Analysis and Design of Hybrid AI/Control Systems

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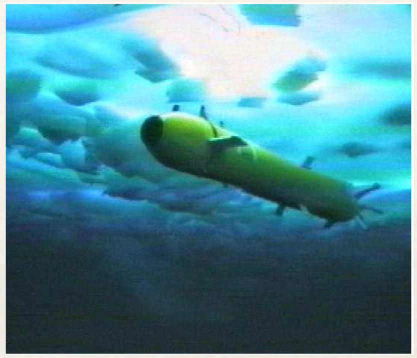
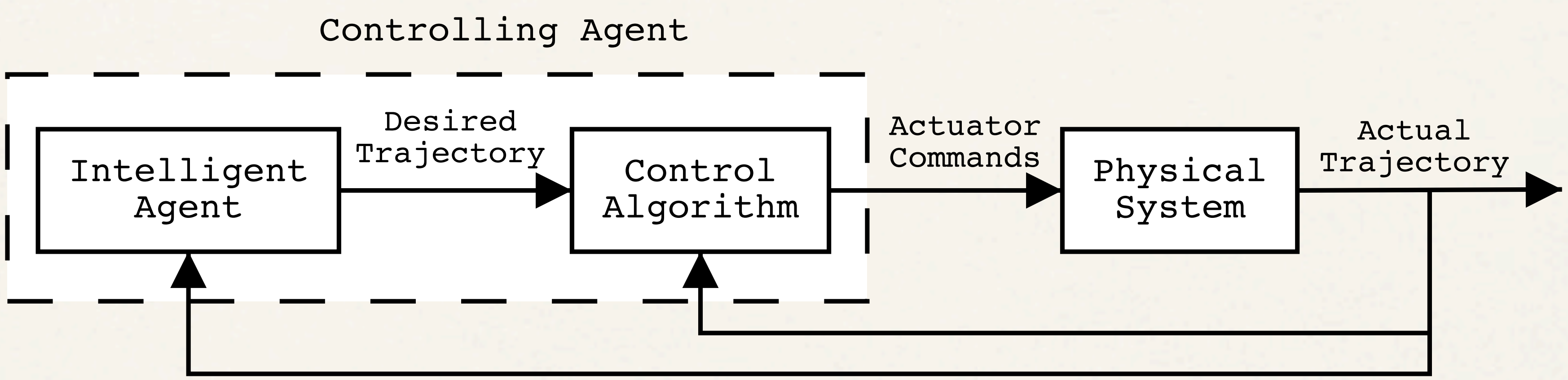
13 May 2011

Dynamically Complex Vehicles

- Increased deployment of complex autonomous systems
  - Unpiloted Aerial Vehicles
  - Autonomous Underwater Vehicles
  - Spacecraft
  - Robotic Manipulators (possibly mounted to one of the above)
- Dynamic are much much more complicated than standard laboratory (wheeled) mobile vehicles



Software Architecture

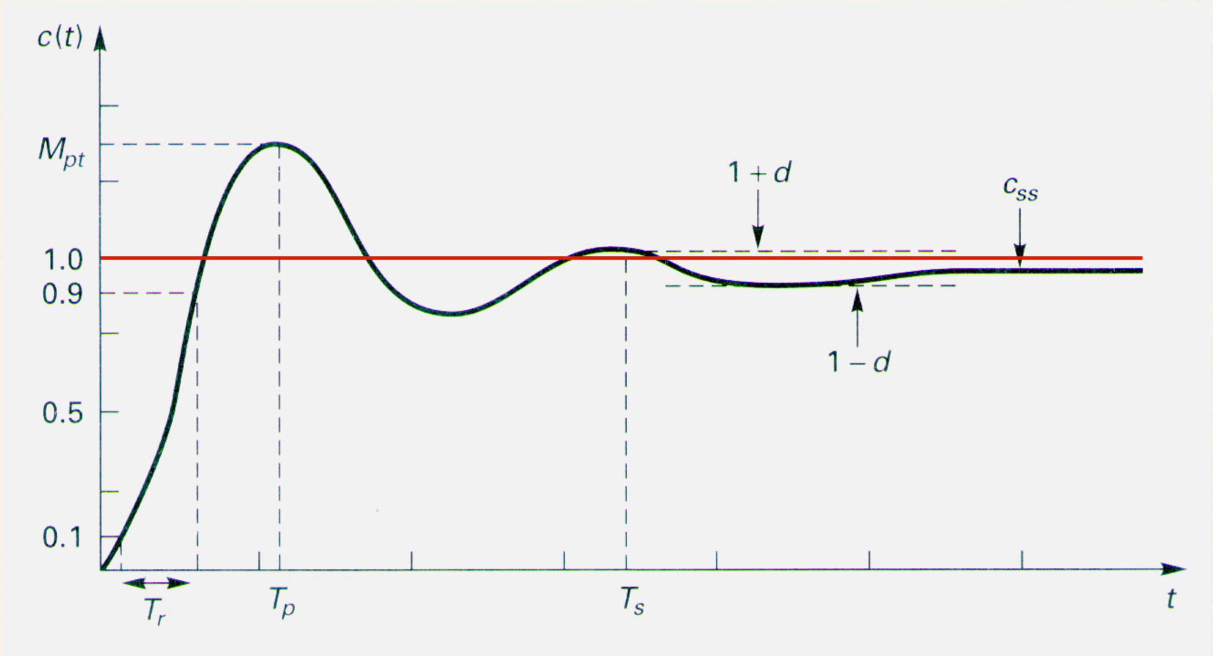


Tiered software architectures are useful for automating these systems:

