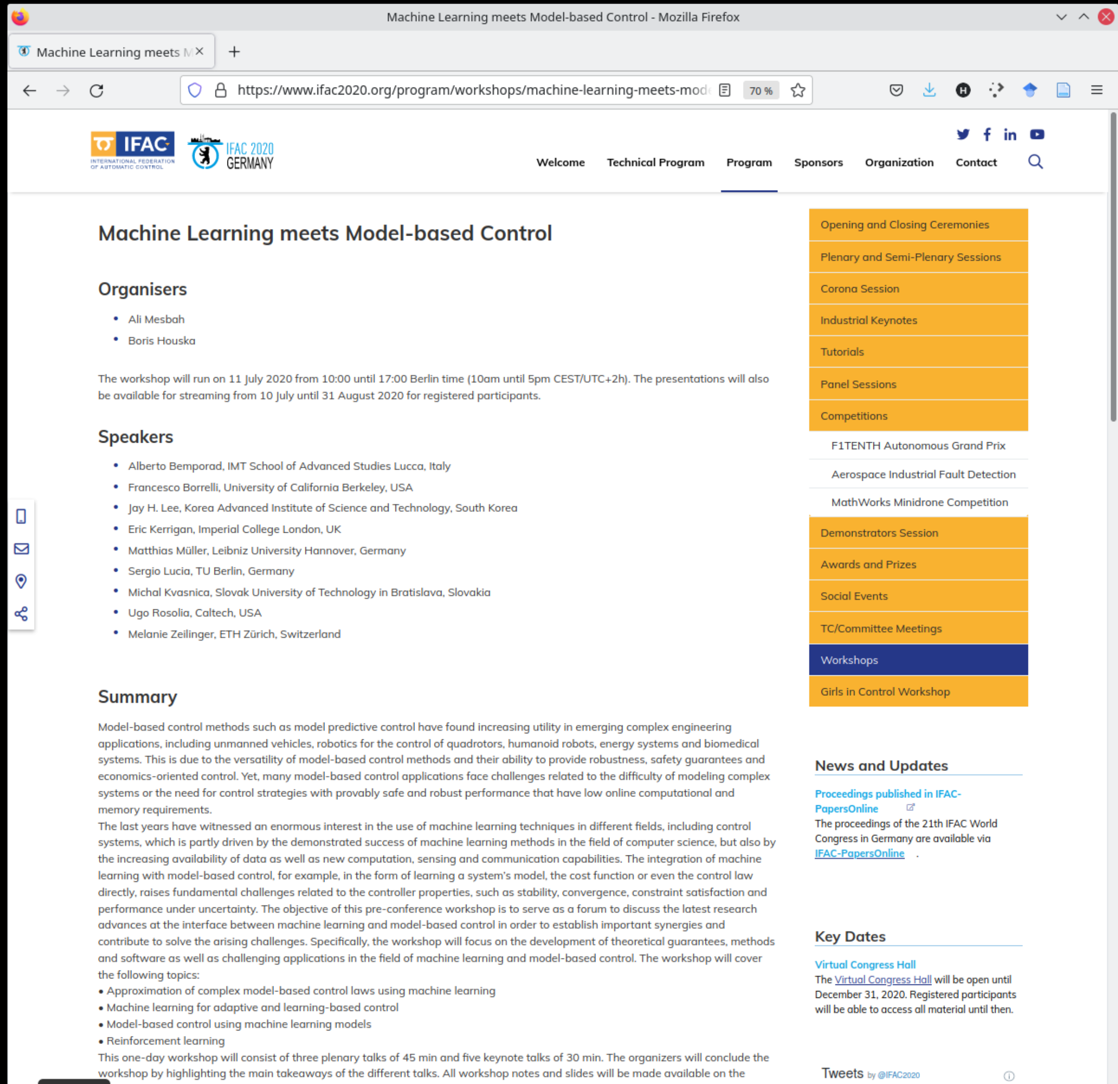
For some Data-driven = machine learning-based

(numerical) optimization on data

... a lot of data

Optimal control

(numerical) optimization on data AND models



Machine Learning meets Model-based Control - Mozilla Firefox

Machine Learning meets M ×

https://www.ifac2020.org/program/workshops/machine-learning-meets-mod 70 %

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Machine Learning meets Model-based Control

Organisers

- Ali Mesbah
- Boris Houska

The workshop will run on 11 July 2020 from 10:00 until 17:00 Berlin time (10am until 5pm CEST/UTC+2h). The presentations will also be available for streaming from 10 July until 31 August 2020 for registered participants.

