Smart Control Algorithm for 2-DOF Helicopter

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Outline

Introduction

- Helicopter are important for short-distance travel
  - air-sea rescue
  - fire fighting
  - traffic control
  - tourism
- Purpose of control system
  - resistance to turbulence
  - enable use of mobile device
- Which is better?
  - Optimal Control (Linear Quadratic Regulator)
  - Optimal Noise Resistant Control (Linear Quadratic Gaussian)
  - Machine Learning (Approximate Dynamic Programming)

Demonstration

Introduction

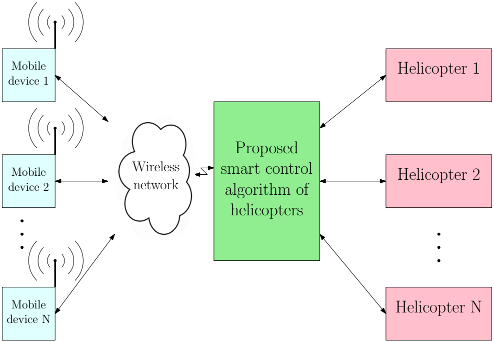

Figure 1: General high-level system architecture

Introduction

- This project will:
  - use a pair of 2-DOF (2-degrees-of-freedom) mechatronics platforms
  - implement control algorithms on embedded system
  - use mobile device for user control
  - encourage research
  - serve as an educational tool

Outline

Various control techniques have been proposed for 2-DOF helicopters such as:

- Sliding mode control [1]
- Fuzzy Logic control [2] [3] [4]
- Data-driven Adaptive Optimal Output-feedback control [5]
- Decentralized discrete-time neural control [6]

These control techniques employ advanced mathematics that are difficult to implement on embedded systems.

Outline

Background Study

Modeling a 2-DOF Helicopter

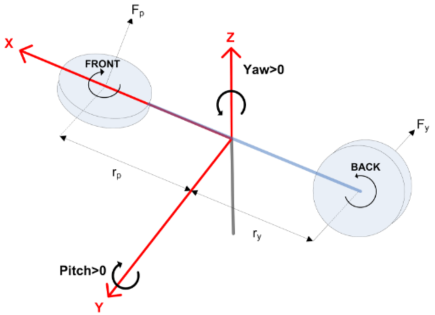

Figure 2: Model of a 2-DOF helicopter

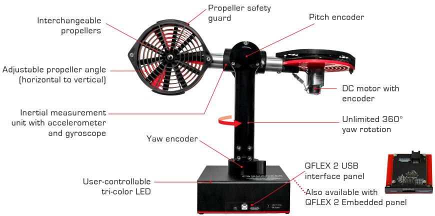

Figure 3: Quanser Aero

- Characterized by fixed base
  - Can change 2 of 3 possible orientations...
    - Pitch (θ)
    - Yaw (ψ)
    - *Not Roll*
  - and cannot change position
    - x direction
    - y direction
    - z direction

- Motors are attached to the propellers to create thrust due to air resistance
  - Main - changes pitch angle
  - Tail - changes yaw angle
- Torque due to rotation also creates a force on opposite axes

Due to the efficiency of the Quanser Aero, we can create a linearized system model:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t), \text{ such that} \tag{1}$$

$$\begin{bmatrix} \dot{\theta} \\ \dot{\psi} \\ \ddot{\theta} \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & -K_{sp}/J_p & -D_p/J_p & 0 \\ 0 & 0 & 1 & -D_y/J_y \end{bmatrix} \begin{bmatrix} \theta \\ \psi \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ K_{pp}/J_p & K_{py}/J_p \\ K_{yp}/J_y & K_{yy}/J_y \end{bmatrix} \begin{bmatrix} V_p \\ V_y \end{bmatrix}$$

- K_{sp} - being the stiffness of the axes
- K_{pp} - pitch motor thrust constant
- K_{py} - thrust constant acting on the pitch angle from the yaw motor
- K_{yp} - thrust constant acting on the yaw angle from the pitch motor
- K_{yy} - yaw motor thrust constant
- J_p - moment of inertia about pitch axis
- J_y - moment of inertia about yaw axis
- D_p - viscous damping of the pitch axis
- D_y - viscous damping of the yaw axis