- "High–level" intelligent agents produce trajectories/goals
- "Low–level" control algorithms execute trajectories
    - Controller simplifies the input/output behavior of the dynamical system as seen by the intelligent agent
    - Potentially makes agent's job easier — reduces scope of behaviors to be accounted for

Hybrid Systems Can Have Nontrivial Dynamics

- Control systems are often treated as a black box
- But the dynamics behavior of a coupled control algorithm / vehicle can be nontrivial
  - Nonzero settling time
  - Overshoot
  - Steady–state offsets
  - Imperfect tracking of complex trajectories



Typical step response, 2nd order linear system
Phillips and Harbor, *Feedback Control Systems*, p. 125

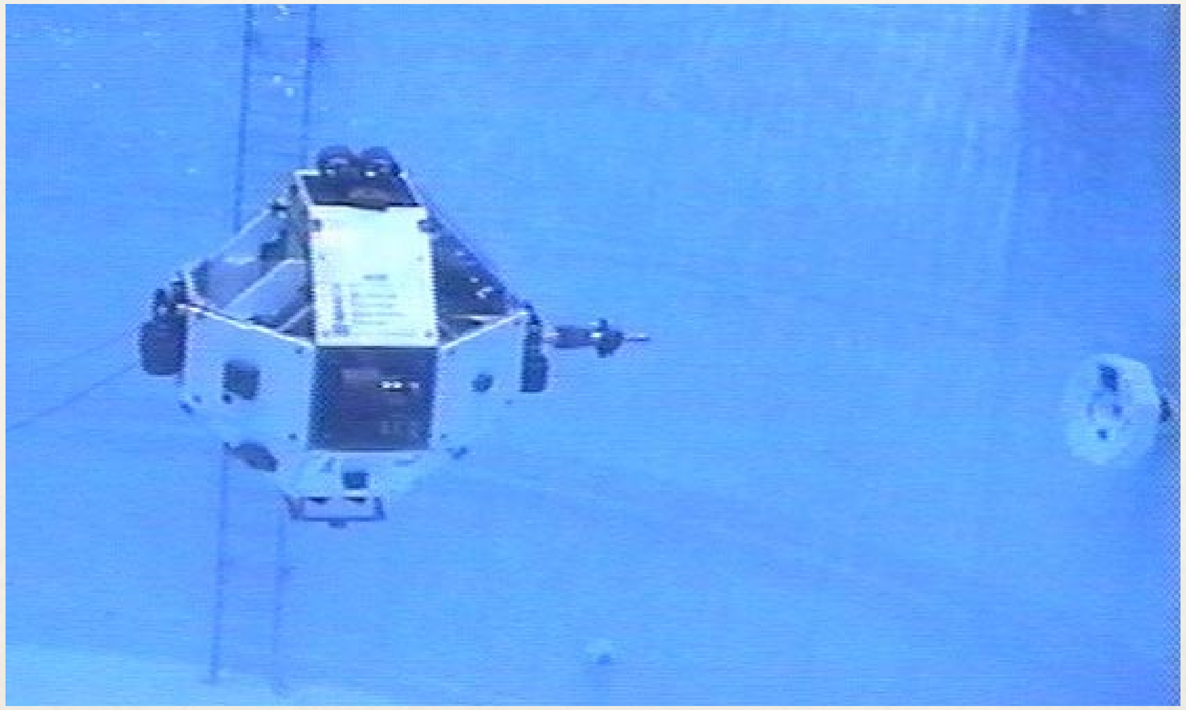
- **Claim**: As a result, undesirable behavior can occur when the controller and agent are linked in a feedback loop *even though* each module functions correctly in isolation

Insert stories here.

Analysis of a Hybrid System

- Research aim: develop an autonomous proximity operations spacecraft
- Testbed: MPOD, a neutral buoyancy spacecraft simulator
- Facility: University of Maryland's Neutral Buoyancy Research Facility

Recently named one of US' "five most awesome college labs" by Popular Science



MPOD Control Algorithms

Standard “PD” linear attitude control algorithm:

$$
\begin{aligned}
\tau_{PD} &= -K_d\tilde{\omega} - K_p\tilde{\epsilon} \\
&\equiv -K_d\sigma \\
\sigma &\triangleq \tilde{\omega} + \lambda\tilde{\epsilon} \;\equiv\; \tilde{\omega} + \frac{K_p}{K_d}\tilde{\epsilon}
\end{aligned}
$$