Speakers

- Alberto Bemporad, IMT School of Advanced Studies Lucca, Italy
- Francesco Borrelli, University of California Berkeley, USA
- Jay H. Lee, Korea Advanced Institute of Science and Technology, South Korea
- Eric Kerrigan, Imperial College London, UK
- Matthias Müller, Leibniz University Hannover, Germany
- Sergio Lucia, TU Berlin, Germany
- Michal Kvasnica, Slovak University of Technology in Bratislava, Slovakia
- Ugo Rosolia, Caltech, USA
- Melanie Zeilinger, ETH Zürich, Switzerland

Summary

Model-based control methods such as model predictive control have found increasing utility in emerging complex engineering applications, including unmanned vehicles, robotics for the control of quadrotors, humanoid robots, energy systems and biomedical systems. This is due to the versatility of model-based control methods and their ability to provide robustness, safety guarantees and economics-oriented control. Yet, many model-based control applications face challenges related to the difficulty of modeling complex systems or the need for control strategies with provably safe and robust performance that have low online computational and memory requirements.
The last years have witnessed an enormous interest in the use of machine learning techniques in different fields, including control systems, which is partly driven by the demonstrated success of machine learning methods in the field of computer science, but also by the increasing availability of data as well as new computation, sensing and communication capabilities. The integration of machine learning with model-based control, for example, in the form of learning a system's model, the cost function or even the control law directly, raises fundamental challenges related to the controller properties, such as stability, convergence, constraint satisfaction and performance under uncertainty. The objective of this pre-conference workshop is to serve as a forum to discuss the latest research advances at the interface between machine learning and model-based control in order to establish important synergies and contribute to solve the arising challenges. Specifically, the workshop will focus on the development of theoretical guarantees, methods and software as well as challenging applications in the field of machine learning and model-based control. The workshop will cover the following topics:
• Approximation of complex model-based control laws using machine learning
• Machine learning for adaptive and learning-based control
• Model-based control using machine learning models
• Reinforcement learning
This one-day workshop will consist of three plenary talks of 45 min and five keynote talks of 30 min. The organizers will conclude the workshop by highlighting the main takeaways of the different talks. All workshop notes and slides will be made available on the

- Opening and Closing Ceremonies
- Plenary and Semi-Plenary Sessions
- Corona Session
- Industrial Keynotes
- Tutorials
- Panel Sessions
- Competitions
  - F1TENTH Autonomous Grand Prix
  - Aerospace Industrial Fault Detection
  - MathWorks Minidrone Competition
- Demonstrators Session
- Awards and Prizes
- Social Events
- TC/Committee Meetings
- Workshops
- Girls in Control Workshop

News and Updates

Proceedings published in IFAC-PapersOnline
The proceedings of the 21th IFAC World Congress in Germany are available via IFAC-PapersOnline .

Key Dates

Virtual Congress Hall
The Virtual Congress Hall will be open until December 31, 2020. Registered participants will be able to access all material until then.

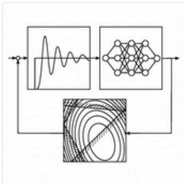
Tweets by @IFAC2020

Workshops

Intersections between Control, Learning and Optimization

FEBRUARY 24 - 28, 2020

Overview



Relationships between the areas of control, learning, and optimization have always been strong, but have recently been expanding and deepening in surprising ways. Optimization formulations and algorithms have historically been vital to solving problems in control and learning, while conversely, control and learning have provided interesting perspectives on optimization methods. Intersections that have been explored recently include relationships between reinforcement learning and model predictive control, and the use of control techniques to analyze the convergence of optimization algorithms. We will bring together researchers who work in Control, Learning, and Optimization to discuss current areas of interaction and explore possibilities for future areas of collaboration.

This workshop will include a poster session; a request for posters will be sent to registered participants in advance of the workshop.

This workshop is partially supported by the DOE-funded **MACSER** project.