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1. Employ state-space representation of 2-DOF helicopter:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$

2. Use state feedback law

$$\mathbf{u} = -\mathbf{K}\mathbf{x}$$

to minimize the quadratic cost function:

$$J(\mathbf{u}) = \int_0^{\infty} (\mathbf{x}^T\mathbf{Q}\mathbf{x} + \mathbf{u}^T\mathbf{R}\mathbf{u} + 2\mathbf{x}^T\mathbf{N}\mathbf{u})\mathrm{dt}$$

3. Find the solution **S** to the Riccati equation

$$\mathbf{A}^T\mathbf{S} + \mathbf{S}\mathbf{A} - (\mathbf{S}\mathbf{B} + \mathbf{N})\mathbf{R}^{-1}(\mathbf{B}^T\mathbf{S} + \mathbf{N}^T) + \mathbf{Q} = 0$$

4. Calculate gain, **K**

$$\mathbf{K} = \mathbf{R}^{-1}(\mathbf{B}^T\mathbf{S} + \mathbf{N}^T)$$

Background Study

Control Algorithm Overview - Optimal Noise Resistant Control

- Utilizes gain calculated in LQR
- Added Kalman filter to reduce external disturbances to the system

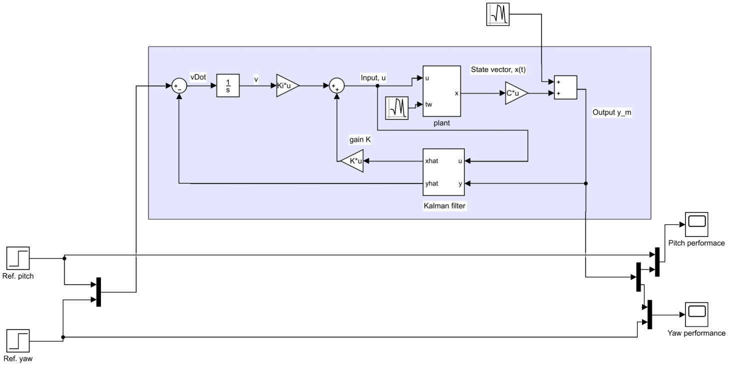

Figure 4: Noise resistant 2-DOF helicopter model

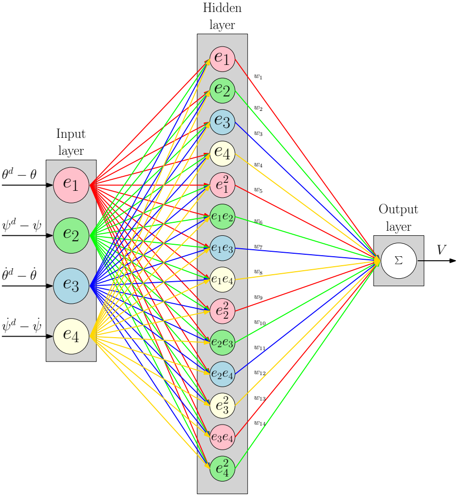

Figure 5: Neural network

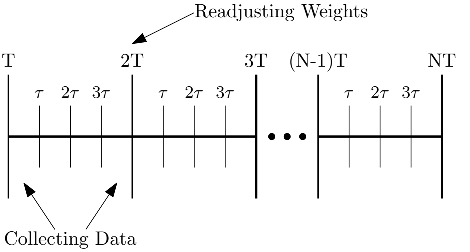

Figure 6: Neural network sampling

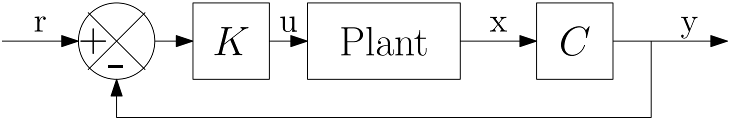

Figure 7: Optimal P type controller [servo]