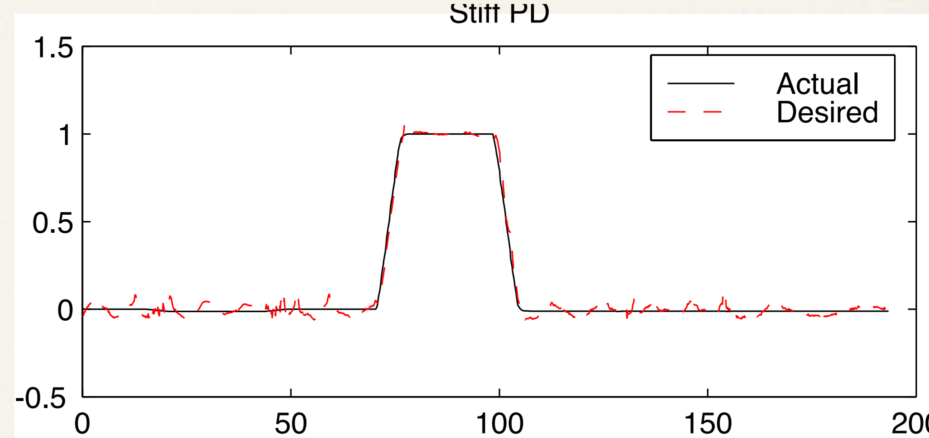
with

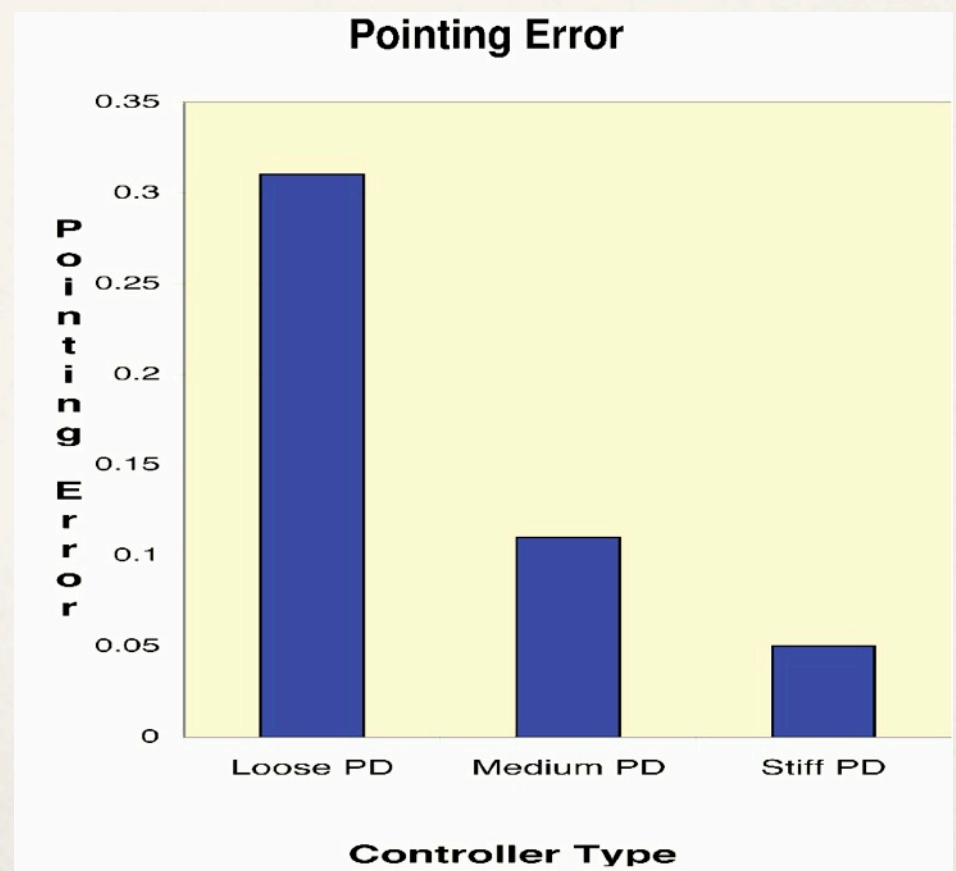
$\tilde{\epsilon}$	configuration error (here, attitude error)
$\tilde{\omega}$	velocity tracking error (here, angular velocity error)
K_p, K_d	proportional and derivative gains