Program Flyer PDF

ORGANIZING COMMITTEE

Moritz Diehl (University of Freiburg)
Ben Recht (University of California, Berkeley (UC Berkeley))
Stephen Wright (University of Wisconsin-Madison)
Melanie Zeilinger (ETH Zurich)

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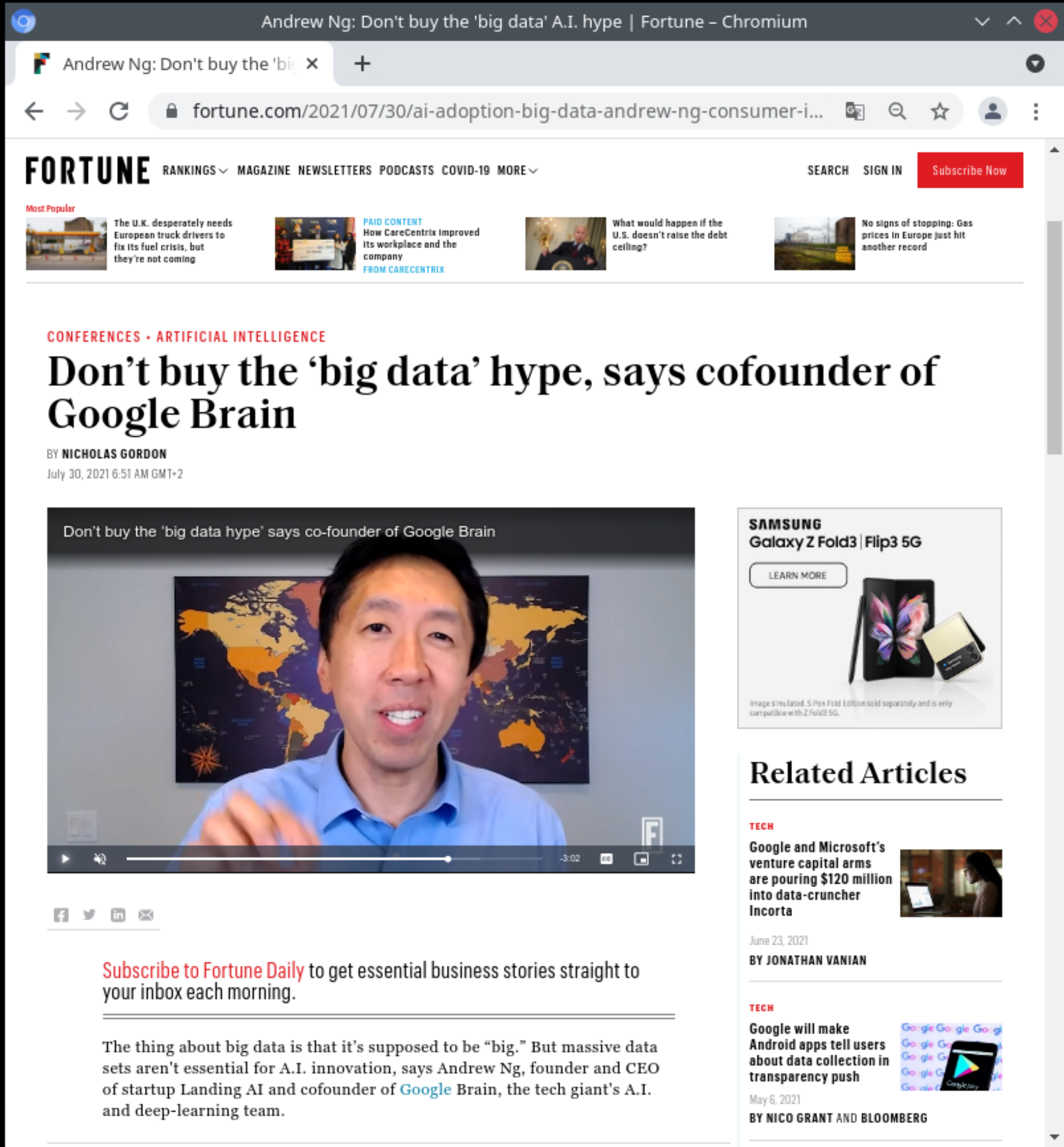

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Don't buy the 'big data' hype, says cofounder of Google Brain

BY NICHOLAS GORDON

July 30, 2021 6:51 AM GMT+2

Don't buy the 'big data hype' says co-founder of Google Brain

-3:02

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The thing about big data is that it's supposed to be "big." But massive data sets aren't essential for A.I. innovation, says Andrew Ng, founder and CEO of startup Landing AI and cofounder of Google Brain, the tech giant's A.I. and deep-learning team.

