Development of a Deep Recurrent Neural Network Controller for Flight Applications

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Outline

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- DLC Limitations and Research Goals
- Background – Direct Policy Search
- Flight Vehicle (Plant) Model
- Architecture - Deep Learning Flight Control
- Optimization - Deep Learning Controller
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Inspiration

Deep Learning (DL):

- Dominant performance in multiple machine learning areas:

  Speech, language, vision, face recognition, etc.
- Replaces time consuming typical hand-tuned machine learning methods

Key Breakthroughs in establishing Deep Learning:

- Optimization methods: Stochastic Gradient Descent, Hessian-free, Nestorov's momentum, etc.
- Deep recurrent neural network (RNN) architectures: deep stacked RNN, deep bidirectional RNN, etc.
- RNN Modules: Gated Recurrent Unit (GRU) and Long Short Term Memory (LSTM)
- Automatic gradient computation
- Parallel computing

Connecting Deep Learning to Control:

- Guided Policy Search – uses trajectory optimization to assist policy learning (S. Levine and V. Koltun, 2013)
- Hessian-free Optimization– deep RNN learning control with uncertainties (I. Sutskever, 2013)

DLC Limitations and Research Goals

Policy Search/Deep Learning (DL) Control Limitations:

- Large number of computations at each time step
- No standard training procedures for control tasks
- Few analysis tools for deep neural network architectures
- Non-convex form of optimization provides few guarantees
- Lack of research in optimization with regards to robustness
- Most RL approaches use the combination of modeled dynamics and real-life trial to tune policy (not useful for flight control)

Research Goals

Develop a robust deep recurrent neural network (RNN) controller with gated recurrent unit (GRU) modules for a highly agile high-speed flight vehicle that is trained using a set of sample trajectories that contain disturbances, aerodynamic uncertainties, and significant control attenuation/amplification in the plant dynamics during optimization.

Direct Policy Search Background

Reinforcement Learning (RL):

Develop methods to sufficiently train an agent by maximizing a cost function through repeated interactions with its environment.

Markovian Dynamics

$$x_{t+1} = f(x_t, u_t) + w, \qquad x_0 \sim p(x_0)$$

Find Parametrized Policy (π_Θ^*) for the finite horizon problem:

$$\pi_\Theta^* = argmax_{\pi_\Theta} J_\Theta = argmax_\pi \Sigma_{t=1}^{t_f} \gamma^t E[r(x_t, u_t)|\pi_\Theta], \qquad \gamma \in [0,1]$$

Certainty-Equivalence (CE) Assumption:

The optimal policy for the learned model corresponds to the optimal policy for the true dynamics

How to use models for long-term predictions:

1. Stochastic inference (i.e. trajectory sampling)
2. Deterministic approximate inference

*M. P. Deisenroth, et al., "A survey on policy search for robotics," Foundations and Trends in Robotics, vol. 2, 2013.

Direct Policy Search Background

Stochastic Sampling:

Expected long-term reward:

$$J_\Theta = argmax_\pi \Sigma_{t=1}^{t_f} \gamma^t \mathrm{E}[r(x_t, u_t)|\pi_\Theta]$$

Approximation of J_Θ:

$$\widetilde{J_\Theta} = \frac{1}{N} \Sigma_{i=1}^{N} \Sigma_{t=1}^{t_f} \gamma^t r(x_t^i) \qquad \lim_{N \to \infty} \widetilde{J_\Theta} = J_\Theta$$

Deterministic Approximations:

Approximation of $p(x_t)$: (e.g. Unscented Transformation or Moment Matching)

$$E[r(x_t, u_t)|\pi_\Theta] = \int r(x_t) p(x_t) dx_t$$

$$p(x_t) \cong \mathrm{N}(x_t | \mu_t^x, \Sigma_t^x)$$

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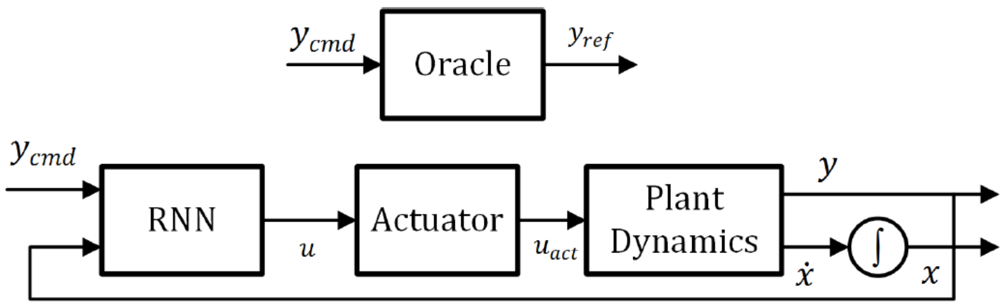
Deep Learning based Flight Control