Three gainsets of low, medium, and high stiffness

MPOD Control Algorithm Performance

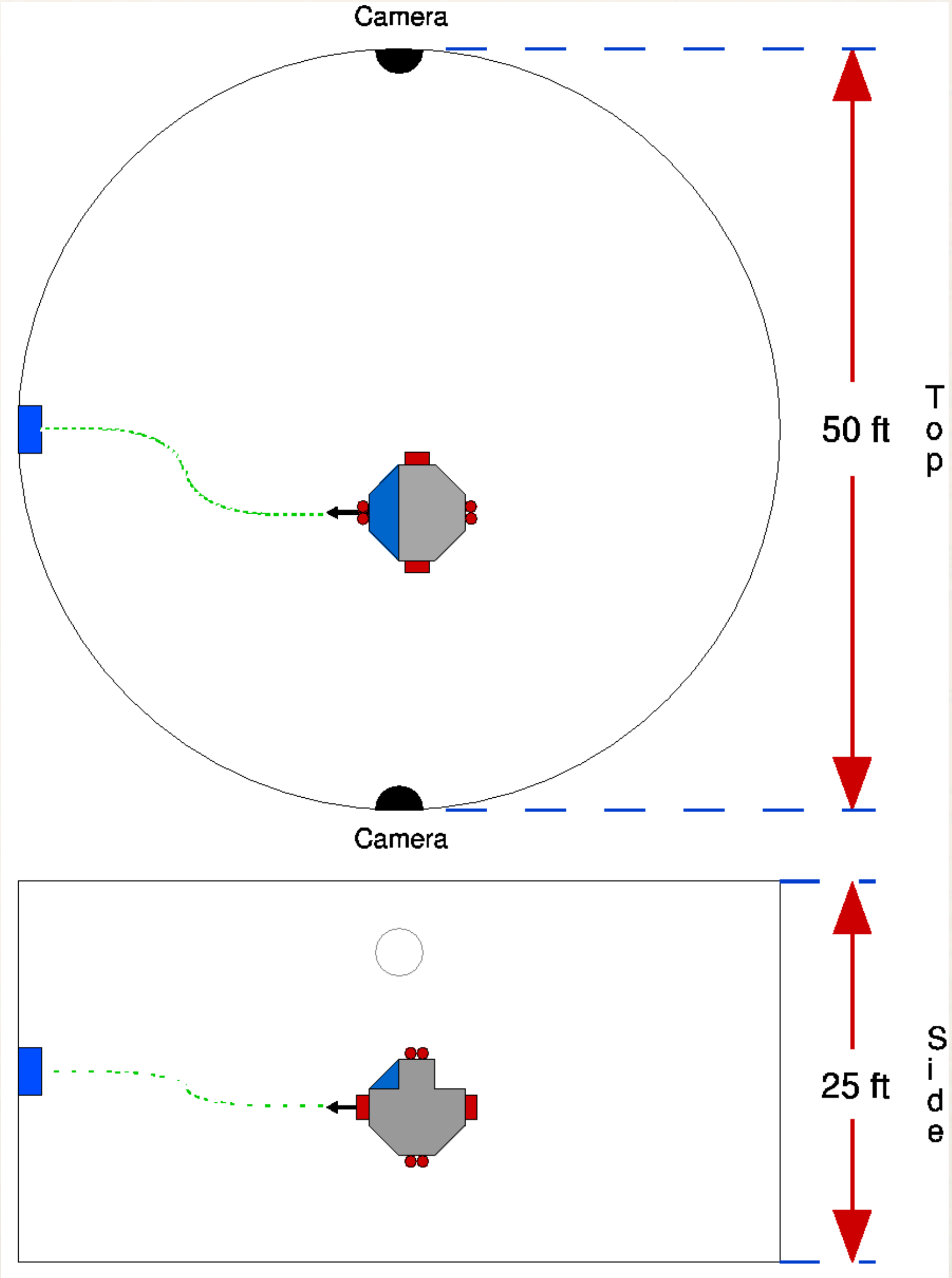
- Gainsets tuned to provide progressively faster responses
- Progressively lower tracking error
- Similar overshoot (≈7%)
- Good performance, as measured by classic linear controller performance metrics





Piloted Docking Task

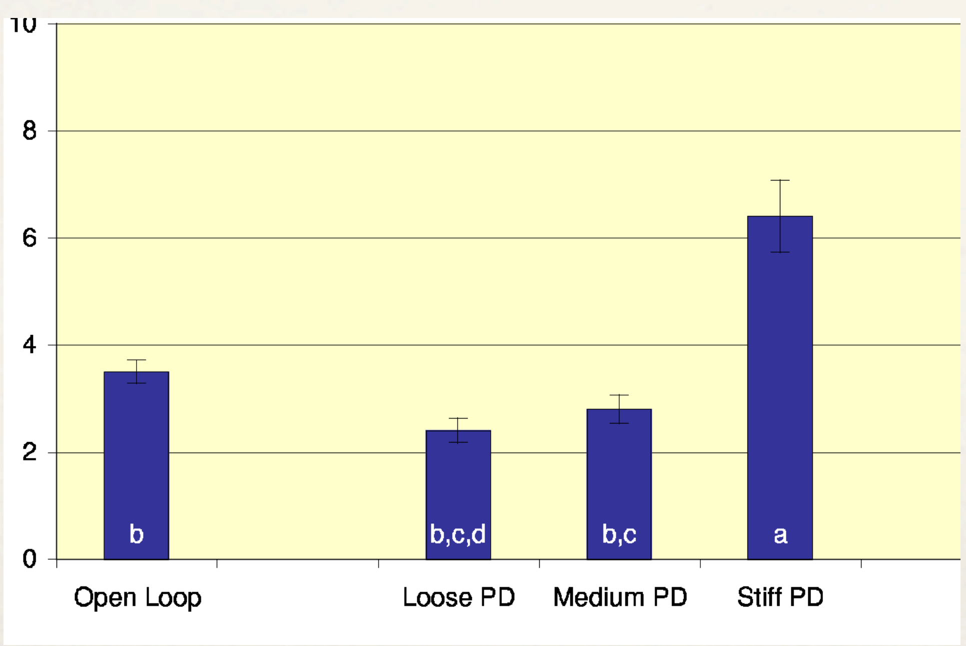
- Pilots instructed to fly MPOD from start position to hard dock with a rigid target
- Desired trajectories generated by human pilots
- Two 3–DOF joysticks, "smoothed" by 1st order low pass filter
- Each pilot flewMPOD to hard dock six times using each controller

