LMI Methods in Optimal and Robust Control

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Lecture 1: The Big Picture

Who Am I?

Website: http://control.asu.edu

Research Interests: Computation, Optimization and Control Focus Areas:

- Control of Nuclear Fusion
- Immunology
- Thermostats, Renewable Energy, and Power Distribution

Expertise with LMI Methods:

- Optimization of Polynomials
- Parallel Computing for Control
- Control of Delayed Systems
- Control of PDE Systems
- Control of Nonlinear Systems

My Background:

- B.Sc. University of Texas at Austin
- Ph.D. Stanford University
- Postdoc at INRIA Paris
- NSE CAREER Awardee

Office: ERC 253: Lab: GWC 531

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References

Required: LMIs in Control Systems by Duan and Yu



LMIs in Systems and Control Theory by S. Boyd Link: Available Online Here



Linear State-Space Control Systems by Williams and Lawrence



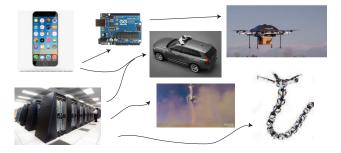
Convex Optimization by S. Boyd Link: Available Online Here



Link: Entire Course Online Here

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What are the challenges?



Megatrends:

- Increased Complexity (Embedded Computation and Control)
- Increased Connectivity (Internet of Things)
- Robots, Drones and Self-Driving Cars
- Increased Demands (Higher Standards)
- Mobile Computing (Mobile Apps)



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- Sources of Complexity: Smarter devices have more complicated action spaces; Ubiquitous computation; Cheap sensors and actuators;
- Sources of Connectivity: RFID, bluetooth, low-energy bluetooth, LAN, WiFi, WAN, 5G LTE, GPS, satellite broadband, TDRS, integrated circuits
 - Problems: delay, lost packets, noise, loss of signal, hacking
- **Sources of Demands:** Improved Efficiency; Expanded Functionality; User Friendliness; Reduced Tolerance for Failure.

Privatization of Space Travel

Challenges

- Safety
- Complexity
- Uncertainty



Links:

Blue Origin Successful Landing Blue Origin Successful Landing: Flight 3 SpaceX Landing, Second Attempt Proton M launch Failure (FCS was for wrong rocket) Kepler Space Telescope

UAVs and Drones (Delay, Sampled-Data)

- Safe Interaction with
 - Crowded Airspace
 - Real-Time Obstacle
 Avoidance

Precision Control with

- Delayed Feedback $\dot{x}(t) = Ax(t) + Bu(t \tau)$
- Lossy Connections $\dot{x}(t) = Ax(t) + Bu(t_k)$



Links: X47 Drone Carrier Landing Raff's TED talk

Self-Driving Vehicles

Challenges:

- Safety (Provable)
- Uncertainty (in model, environment)
- Other Drivers (Multi-Agent)
- Obstacles

Self-Driving Vehicles

- Google (Waymo)
- Über
- Tesla, Mobileye
- Toyota, Nutonomy

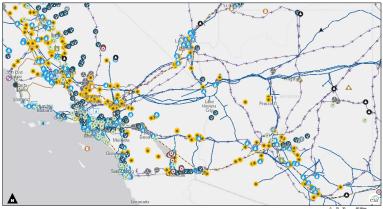




Links:

Toyota's Research Expansion in Automation Uber's self-driving Taxis are in Pittsburg Self-Driving Cars Flood into Arizona

Interconnectivity (Decentralized Control)



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- A. Surface Coal Mine
- Underground Coal Mine
- Ø Biomass Power Plant
- Coal Power Plant
- Geothermal Power Plant
- Hydroelectric Power Plant
- Natural Gas Power Plant
- Nuclear Power Plant
 Other Power Plant
- Petroleum Power Plant
- Pumped Storage Power Plant
- rumped Stolager ower ri
- nt 🙁 Solar Power Plant

- Wind Power Plant
- Petroleum Refinery
- Biodiesel Plant
- Ethanol Plant
- Natural Gas Processing Plant (z)
- Ethylene Cracker

- HGL Market Hub (z)
- Natural Gas Market Hub (z)
- Electricity Border Crossing
- Natural Gas Pipeline Border Crossing

Robotics (Hybrid and Nonlinear Dynamics, PDE systems)