Deep Learning Training Architecture

Generalized Form of the Discrete Plant Dynamics

$$
\begin{aligned}
x_{t+1} &= f(x_t, (\lambda_u(u_t^{act} + \rho_u)) + d_u, \rho_\alpha, \rho_q) + \zeta_p \\
y_t &= f(x_t, (\lambda_u(u_t^{act} + \rho_u)) + d_u, \rho_\alpha, \rho_q) + \zeta_p
\end{aligned}
$$

x_t are the states of the plant
u_t^{act} is the actuator output
y_t is the output vector
ζ_p is the plant noise
λ_u is the control effectiveness
d_u is an input disturbance
$\rho_u, \rho_\alpha, \rho_q$ are uncertainty parameters

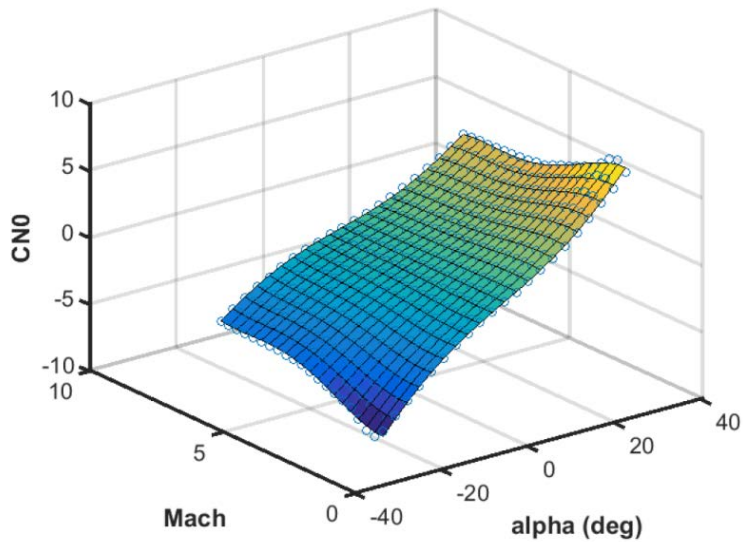
Flight Vehicle Model

Longitudinal Rigid Body Dynamics:

$$
\begin{aligned}
\dot{V}_T &= \frac{1}{m}(Tcos(\alpha) - D) - gsin(\theta - \alpha) \\
\dot{\alpha} &= \frac{1}{mV_T}(-Tsin(\alpha) - L) + q + \frac{g}{V_T}cos(\theta - \alpha) \\
\dot{\Theta} &= q \\
\dot{q} &= \frac{M}{I_{YY}} \\
\dot{h} &= V_T sin(\theta - \alpha)
\end{aligned}
$$

$$x = [V_T,\, \alpha,\, \Theta,\, q,\, h]$$

$$y = [\alpha,\, q,\, A_z,\, \bar{q}]$$



Force and Moment Equations:

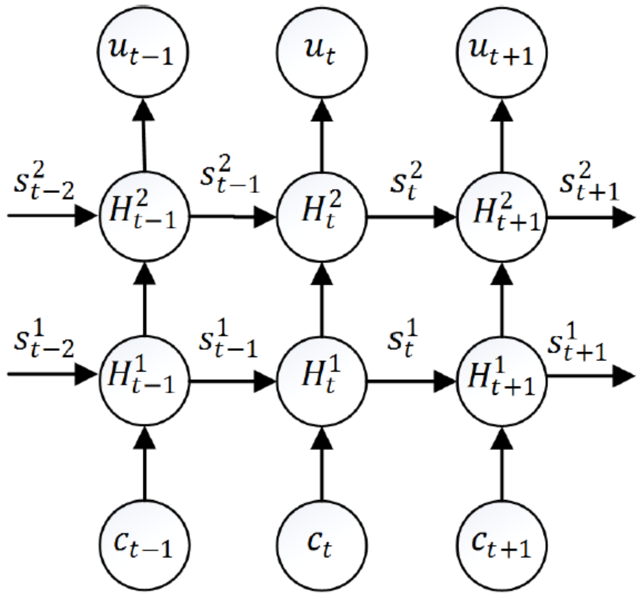
$$
\begin{aligned}
A &\approx \frac{1}{2}\rho V_T^2 S C_A & L &= Ncos(\alpha) - Asin(\alpha) \\
N &\approx \frac{1}{2}\rho V_T^2 S C_N & D &= Nsin(\alpha) + Acos(\alpha) \\
M &\approx \frac{1}{2}\rho V_T^2 S c_{ref} C_m
\end{aligned}
$$