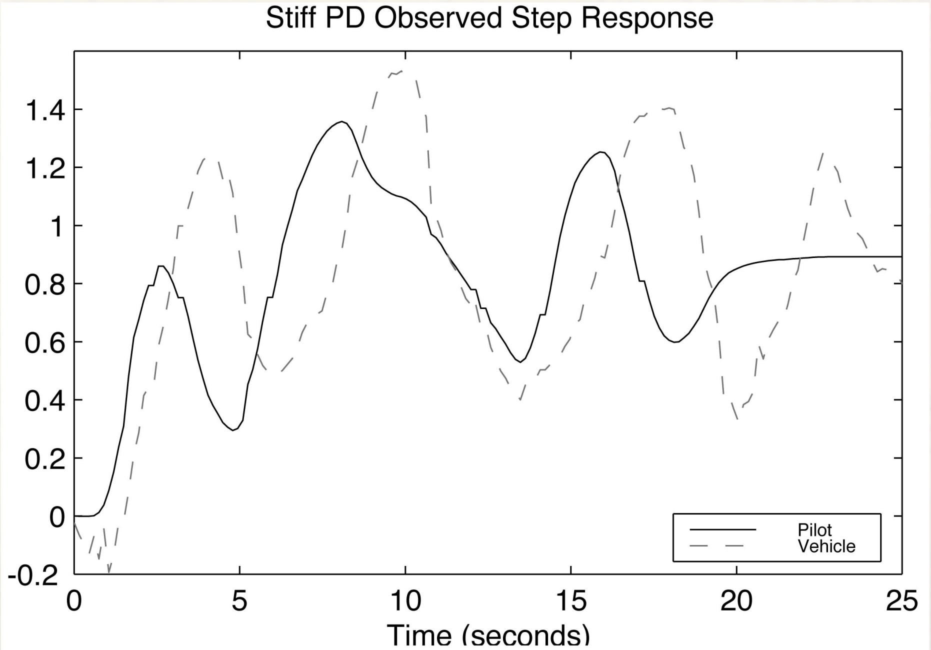


Pilot Performance

- Pilot performance strongly dependent on gainset
- "Stiff" PD controller exhibited worst pilot performance; pilot physical and mental workload far higher
- Strange oscillatory episodes observed with stiff PD controller

"Total Pilot Effort"





Pilot–Induced Oscillation

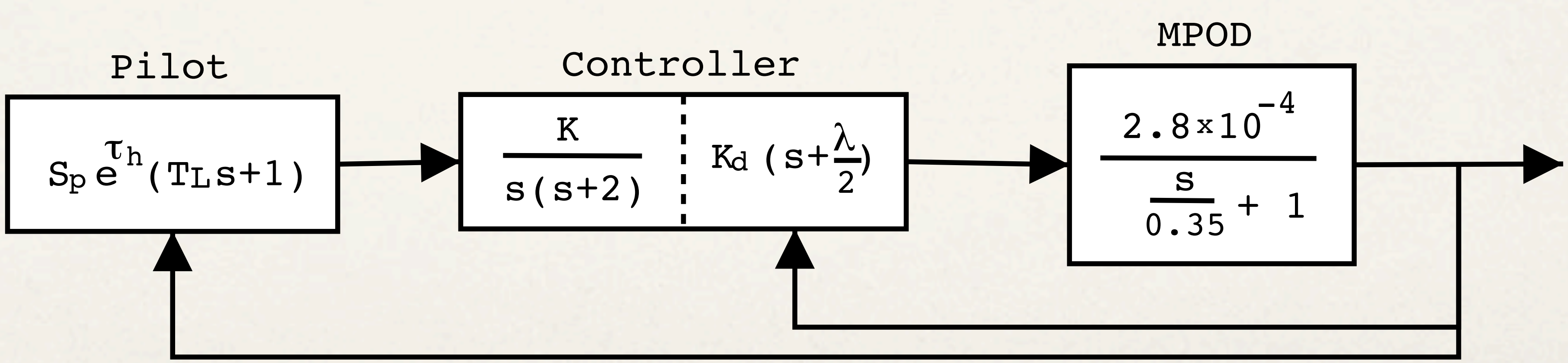
Predicting Undesirable Interactions

- Similar problem seen in aircraft industry: pilot–induced oscillations (PIO)
- Result of the interaction between the pilot (a non–mathematical system!) and a vehicle/control system
- Rapid oscillatory motion, often with catastrophic results
- Often seen with
  - Experienced pilots (including test pilots and astronauts)
  - Variety of aircraft: F—15, YF—22, MD–11, C–17, Space Shuttle, etc
  - Often when performing high precision operations such as landing
- Tools for analyzing system dynamical behavior are mathematical
- Most intelligent agents (including humans) are inherently non–mathematical

How do you mathematically analyze a non–mathematical system?