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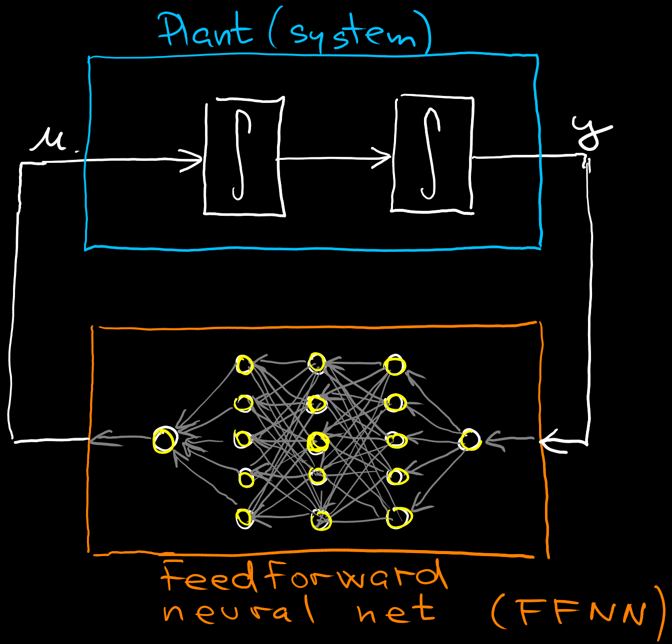
May 6, 2021

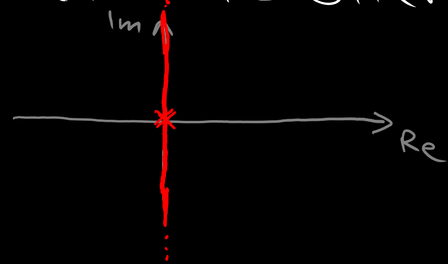
BY NICO GRANT AND BLOOMBERG

Can/shall we relly just on learning (from data)?



– undergrad's know that it is impossible to stabilize with a proportional controller

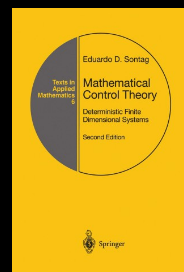
$$\boxed{u(t) = -K \cdot y(t)}$$



– but from E. Sontag's book we know that even nonlinear

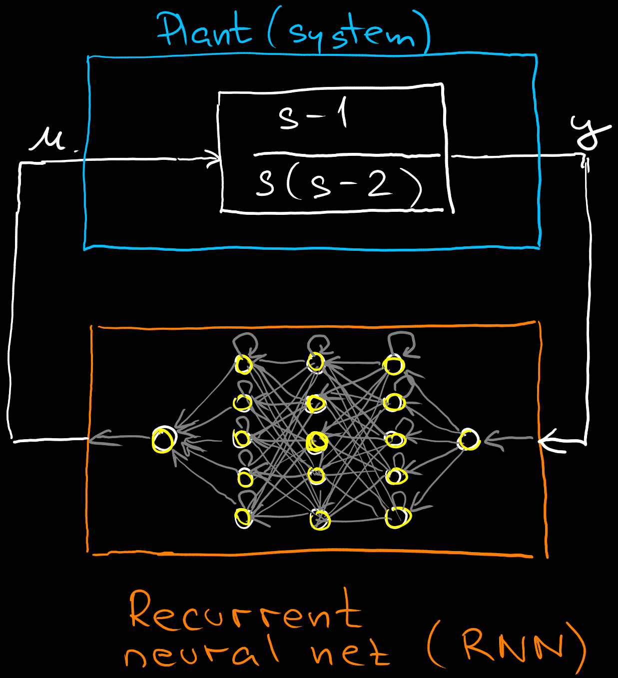
$$\boxed{u(t) = -f\big(y(t)\big)}$$

doesn't help



Sontag, E. Mathematical Control Theory. 2nd ed.
Texts in Applied Mathematics. New York, NY: Springer, 1998.
http://www.sontaglab.org/FTPDIR/sontag_mathematical_control_theory_springer98.pdf.

Can/shall we relly just on learning (from data)?



