Smart Control of 2 Degree of Freedom Helicopters

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Objective and Contribution

Objective

- Develop a platform allowing mobile devices to control
- the motion of a group of helicopters **Contribution**
- Determine trade-offs between traditional control techniques and machine learning
- Multi-Helicopter Application

Applications

- Teleoperation approach to search and rescue
- Aerial turbulence resistance

Problem Setup Helicopter 1 Helicopter 2 Helicopter N

Figure 1: High level architecture of the proposed system.

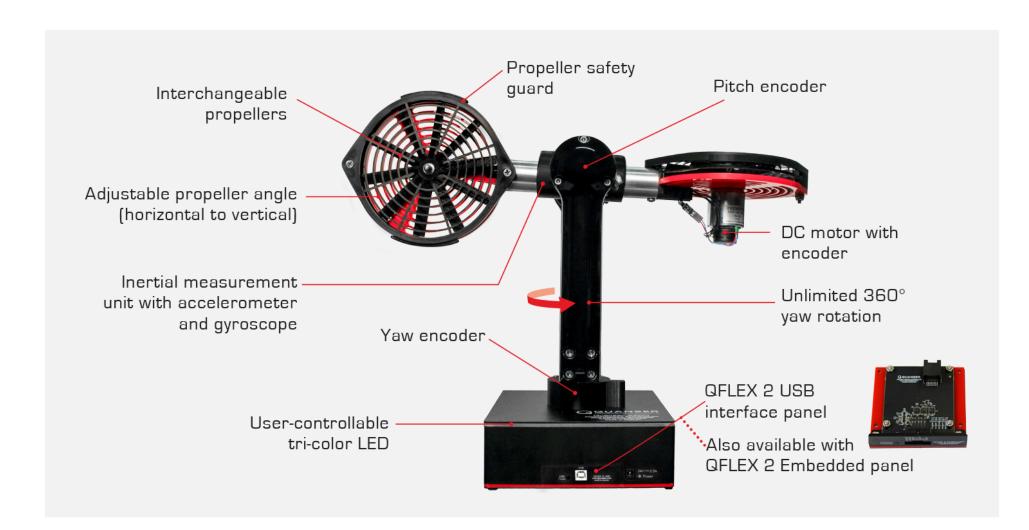
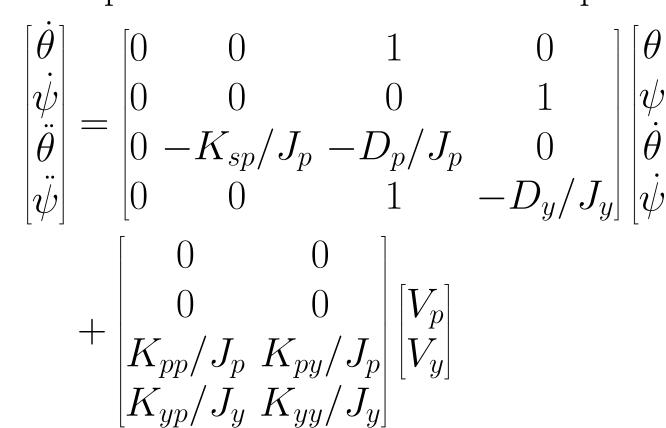


Figure 2: 2-DOF helicopter (Quanser Aero).

• State-space representation of 2-DOF helicopter



Motion (Trajectory) Control Algorithm

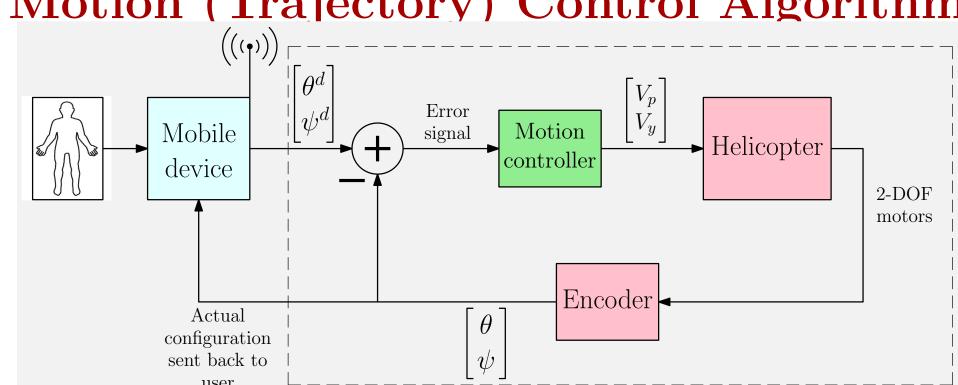


Figure 3: A desired orientation is given by a user. The difference between this input and the actual position is calculated. The controller the calculates the proper amount of voltage to apply to the DC motors.