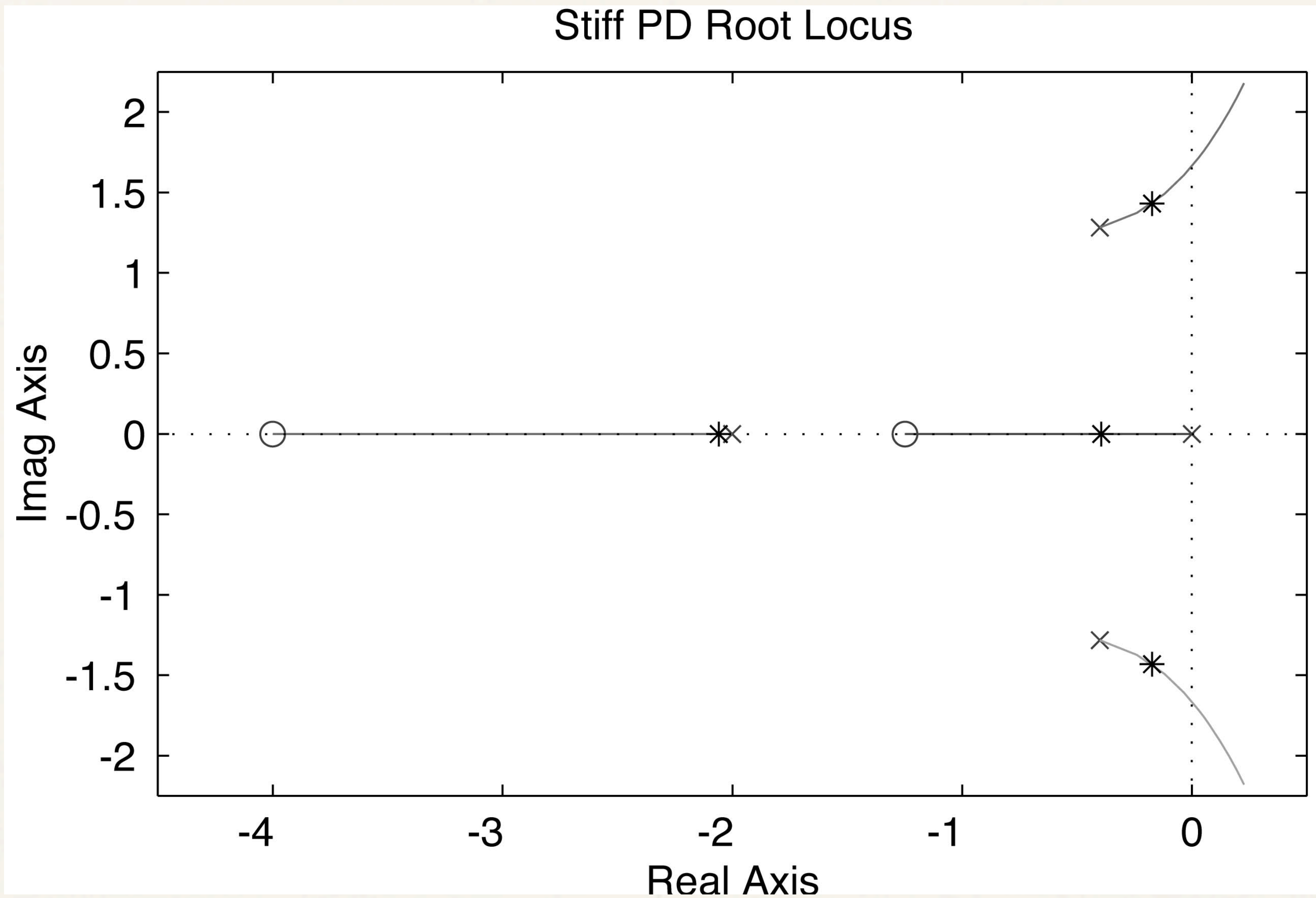
Mathematical Analysis of MPOD PIO

- Analysis of PIO requires mathematical models of vehicle, controller, and pilot
- Most widely accepted pilot model: the "crossover model"*
  - Represents actions of pilot performance setpoint maintenance task (e.g. maintaining a heading)
  - Pilot acts as a linear PD controller with time delay



* McRuer, *et al*, "A Review of Quasi-Linear Pilot Models", IEEE Transactions on Human Factors in Electronics , Sept. 1967.

PD Controllers Can Lead To PIO



- Root locus plot indicates instability for stiff PD system with large pilot gains
- Apparent C.L. pole locations (represented by $\ast$'s) indicate highly oscillatory system

Preventing Undesirable Interactions

What can be done to prevent undesirable interactions?

Idea —
Linear control algorithms are simple:

$$\tau_{PD} = -K_d \sigma$$

But their closed–loop dynamic are complex:

$$G_{CL}(s) = \frac{K}{s(s+2)} \times \frac{\omega_n^2 \left(\frac{2}{\lambda} s + 1\right)}{s^2 + 2\zeta\omega_n s + \omega_n^2}$$

Is there any way to simplify the closed–loop behavior?

Control Algorithms With Better Performance

Some nonlinear control algorithms exhibit better performance:

$$\begin{aligned}\tau_{NL} &= -K_d\sigma + H(\epsilon)\dot{\omega_r} + C(\epsilon,\omega)\,\omega_r + E(\epsilon,\omega)\\ \omega_r &= \omega - \sigma\end{aligned}$$

