EECE 574 - Adaptive Control

Overview

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Lectures: Thursday 09h30-12h00
Location: MCLD 207

Objectives

- Course Objective:

  To give an overview of the theory and practice of the mainstream adaptive control techniques

- Four assignments: 15% each
- Project: 40%
- Textbook:

  K.J. Åström and B. Wittenmark, Adaptive Control, Addison-Wesley Publishing Co., Inc., Reading, Massachusetts, 1995. (This book is out of print, but is downloadable from the internet)

Related Books

- N. Hovakimyan, C. Cao, $\mathcal{L}_1$ Adaptive Control theory, SIAM Press, Philadelphia, 2010.
- P. Ioannou and B. Fidan, Adaptive Control Tutorial, SIAM Press, Philadelphia, 2006.
- V. Bobal, J. Bohm, J. Fessl and J. Macacek, Digital Self-Tuning Controllers, Springer-Verlag, Berlin, 2005.
- Landau, Lozano and M'Saad, Adaptive Control, Springer-Verlag, Berlin, 1998.
- Isermann, Lachmann and Matko, Adaptive Control Systems, Prentice-Hall, Englewood Cliffs, NJ, 1992.
- Wellstead and Zarrop, Self-Tuning Systems Control and Signal Processing, J. Wiley and Sons, NY, 1991.
- Bitmead, Gevers and Wertz, Adaptive Optimal Control, Prentice-Hall, Englewood Cliffs, NJ, 1990.
- Goodwin and Sin, Adaptive Filtering, Prediction, and Control, Prentice-Hall, Englewood Cliffs, NJ, 1984.
- Ljung, and Söderström, Theory and Practice of Recursive Identification, MIT Press, Cambridge, MA, 1983.

Course Outline

1. Introduction
2. Identification
3. Control Design
4. Self-Tuning Control
5. Model-Reference Adaptive Control
6. Properties of Adaptive Controllers
7. Auto-Tuning and Gain Scheduling
8. Implementation and Practical Considerations
9. Extensions

What Is Adaptive Control?

- According to the Webster's dictionary, to **adapt** means:
  - to adjust oneself to particular conditions
  - to bring oneself in harmony with a particular environment
  - to bring one's acts, behaviour in harmony with a particular environment
- According to the Webster's dictionary, **adaptation** means:
  - adjustment to environmental conditions
  - alteration or change in form or structure to better fit the environment

When is a Controller Adaptive?

- Linear feedback can cope with parameter changes (within some limits)
- According to G. Zames[1]:
  - A **non-adaptive** controller is based solely on **a-priori** information
  - An **adaptive** controller is based on **a posteriori** information as well

[1] 35th CDC, Kobe, Dec 1996

A Narrow Definition of Adaptive Control

- *An adaptive controller is a* **fixed-structure** *controller with* **adjustable parameters** *and a mechanism for* **automatically** *adjusting those parameters*
- In this sense, an adaptive controller is one way of dealing with **parametric** uncertainty
- Adaptive control theory essentially deals with finding parameter ajustment algorithms that guarantee global stability and convergence

Why Use Adaptive Control?

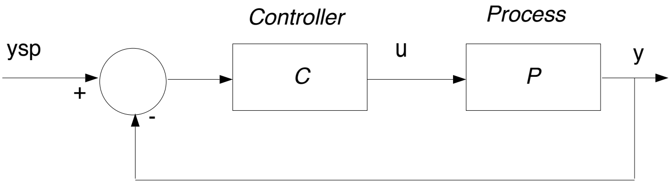
- Control of systems with time-varying dynamics
- If dynamics change with operating conditions in a known, predictable fashion, use **gain scheduling**
- If the use of a fixed controller cannot achieve a satisfactory compromise between **robustness** and **performance**, then and **only then**, should adaptive control be used

Use the simplest technique that meets the specifications [2]

[2]. . . or as A. Einstein apparently once said: *"make things as simple as possible, but no simpler"*

Feedback and Process Variations

Consider the feedback loop:



The closed-loop transfer function is

$$T = \frac{PC}{1 + PC}$$

Differentiating T with respect to P:

$$\frac{dT}{T} = \frac{1}{1 + PC}\frac{dP}{P} = S\frac{dP}{P}$$

T and S are respectively known as the **complementary sensitivity** and the **sensitivity** functions. Note that

$$S + T = 1$$

Feedback and Process Variations

- The closed-loop transfer function is NOT sensitive to process variations at those frequencies where the loop transfer function $L = PC$ is large
- Generally $L >> 1$ at low frequencies, and $L << 1$ at high frequencies
- However, $L >> 1$ can only be achieved in a limited bandwidth, particularly when unstable zeros are present

Judging the Severity of Process Variations

- Difficult to judge impact of process variations on closed-loop behaviour from open-loop time responses
    - Significant changes in open-loop responses may have little effect on closed-loop response
    - Small changes in open-loop responses may have significant effect on closed-loop response
- Effect depends on the desired closed-loop bandwidth
- Better to use frequency responses

Effect of Process Variations

Consider the system given by

$$G(s) = \frac{1}{(s+1)(s+a)}$$

Open loop step responses for $a = -0.01$, 0, 0.01:

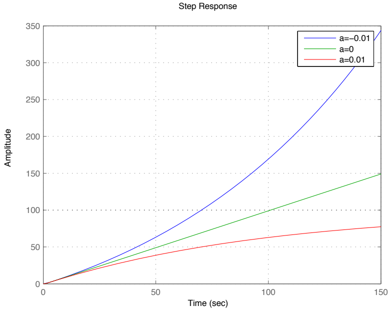


Figure: Open-loop responses

Effect of Process Variations

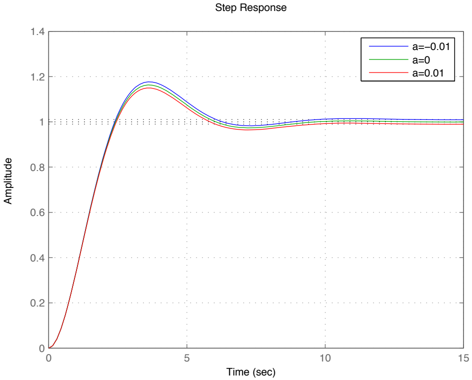


Figure: Closed-loop responses for unit feedback

Effect of Process Variations

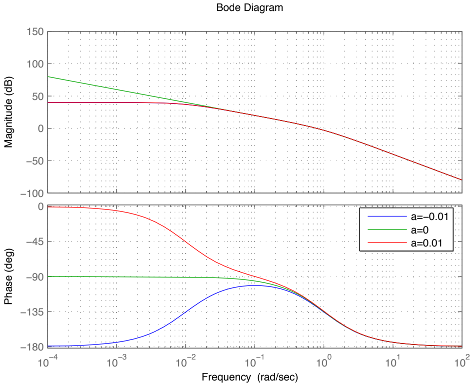


Figure: Open-loop Bode plots

Effect of Process Variations

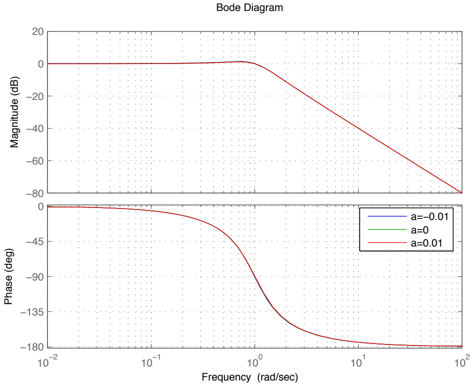


Figure: Closed-loop Bode plots

Effect of Process Variations

Consider now the system

$$G(s) = \frac{400(1 - sT)}{(s+1)(s+20)(1+sT)}$$

Open-loop responses for $T = 0, 0.015, 0.03$:

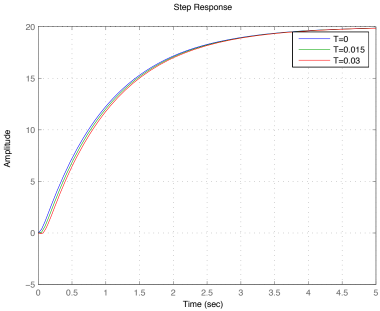


Figure: Open-loop responses

Effect of Process Variations

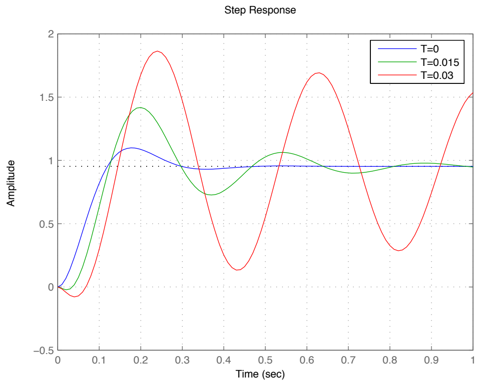


Figure: Unit-feedback closed-loop responses

Effect of Process Variations

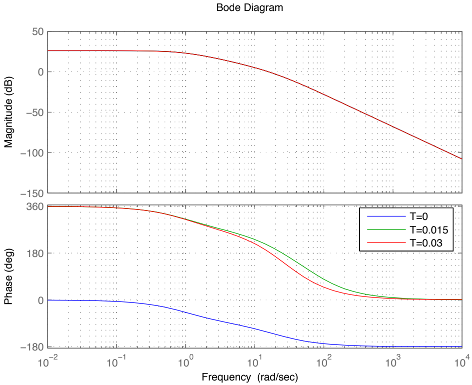


Figure: Open-loop Bode plots

Effect of Process Variations

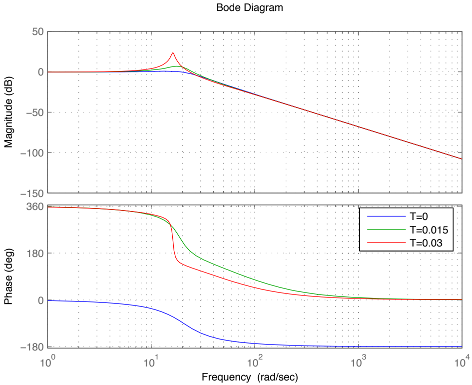


Figure: Unit-feedback closed-loop Bode plots

Effect of Process Variations

Consider now the same system but with a controller $C(s) = 0.075/(s+1)$:

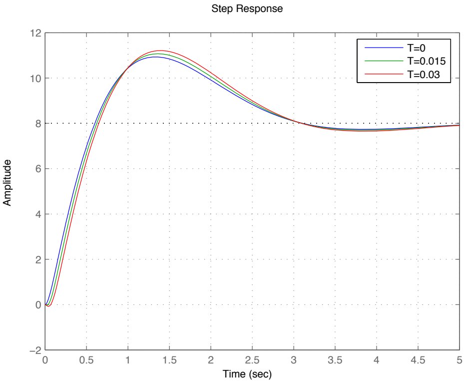


Figure: New closed-loop responses

Effect of Process Variations

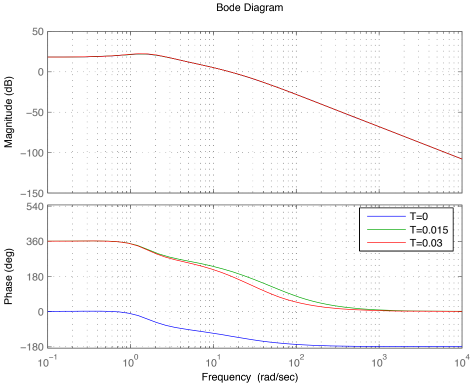


Figure: New closed-loop Bode plots

Mechanisms for Process Dynamics Changes

- Nonlinear actuators or sensors
  - Nonlinear valves
  - pH probes
- Flow and speed variations
  - Concentration control
  - Steel rolling mills
  - Paper machines
  - Rotary kilns

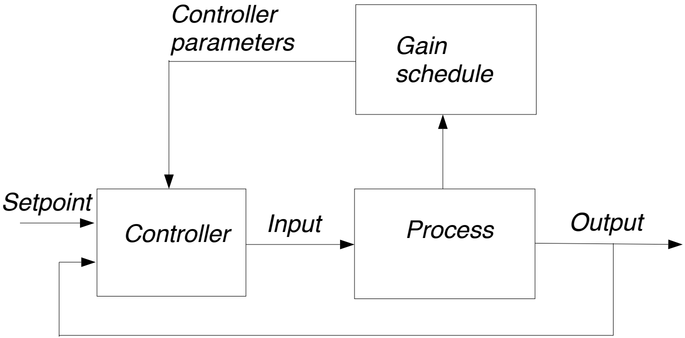
Mechanisms for Process Dynamics Changes

- Wide operating range with a nonlinear system
    - Flight control
- Variations in Disturbance Dynamics
    - Wave characteristics in ship steering
    - Raw materials in process industries