HARD Robots

- Uncertain Terrain
- Interactions with the environment

If x(t)>0:

$$\dot{x}(t) = Ax(t)$$

If $x_1(\texttt{t})\texttt{=0}$ AND $x_2(\texttt{t})\texttt{<0}\texttt{:}$ Set $x_2(t) = -x_2(t)$

Link:

Boston Dynamics, Atlas Mark 3

SOFT Robots

- Infinite Degrees of Freedom
- Material Dynamics

Link:

Robotic Worm





Arduino and Raspberry Pi

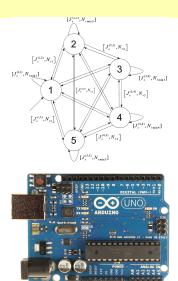
Trends:

- Rapid prototyping
- Internet of Things
- Control is Everywhere

Challenges

- Noisy Sensors
- Data-Driven Modeling
- Dynamics with logical switching $\dot{x} = Ax + Bu(t) \label{eq:alpha}$
 - If Occupied=True : $u(t) = K_1 x(t) \label{eq:ut}$

Else : $u(t) = K_2 x(t)$



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This course is on **RECENT** Developments in Control

- Techniques Developed in the Last 20 years
- Computational Methods
 - No Root Locus
 - No Bode Plots
 - No PID (Proportion-Integral-Differential)

We focus on State-Space Methods

- In the time-domain
- We use large state-space matrices

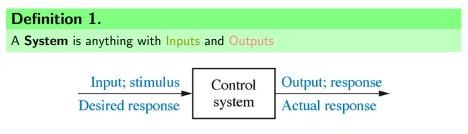
$$\frac{d}{dt} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \end{bmatrix} = \begin{bmatrix} -1 & 1.2 & -1 & .8 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_1(t) \\ u_2(t) \end{bmatrix}$$

- We require Matlab
 - Need robust control toolbox.
 - Recommend using YALMIP.

Link: Installs YALMIP and some other toolboxes

M. Peet

Well... What is a System?



There should ALWAYS be Inputs and Outputs!

- If No Inputs: You can't change anything.
- **IF No Outputs**: Then it doesn't matter anyway.



In Controls, we separate internal signals from external signals. **Output Signals:**

- z: Output to be controlled/minimized
- y: Output used by the controller

Input Signals:

- w: Disturbance, Tracking Signal, etc.
- u: Output from controller
 - Input to actuator

State-Space System



A state-space system has the form (9-matrix representation)

$$\dot{x}(t) = Ax(t) + B_1w(t) + B_2u(t)$$

$$z(t) = C_1x(t) + D_{11}w(t) + D_{12}u(t)$$

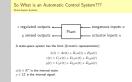
$$y(t) = C_2x(t) + D_{21}w(t) + D_{22}u(t)$$

 $x(t) \in \mathbb{R}^n$ is the internal state. $x \in L_2^n$ is the internal signal.



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—So What is an Automatic Control System???

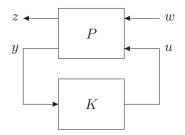


Notation Matters

- $y \in L_2$ is a function
- $y(t) \in \mathbb{R}^m$ is a real number
- Systems (e.g. K) map signals to signals

– We can say
$$y = Ku$$

– We can NOT say y(t) = Ku(t)



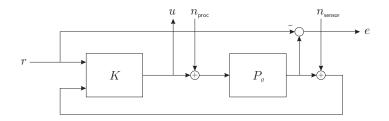
The controller, K, determines how to use the signal y to get the signal u.

• Can be dynamic: $u(t) = F\hat{x}(t)$, $\dot{\hat{x}}(t) = A\hat{x}(t) + L(y(t) - C\hat{x}(t))$

• Can be *static*:
$$u(t) = Fy(t)$$
.

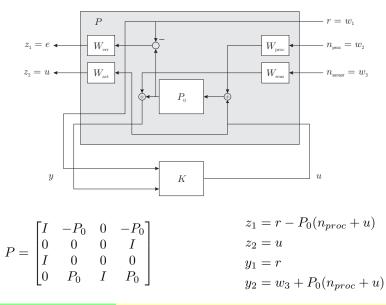
Our job is to find the BEST K.

Consider the Tracking Problem



r= reference input	$w_2 = n_{proc}$	$w_1 = r$
e = tracking error	$w_3 = n_{sensor}$	u = u
$n_{proc} = \text{ process noise}$	$z_1 = e$	$y_1 = r$
$n_{sensor} = \text{ sensor noise}$	$z_2 = u$	$y_2 = y_p$

Tracking Control



What is Optimization?