- not ~~strongly~~ stabilizable plant
- root locus or LQ/LQG/H_2/H_∞ can give a stabilizing controller
- RNN must be open-loop unstable (how to train?)
- Or RNN must lear periodic jumps (how to implement and train?)
- Reinforcement learning reported to have hard times

personal comm. with Mario Sznaier (Northeastern Uni.), Sept'21

Data-driven control ≈ model-free direct adaptive control

≈ machine-learning based control

≈ optimization over data

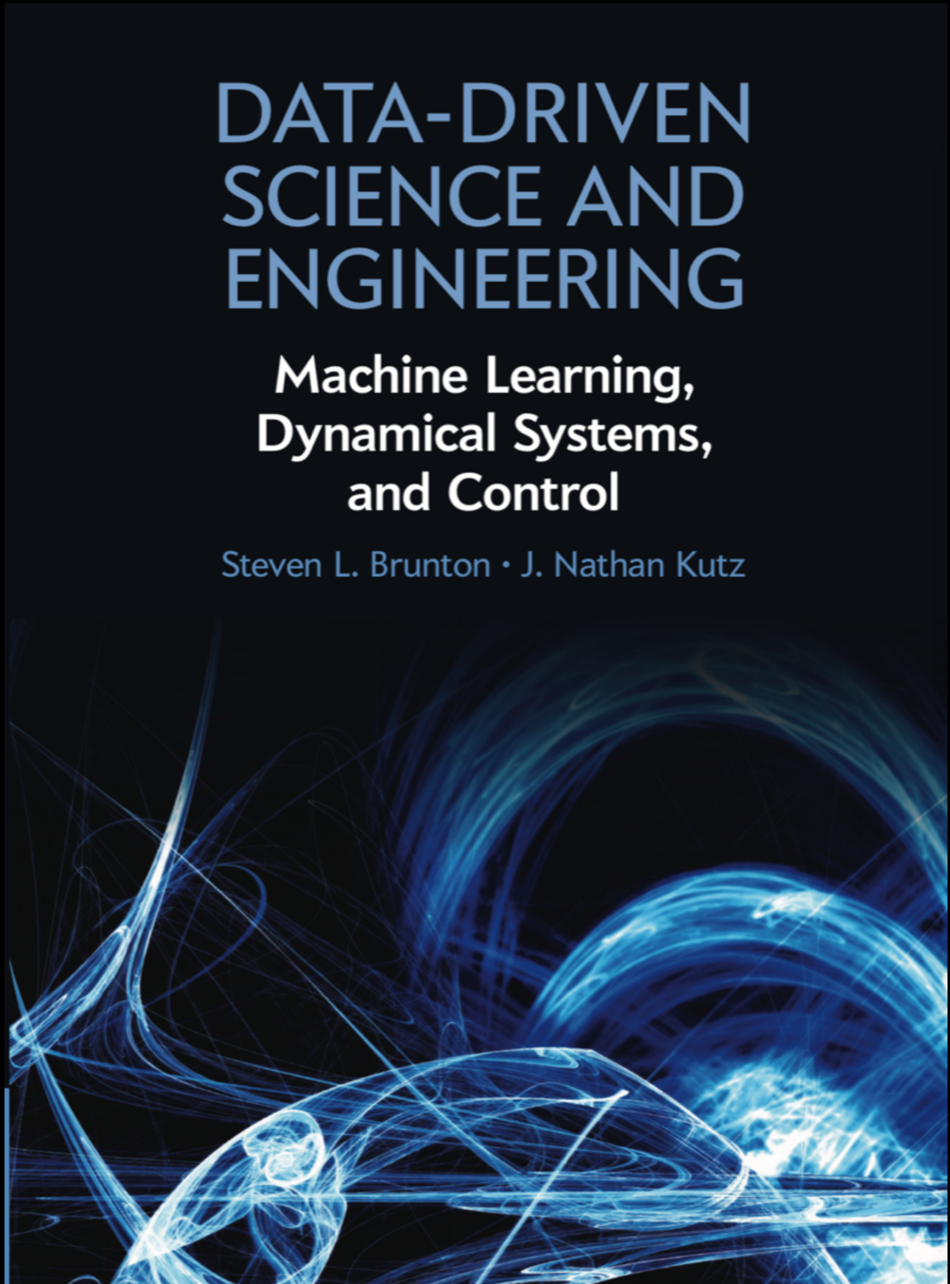