Gain Scheduling

- In many cases, process dynamics change with operating conditions in a known fashion
  - Flight control systems
  - Compensation for production rate changes
  - Compensation for paper machine speed
- Controller parameters change in a **predetermined** fashion with the operating conditions
- Is gain scheduling adaptive?

Gain Scheduling



Development of Adaptive Control

- Mid 1950s: Flight control systems (eventually solved by gain scheduling)
- 1957: Bellman develops dynamic programming
- 1958: Kalman develops the self-optimizing controller “which adjusts itself automatically to control an arbitrary dynamic process”
- 1960: Feldbaum develops the dual controller in which the control action serves a dual purpose as it is “directing as well as investigating”

Development of Adaptive Control

- Mid 60s-early 70s: Model reference adaptive systems

But now came a technical problem that spelled the end. The Honeywell adaptive flight control system began a limit-cycle oscillation just as the plane came out of the spin, preventing the system's gain changer from reducing pitch as dynamic pressure increased. The X-15 began a rapid pitching motion of increasing severity. All the while, the plane shot downward at 160,000 feet per minute, dynamic pressure increasing intolerably. . . . As the X-15 neared 65,000 feet, it was speeding downward at Mach 3.93 and experiencing over 15 g vertically, both positive and negative, and 8 g laterally. It broke up into many pieces amid loud sonic rumblings, . . . Then an Air Force pilot, . . . , spotted the main wreckage . . . . Mike Adams was dead and the X-15 destroyed.

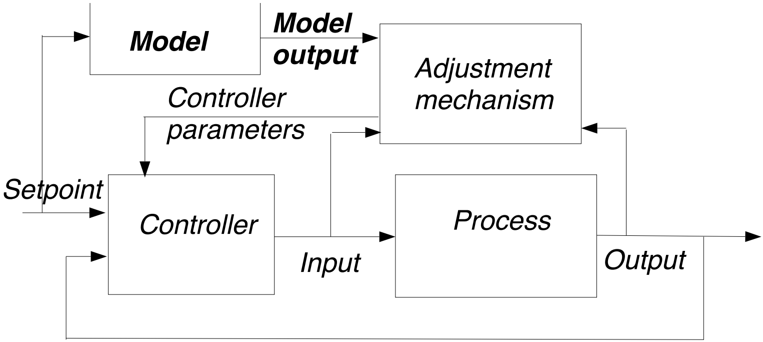
Development of Adaptive Control

- Late 60s-early 70s: System identification approach with recursive least-squares
- Early 1980s: Convergence and stability analysis
- Mid 1980s: Robustness analysis
- 1990s: Multimodel adaptive control
- 1990s: Iterative control
- 2000s: $\mathcal{L}_1$ adaptive control: fast adaptation with guaranteed robustness.

Model Reference Adaptive Control

- Performance specifications given in terms of reference model
- Originally introduced for flight control systems (MIT rule)
- Nontrivial adjusment mechanism

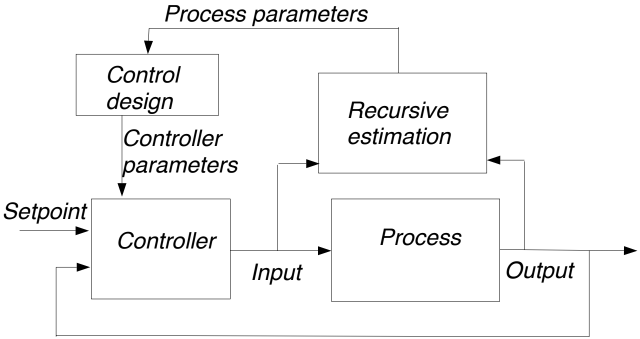
Model Reference Adaptive Control



Self-Tuning Controller

- Model-based tuning consists of two operations:
  - Model building via identification
  - Controller design using the identified model
- Self-tuning control can be thought of as an automation of this procedure when these two operations are performed on-line