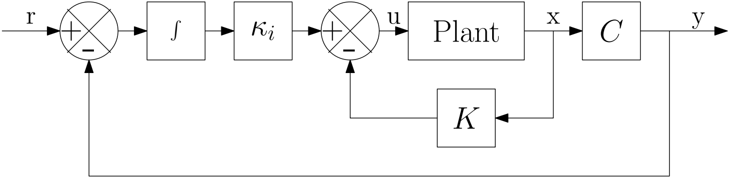

Figure 8: Optimal PI type controller [servo]

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Background Study
Prior Work

- extensive modeling & simulations
- implementation of two motion control algorithms (LQR & ADP)
- one helicopter

Outline

Subsystem Level Functional Requirements

Block Diagram

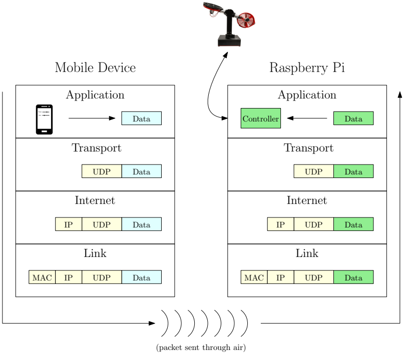

Figure 9: Communication model

Subsystem Level Functional Requirements
Block Diagram

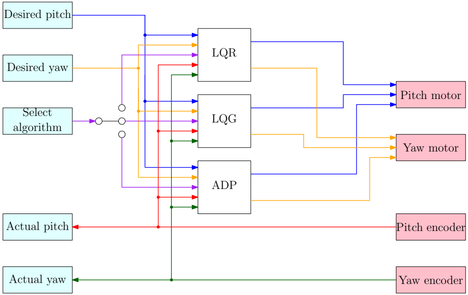

Figure 10: Low level smart control diagram

Outline

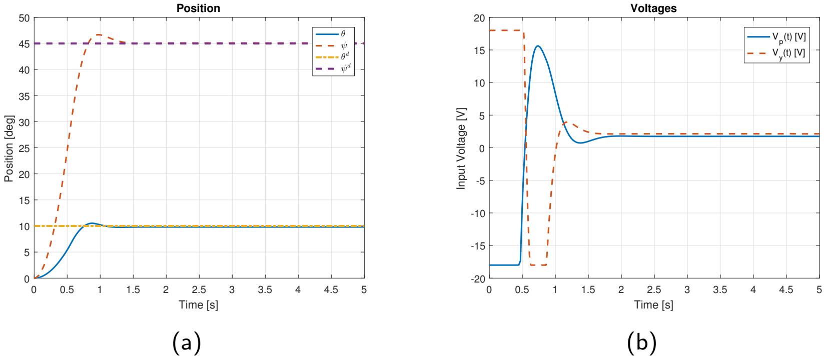

Figure 11: Optimal control (P type controller) simulation (a) position and (b) voltage w/ step input