Aerodynamic Coefficients (Longitudinal):

$$
\begin{aligned}
C_A &= C_{A_{ALT}}(h,\, M) + C_{A_{AB}}(\alpha,\, M) \\
&\quad + \sum_{i=1}^{4} C_{A_{\delta_i}}(\alpha,\, M,\, \delta_i) \\
C_N &= C_{N_0}(\alpha,\, M) + \sum_{i=1}^{4} C_{N_{\delta_i}}(\alpha,\, M,\, \delta_i) \\
C_m &= C_{m_0}(\alpha,\, M) + \sum_{i=1}^{4} C_{m_{\delta_i}}(\alpha,\, M,\, \delta_i) \\
&\quad + C_{m_q}(\alpha,\, M,\, q) + q\rho_q + \alpha\rho_\alpha
\end{aligned}
$$

Deep Learning Controller - Architecture

Stacked Recurrent Neural Network (S-RNN)



Algorithm 1 Gated Recurrent Units (GRU)

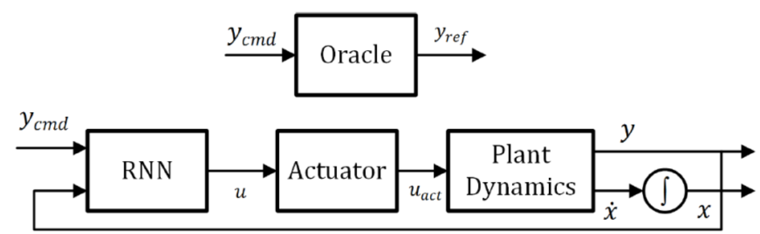
1: $z = \sigma(c_t U^u + s_{t-1} W^u + b_1)$
2: $r = \sigma(c_t U^r + s_{t-1} W^r + b_2)$
3: $h = tanh(c_t U^h + (s_{t-1} * r) W^h + b_3)$
4: $s_t = (1 - z) * h + z * s_{t-1}$
5: $*$ represents element-wise multiplication

$$u_t = s_t V + c$$

Θ_i matrix of parameters for each GRU module
$\Theta_i = [U^u, W^u, U^r, W^r, U^h, W^h, b_1, b_2, b_3]$
Θ total parameters of the controller
$\Theta = [\Theta_1, \Theta_2, \dots, \Theta_L, V, c]$
L total layers of GRU modules

Controller Input Vector:

$c_t = [e_i, \alpha, q, \bar{q}]$
$e = y_{sel} - y_{cmd}$
$e_i = \int_0^{t_f} e \, dt$



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Deep Learning Controller - Optimization

Estimated Expected Long-Term Reward:

$$\tilde{J}(\Theta) = \frac{1}{N}\Sigma_{i=1}^{N} J_i(\Theta)$$

Cost function for each trajectory, i:

$$J_i(\Theta) = \Sigma_{t=0}^{t_f} \gamma^t \chi(x_t, u_t)$$

$label = P$: only uncertainties
$label = R$: uncertainties, noise, and disturbances

Instantaneous Measurement:

$$\chi(x_t, u_t) = \begin{cases} k_1 e_t^2 + k_2 f_{\dot{u}}^2 & if\ label = P \\ k_3 f_e^2 + k_4 f_{\dot{u}}^2 & if\ label = R \end{cases}$$

$$f_e = \max(|e_t| - b_e, 0)$$
$$f_{\dot{u}} = \max(|\dot{u}_t| - b_{\dot{u}}, 0)$$