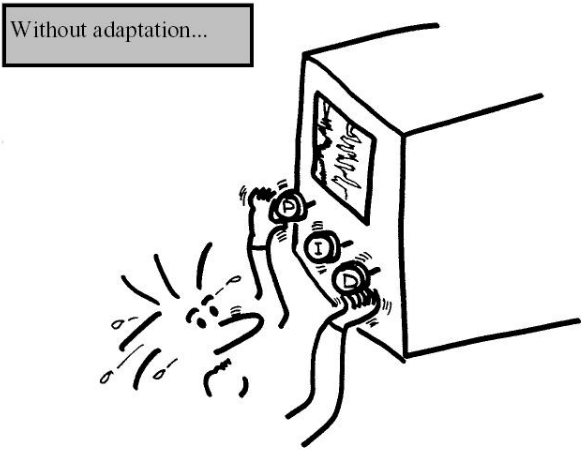
Self-Tuning Controller



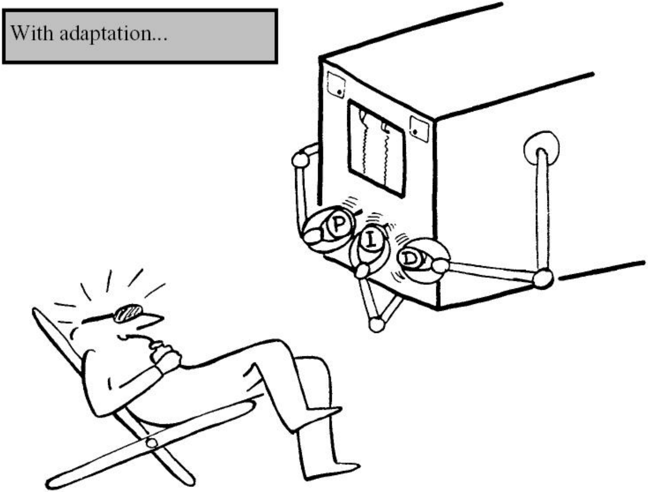
Self-Tuning vs. Auto-Tuning

- **Self-tuning**
  - Continuous updating of controller parameters
  - Used for truly time-varying plants
- **Auto-tuning**
  - Once controller parameters near convergence, adaptation is stopped
  - Used for time invariant or very slowly varying processes
  - Used for periodic, usually on-demand tuning

Final Motivation...

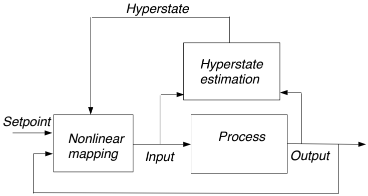


Final Motivation...



Dual Control: A Rigorous Approach to Adaptive Control

- Use of nonlinear stochastic control theory to derive an adaptive controller
- No distinction between parameters and state variables – Hyperstate
- The controller is a nonlinear mapping from the hyperstate to the control variable



A Rigorous Approach to Adaptive Control

- Can handle very rapid parameter changes
- Resulting controller has very interesting features:
    - Regulation
    - Caution
    - Probing
- Unfortunately solution is untractable for most systems

Illustration of Dual Control

Consider the simple process

$$y(t+1) = y(t) + bu(t) + e(t+1)$$

where $e(t)$ is zero-mean white noise $N(0, \sigma)$, $y(t)$and $u(t)$ are the output and the input signals.

One-stage control

Find $u(t)$ that minimizes

$$I_1 = E[y^2(t+1)|y(t), u(t)]$$

Certainty Equivalence Controller

In case b is known, the solution is trivial:

$$\min I_1 = \min\,[y(t-1) + bu(t-1)]^2 + \sigma^2 = \sigma^2$$

since $e(t)$ is independent of $y(t-1)$, $u(t-1)$ and b.