An Optimization Problem has 3 parts.

$\min_{x \in \mathbb{F}} f(x):$	subject to
$g_i(x) \ge 0$	$i=1,\cdots K_1$
$h_i(x) = 0$	$i=1,\cdots K_2$

Variables: $x \in \mathbb{F}$

- The things you must choose.
- \mathbb{F} represents the set of possible choices for the variables.
- Can be vectors, matrices, functions, systems, locations, colors...

However, computers prefer vectors or matrices.

Objective: f(x)

• A function which assigns a *scalar* value to any choice of variables.

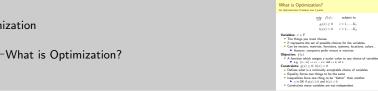
• e.g.
$$[x_1, x_2] \mapsto x_1 - x_2$$
; red $\mapsto 4$; et c.

Constraints: $g(x) \ge 0$; h(x) = 0

- Defines what is a minimally acceptable choice of variables.
- Equality forces two things to be the same
- Inequalities force one thing to be "better" than another

• x is OK if $g(x) \ge 0$ and h(x) = 0.

• Constraints mean variables are not independent.



 $\min_{x \in Y} f(x)$: subject to

 $g_i(x) \ge 0$ $i = 1, \dots K_1$

 $h_i(x) = 0$ $i = 1, \dots K_7$

The word "better" is defined using a notion of positivity (A Complete or Partial Ordering)

EVERYTHING is an Optimization Problem

- Teaching
- Studying
- Choosing a Class
- Getting Lunch
- Getting to Class
- Doing chores

The Trick is Modeling the Optimization Problem

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Lecture 1

Optimization

For Humans:

Almost always IMPOSSIBLE (or at least tedious)

For Computers:

- Easy if the Problem is CONVEX. (Polynomial Time)
- Otherwise IMPOSSIBLE. (NP-Hard)

We will talk about this a bit more later!

Now What is an LMI?

An LMI is a type of constraint

Definition 2.

A symmetric matrix $(P = P^T)$ is **Positive Definite** (denoted P > 0) if all of its eigenvalues are positive.

A Linear Matrix Inequality (LMI) is a constraint that looks like

 $A_i P B_i + Q_i > 0$

where P is the variable and A_i , B_i , Q_i are matrices.

Question: Why do we have a whole controls course devoted to LMIs?

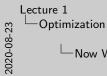
- LMI constraints are convex (Computers can solve them)
- Positive matrices can be used to study systems.

This is because we are really optimizing Lyapunov functions.

 $V(x) = x^T P x \ge 0 \text{ if } P > 0.$

Almost ALL computational methods in Control are based on LMIs.

• Or at least be reformulated as an LMI.



—Now What is an LMI?

LMIs define a Partial Ordering

- One matrix may not be better or worse than another
- The LMI means the LHS must be better in EVERY way.

Now What is an LMM? At the sense th

Now What is an LMI?

An Example: The Lyapunov Inequality

The system

$$\dot{x} = Ax$$

is stable (eigenvalues have negative real part) if and only if there exists a $P>0\,$ such that

 $A^TP + PA < 0$

```
YALMIP Code for Stability Analysis:
> A = [-1 2 0; -3 -4 1; 0 0 -2];
> P = sdpvar(3,3);
> F = [P >= eye(3)];
> F = [F, A'*P+P*A <= 0];
> optimize(F);
```

If Feasible, YALMIP Code to Retrieve the Solution:

```
> Pfeasible = value(P);
```

Class Project

In lieu of a final exam, we will have two class projects (Alone or in pairs).

- 1. Write a Wikibook Chapter
 - Include a minimum of 10 pages (20 for pairs)
- 2. Do Research/Solve a Problem
 - Can be based on existing research.

Some Project Ideas:

- Gain Scheduling for Missile Attitude Control (Switched Systems)
- Control of Robots over the internet (Sampled-Data Systems)
- Spacecraft Attitude Control with delayed communication (Delay Systems)
- Social Cognitive Therapy using Discrete Inputs (Mixed-Integer Control)
- Self-Driving Vehicles (Decentralized Control)
- Soft Robotics (Decentralized Control)
- Thermostat Programming (Dynamic Programming)
- Flow Control (PDEs)
- Controller/Estimator Design using Arduino and Simulink (Robust Control)
- System Identification using LMIs
- Mobile App for solving an optimization or control problem.

For those who dislike Projects, we can arrange to take a Final Exam instead.