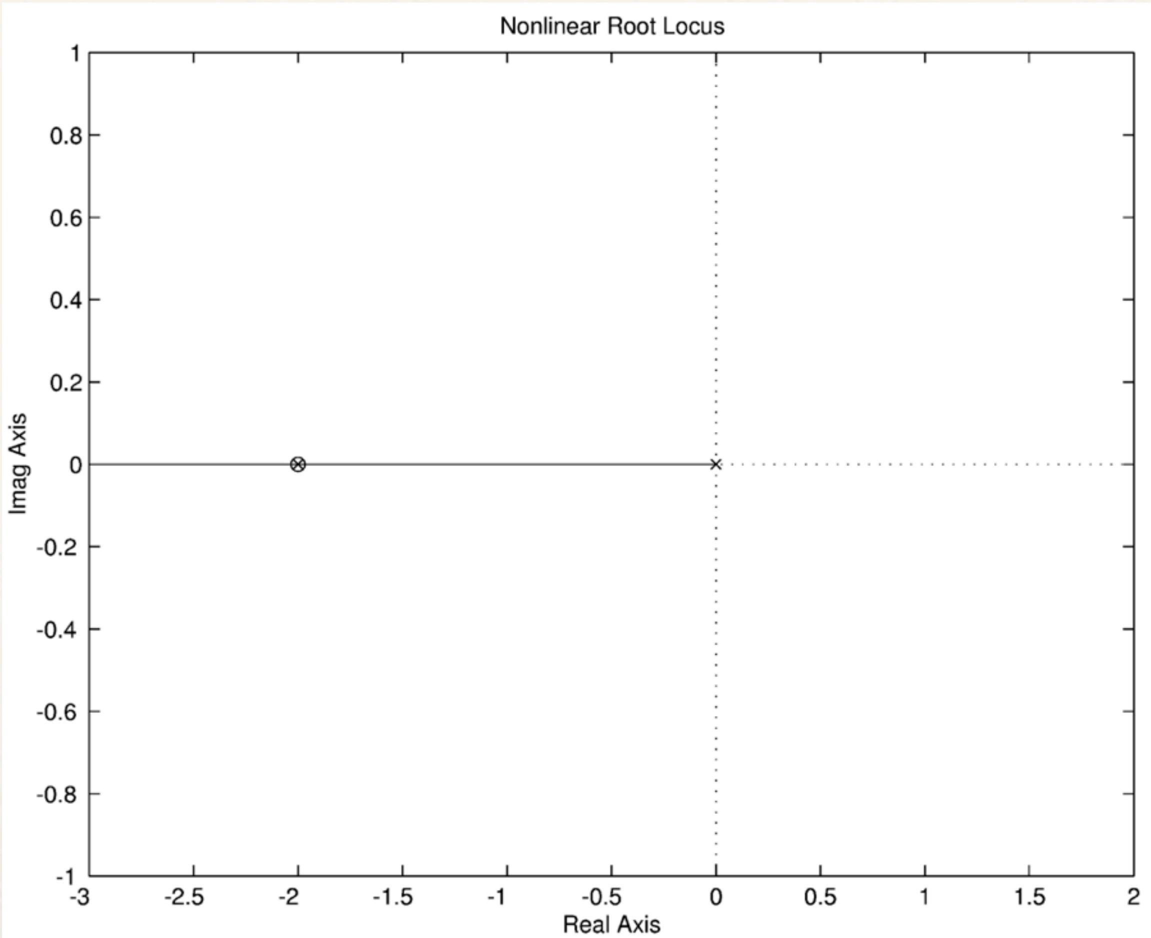
where

H — Inertia matrix
C — Coriolis and centripetal forces
E — environmental forces (drag, gravity, etc.)

(theoretically) guarantees asymptotically perfect tracking of arbitrarily complex desired trajectories (assuming continuous second derivatives).

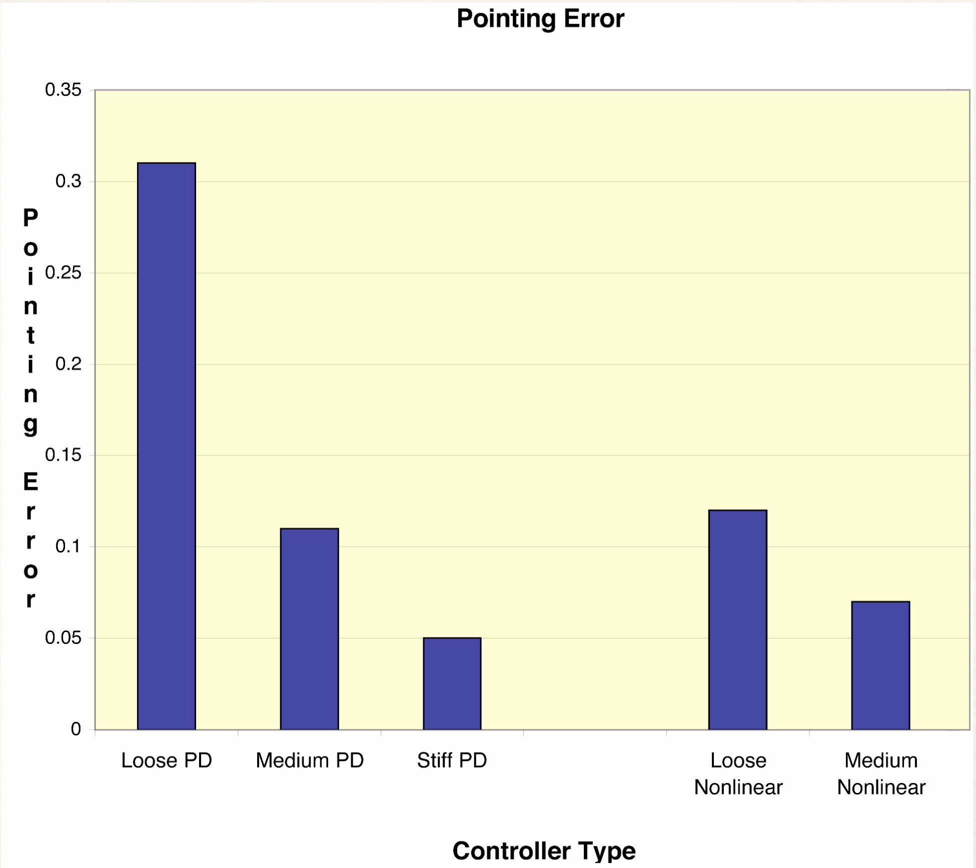
Nonlinear Controller Seems to Eliminate PIO