$$u(t) = -\frac{y(t)}{b} \qquad\qquad I_{1\text{opt}} = \sigma^2$$

Certainty Equivalence Controller

Now, assume that b is unknown.
We now have an estimate $\hat{b}$ with covariance p_b
If least-squares is used:

$$\hat{b} = \left\{ \sum_{s=1}^{t} [y(s) - y(s-1)] u(s-1) \right\} / \sum_{s=1}^{t} u^2(s-1)$$

$$p_b = \sigma^2 / \sum_{s=1}^{t} u^2(s-1)$$

Certainty Equivalence Controller

The most direct way to control the system is simply to replace b by $\hat{b}$ in the controller above, thus ignoring the uncertainty:

$$u_{ce}(t) = -\frac{y(t)}{\hat{b}}$$

then

$$I_{1\mathrm{ce}} = \sigma^2 + \frac{p_b}{\hat{b}^2} y^2(t-1)$$

Cautious Controller

Performing the minimization of I_1 actually gives:

$$u(t) = -\frac{\hat{b}}{\hat{b}^2 + p_b} y(t)$$

and the minimum performance index

$$I_{1\text{caut}} = \sigma^2 + \frac{p_b}{\hat{b}^2 + p_b} y^2(t-1)$$

Cautious Controller

- Because p_b is positive, the cautious controller has a smaller gain than the certainty equivalence one, which by ignoring uncertainty may be at times too **bold**
- **Turn-off phenomenon:**
  - When the uncertainty p_b is large, controller gain is small and so does the control action
  - So, unless an external perturbation is added to the input, no learning can take place and the uncertainty p_b cannot be reduced
- This highlights the importance of **probing** signals

Dual Controller

N-stage control

Find $u(t)$ that minimizes

$$I_N = E[\sum_{1}^{N} y^2(t+i)|y(t), u(t)]$$

- By using the N-stage control problem with $N > 1$, it can be shown that the effect of present inputs on the future values of $\hat{b}$ and p_b enters the minimization of I_N
- Indeed it is sometimes beneficial to sacrifice short term performance by sending a probing signal to reduce the uncertainty, and thus improve performance in the long term

Dual Controller

- Using dynamic programming, a functional equation (Bellman equation) can be derived
- However, this equation can only be solved numerically and for very simple cases
- For large N, the control tends towards a steady-state control law

Dual Controller

Define

$$\eta = \frac{y}{\sigma} \qquad \beta = \frac{\hat{b}}{p_b} \qquad \mu = -\frac{\hat{b}u}{y}$$

- $\mu = 1$ corresponds to the certainty-equivalence controller
- $\mu = \beta^2/(1+\beta^2)$ corresponds to the cautious controller
- Dual controller for large N is:

$$\mu = \frac{\beta^2 - 0.56\beta}{\beta^2 + 0.08\beta + 2.2} + \left(\frac{1.9\beta}{\beta^4 + 1.7}\right)\frac{1}{\eta}$$

Dual Controller

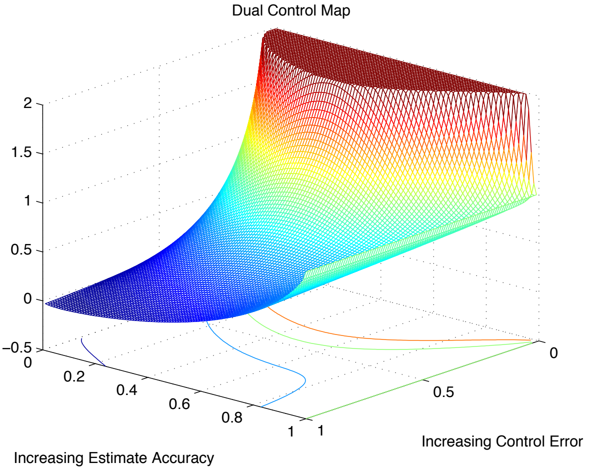


Figure: Dual control map

Properties of the Dual Controller

- Dual control finds the best compromise between
  - **boldness**
  - **caution**
  - **probing**
- Low uncertainty $\rightarrow$ boldness prevails
- Large uncertainty + large control error $\rightarrow$ caution prevails
- Large uncertainty + small control error $\rightarrow$ probing prevails

Implications for Adaptive Control

- The dual controller is in general **impossible** to compute
- Most current adaptive control methods **enforce** certainty equivalence
- Thus, learning is **passive** rather than **active**
- **Passive** learning is a shortcoming of current adaptive control methods
- Practical methods of active learning attractive for
  - Commissioning of adaptive controllers
  - Adaptive control of processes with rapidly time-varying dynamics