• 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:

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

3 Find the solution S to the Riccati equation

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

• Calculate gain, **K**

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

Optimal Noise Resistant Control Algorithm

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

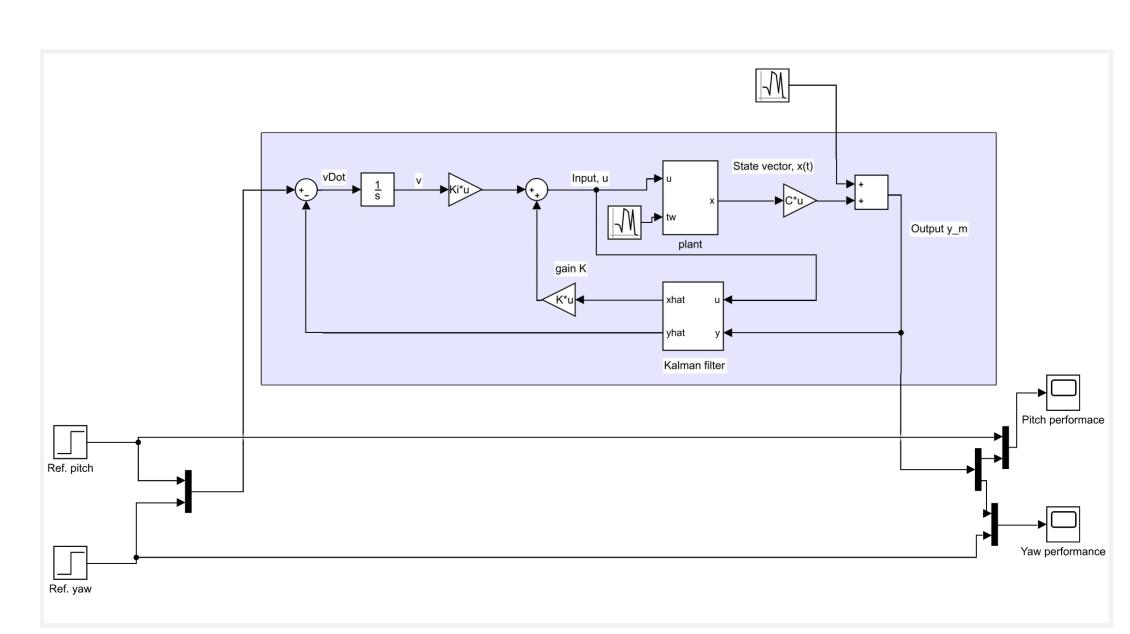


Figure 4: Noise resistant 2-DOF helicopter model.

Reinforcement Learning Algorithm - Uses neural network based on difference between desired