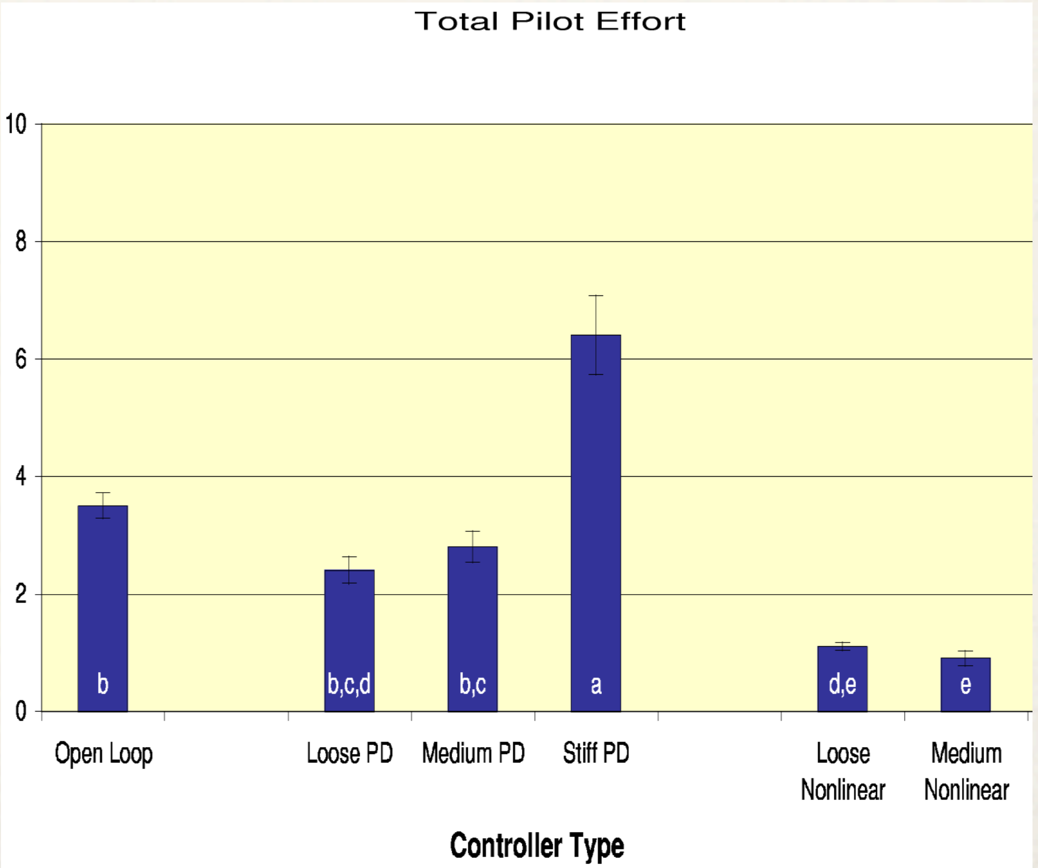
- Asymptotically perfect tracking (theoretically) implies that controller causes closed--loop dynamics to become trivial
- Root--locus plot always stable



N.L. Control → Better Pilot Performance

- Nonlinear controllers reduce tracking error moderately...
- But they improve pilot performance a lot.





What's The Difference?

Linear control algorithms are simple:

$$\tau_{PD} = -K_d \sigma$$

But they lead to complex closed–loop dynamics:

$$G_{CL}(s) = \frac{K}{s(s+2)} \times \frac{\omega_n^2 \left(\frac{2}{\lambda} s + 1\right)}{s^2 + 2\zeta\omega_n s + \omega_n^2}$$

Nonlinear control algorithms are more complex:

$$\tau_{NL} = -K_d \sigma + H(\epsilon)\, \dot{\omega}_r + C(\epsilon, \omega)\, \omega_r + E(\epsilon, \omega)$$

But they exhibit much simpler closed–loop dynamics:

$$G_{CL}(s) = \frac{K}{s(s+2)}$$

Conclusions

- Humans are the "gold standard" of intelligent agents, but unexpected behaviors can emerge even in piloted systems
- Similar behaviors can certainly emerge from more autonomous tiered systems
- Initial claim is verified:
  validating hardware/software components in isolation is *not* sufficient to guarantee desired performance

Lessons Learned

- Tools for analyzing complex software systems are not well developed
- But...
- Taking PIO analysis as inspiration, mathematically approximating non–mathematical systems can be effective and give important insights into system behavior
- System behavior is greatly simplified when individual component input/output behavior is as simple as possible
  - Simple *components* often do not lead to simple *behaviors* or simple *interactions*
- Differential equations are your friends