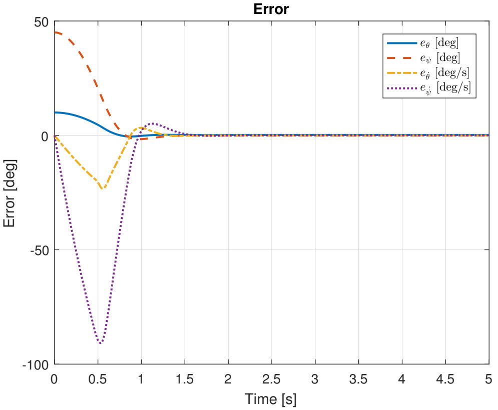

Figure 12: Optimal control (P type controller) simulation w/ constant signal

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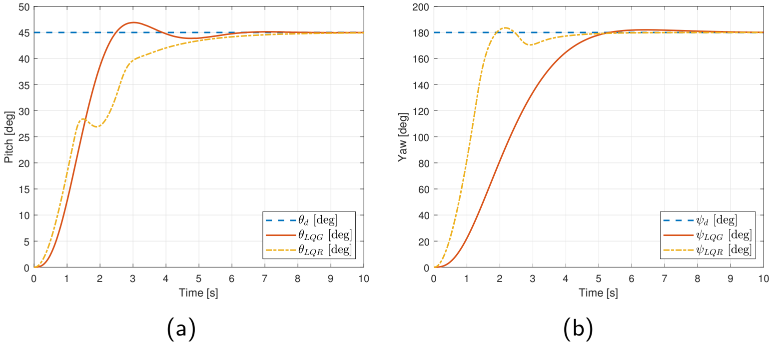
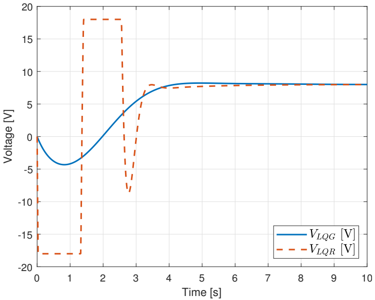


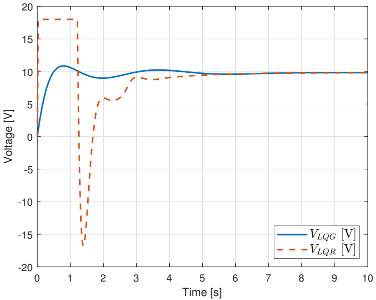
Figure 13: Noise resistant control vs optimal control (PI type controller) simulation (a) pitch position and (b) yaw position w/ step input

Simulation

Noise Resistant and Optimal Control (PI Type Controller) Simulation



(a)



(b)

Figure 14: Noise resistant control vs optimal control (PI type controller) simulation (a) pitch voltage and (b) yaw voltage w/ step input

Outline

Optimal Control P and PI Type Controller USB

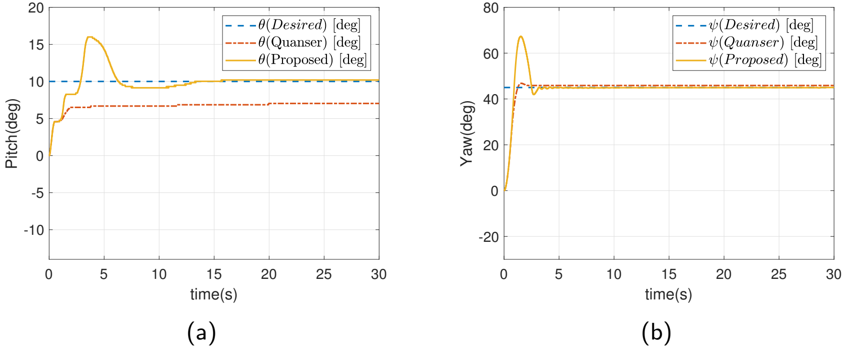


Figure 15: USB implementation comparison between optimal control (P type controller) and optimal control (PI type controller) for (a) pitch and (b) yaw configurations w/ step input

Implementation

Optimal Control P and PI Type Controller USB

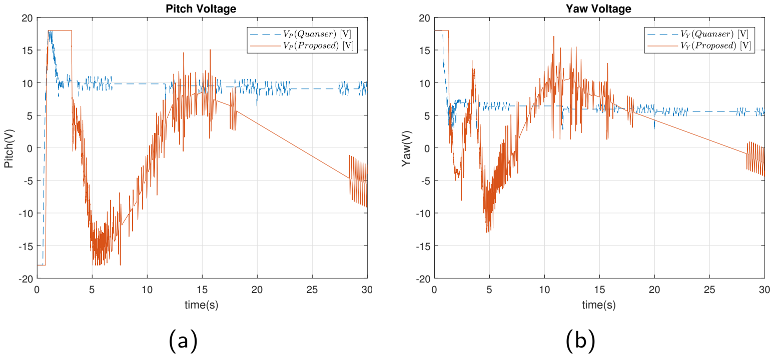


Figure 16: USB implementation comparison between optimal control (P type controller) and optimal control (PI type controller) for (a) pitch and (b) yaw voltages w/ step input