and actual orientation to determine optimal gain

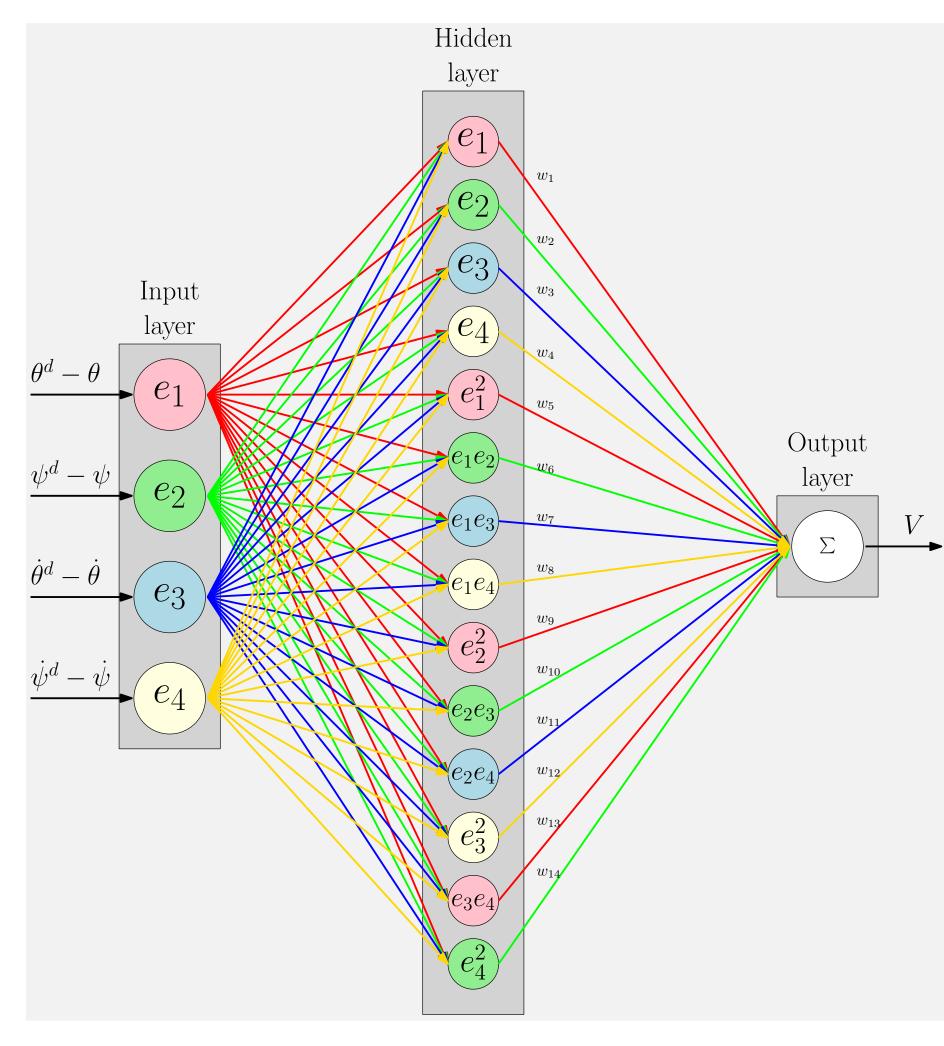


Figure 5: ADP Neural Network

Simulation Results $\begin{array}{c|c} & V_{LQG} \text{ [V]} \\ \hline - & - & V_{LQR} \text{ [V]} \end{array}$ V_{LQG} [V] - - - V_{LQR} [V]

Figure 6: A comparison between LQG and LQR control for a step input is shown for (a) the main rotor and (b) the tail rotor and the corresponding voltages in (c) and (d)