Selected methods

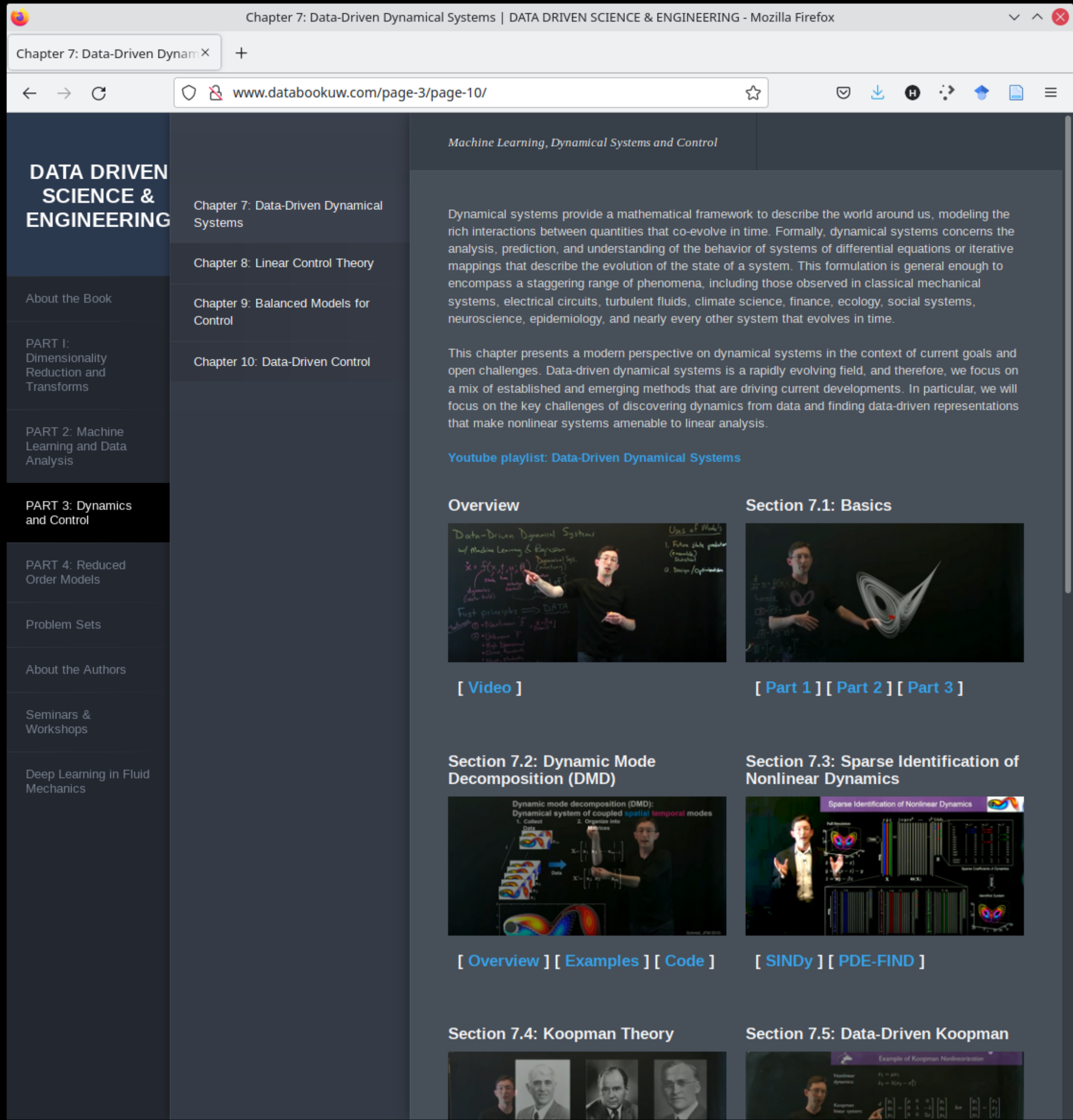
TODAY (?)

- Extremum seeking control (ESC)
- Iterative learning control (ILC)
- Virtual reference feedback tuning (VRFT)
- Dynamic mode decomposition (DMD) & Koopman operator based approaches
- Unfalsified control
- Iterative feedback tuning
- Machine learning based
- Reinforcement learning (RL)

Major tip on a literature

http://databookuw.com





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