	Pitch Step	Yaw Step
LQR P	3.5025	5.8502
LQR PI	1.2349	5.5058
Improvement	64.7437%	0.5408%
	Pitch Square	**Yaw Square**
LQR P	6.2819	20.4623
LQR PI	6.9206	21.0709
Improvement	-10.1675%	-2.9740%
	Pitch Sine	**Yaw Sine**
LQR P	4.2469	2.8644
LQR PI	1.3383	1.7852
Improvement	68.4872%	63.2998%

Table 1: Root mean squared error

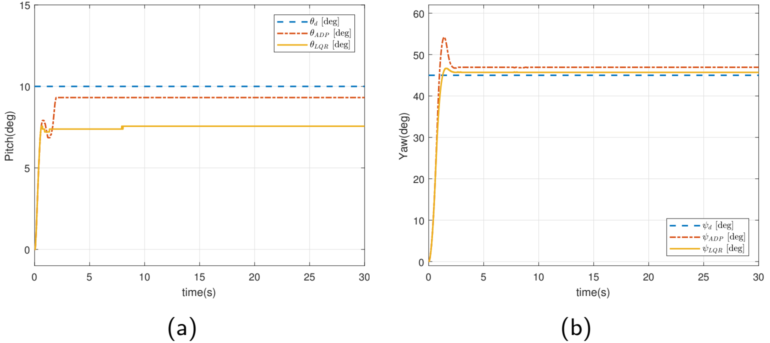


Figure 17: USB implementation comparison between machine learning and optimal control (P type controller) for (a) pitch and (b) yaw orientations w/ step input

Implementation

Machine Learning and Optimal Control (P Type Controller) USB

	Pitch Step	Yaw Step
ADP P	1.3067	6.1991
LQR P	3.5025	5.8502
Improvement	62.6923%	-5.9638%
	Pitch Square	**Yaw Square**
ADP P	6.5790	21.1923
LQR P	6.2819	20.4623
Improvement	-4.7294%	-0.3567%
	Pitch Sine	**Yaw Sine**
ADP P	2.1877	3.6307
LQR P	4.2469	2.8644
Improvement	48.4871%	-26.7525%

Table 2: Root mean squared error

Outline

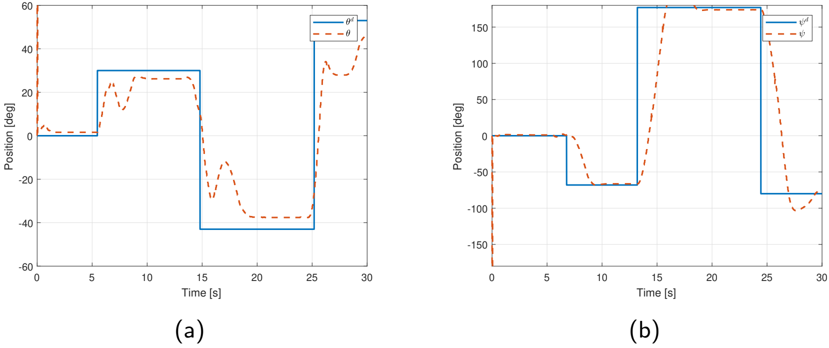


Figure 18: Optimal control (P type controller) (a) pitch position and (b) yaw position w/ input from mobile phone

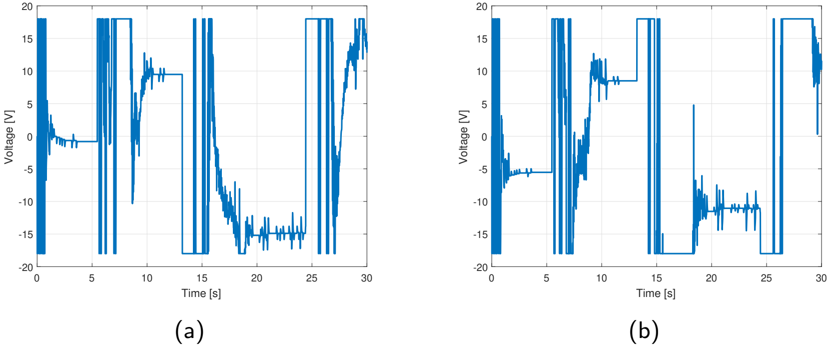


Figure 19: Optimal control (P type controller) (a) pitch voltage and (b) yaw voltage w/ input from mobile phone