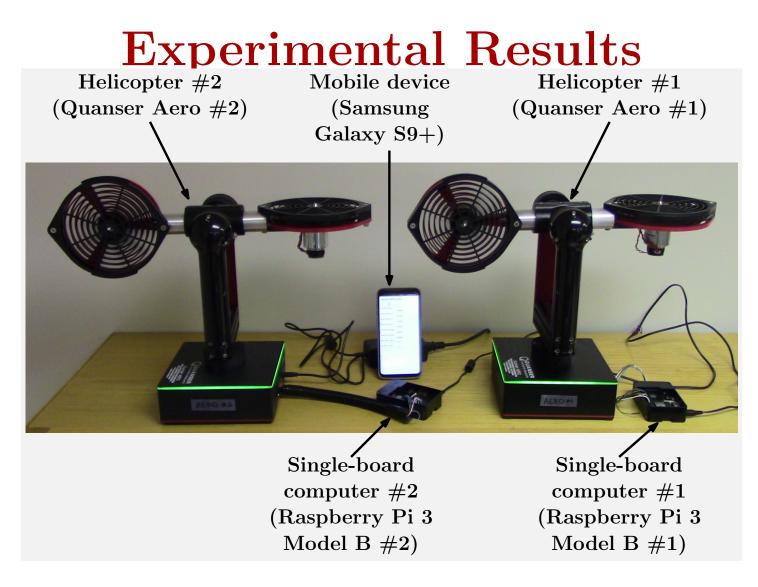


Figure 7: Experimental Setup

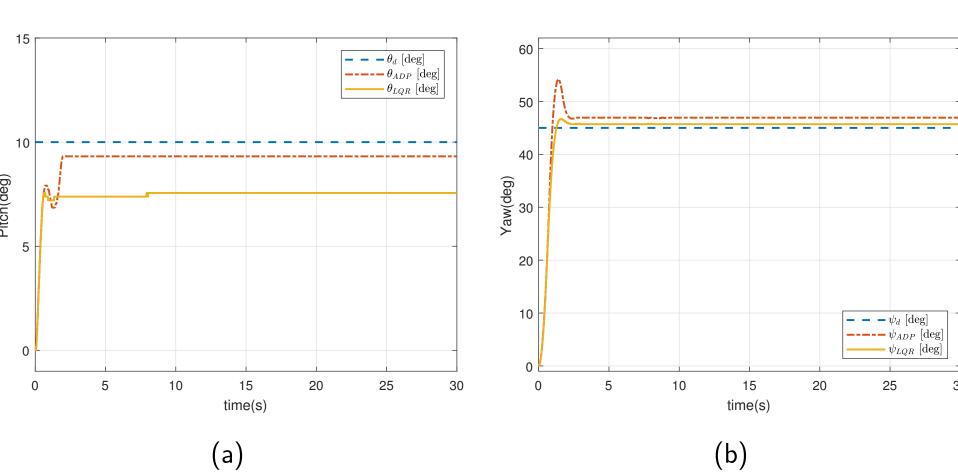


Figure 8: ADP experimental results for (a) the main rotor and (b) the tail rotor given a step input

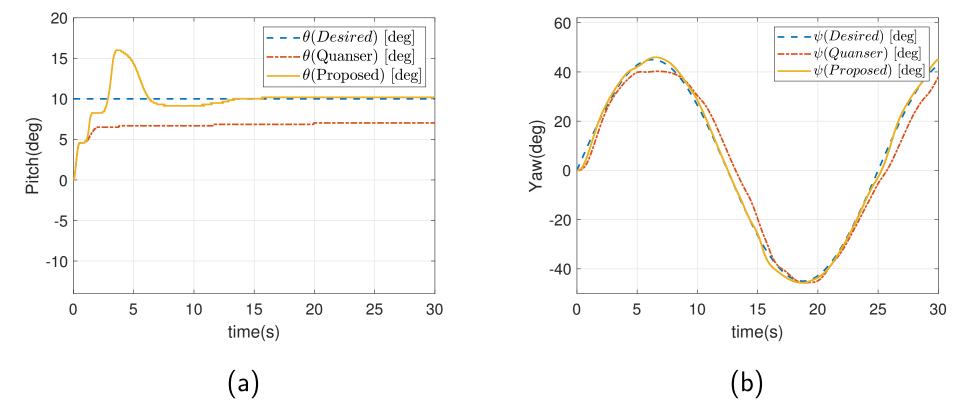
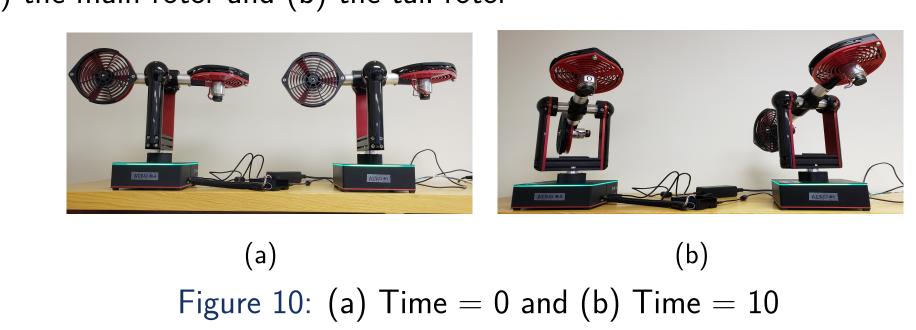


Figure 9: Comparison between P and PI control for a step input is shown for (a) the main rotor and (b) the tail rotor



Conclusion and Future Work

- Model-based reinforcement learning technique (ADP) is useful when system model is unknown
- Implement PI controller for ADP algorithm
- Use digital compass to increase accuracy of orientation and help identify initial position