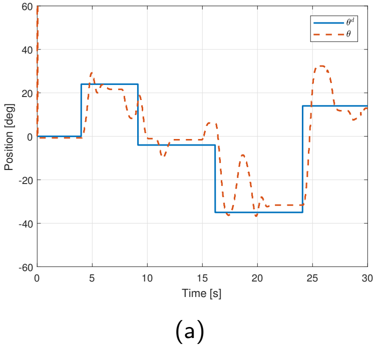


Figure 20: Machine learning (a) pitch position and (b) yaw position w/ input from mobile phone

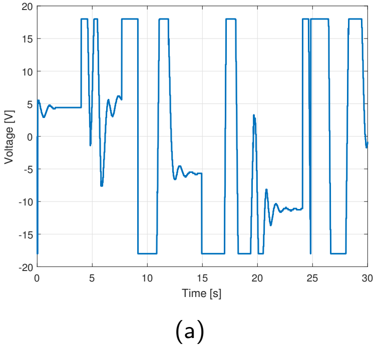


Figure 21: Machine learning (a) pitch voltage and (b) yaw voltage w/ input from mobile phone

Future Directions

- Discretization of System
- Digital Compass
- Enhanced Smart Control

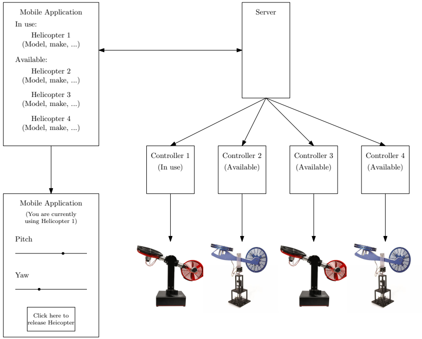


Figure 22: Enhanced smart control

- Implmentation on 6-DOF Helicopter

Summary

- Embedded implementation of control algorithms
- Mobile interface
- PI type control improves steady-state error
- Machine Learning is best when system parameters are unknown or time-varient

Acknowledgement

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For Further Reading I

[1] Q. Ahmed, A. I. Bhatti, S. Iqbal, and I. H. Kazmi, "2-sliding mode based robust control for 2-dof helicopter," in *2010 11th International Workshop on Variable Structure Systems (VSS)*, June 2010, pp. 481–486.

[2] W. Chang, J. Moon, and H. Lee, "Fuzzy model-based output-tracking control for 2 degree-of-freedom helicopter," *Journal of Electrical Engineering Technology*, vol. 12.00, no. 1, pp. 1921–1928, 2017, quanser product(s): 2 DOF Helicopter.

[3] E. Kayacan and M. Khanesar, "Recurrent interval type-2 fuzzy control of 2-dof helicopter with finite time training algorithm," in *IFAC-PapersOnLine*, July 2016, pp. 293–299.

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For Further Reading II

[4] P. Mndez-Monroy and H. Bentez-Prez, “Fuzzy control with estimated variable sampling period for non-linear networked control systems: 2-dof helicopter as case study,” *Transactions of the Institute of Measurement*, vol. no. 7, October 2012.

[5] W. Gao and Z. P. Jiang, “Data-driven adaptive optimal output-feedback control of a 2-dof helicopter,” in *2016 American Control Conference (ACC)*, July 2016, pp. 2512–2517.

[6] M. Hernandez-Gonzalez, A. Alanis, and E. Hernandez-Vargas, “Decentralized discrete-time neural control for a quanser 2-dof helicopter,” *Applied Soft Computing*, 2012.