Time-varying funnel:

$$\beta_{\dot{u}}(t) = \{x \in \mathbb{R}^n | U(x,t) \le b_{\dot{u}}(t)\}$$
$$\beta_e(t) = \{x \in \mathbb{R}^n | E(x,t) \le b_e(t)\}$$

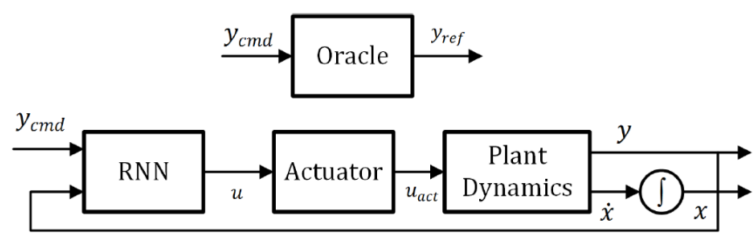
TABLE I

RANGE OF INITIAL CONDITIONS AND UNCERTAINTY VARIABLES

	MIN	MAX
α_0[deg]	-25	25
q_0[deg/sec]	-75	75
$Mach_0$	1.0	2.0
alt_0[km]	7	14

	MIN	MAX
R_α	-0.5	0.1
R_q	-7	5
R_u	-5	5
Λ_u	0.25	3.0

$[R_\alpha, R_q, R_u, \Lambda_u] \sim Uniform[min, max]$
$[\rho_\alpha^i, \rho_q^i, \rho_u^i, \lambda_u^i]$ are uncertainties (ith trajectory)
N is the number of sampled trajectories
t_f is the duration of each sampled trajectory
k_1, k_2, k_3, k_4 are positive constant gains
$b_e, b_{\dot{u}}$ are static constant bounds of the funnel
$e_t = y_{sel} - y_{ref}$



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DLC – Incremental Training

Algorithm 2 Incremental Training Procedure

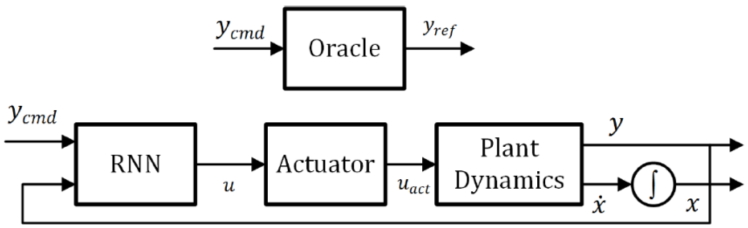
1: Randomly initialize controller parameters (Θ)
2: STEP 1: Optimize Θ for RNN/GRU using cost function (21) with linear dynamics and labels=P
3: STEP 2: Re-optimize Θ using nonlinear dynamics, labels=P, with small uncertainties in aerodynamics
4: STEP 3: Re-optimize Θ using nonlinear dynamics, labels=(R,P), with uncertainties, disturbances, and noise

Optimization Specifications:

RNN/GRU, RNN, TD-FNN
L-BFGS (Quasi-Newton) Optimization

N = 2,970 Sample Trajectories
540 Performance Trajectories
2,430 Robust Trajectories

3.1 GHz PC with 256 GB RAM and 10 cores
Parallel Processing
~40 hours for 1,000 sample trajectories for optimization



DLC - Results

Flight Condition:

Mach	α (deg)	q (deg/sec)	Altitude (km)
1.7	0	0	14

Initial Conditions:

	MIN	MAX
α_0(deg)	-30	30
q_0(deg/sec)	-100	100
R_α	-0.5	0.1
R_q	-7	5
R_u	-5	5
Λ_u	0.25	3.0

Augmented polynomial short period model:

$$
\begin{aligned}
\dot{e}_I &= \alpha - \alpha_{cmd} \\
\dot{\alpha} &= f(\alpha, q, \delta_e, \rho_\alpha, \rho_q, \rho_u, \lambda_u) \\
\dot{q} &= f(\alpha, q, \delta_e, \rho_\alpha, \rho_q, \rho_u, \lambda_u)
\end{aligned}
$$

DLC - Results

Flight Condition:

Mach	α (deg)	q (deg/sec)	Altitude (km)
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Performance Metrics:

$$ATE = \frac{1}{N}\Sigma_{i=1}^{N}\Sigma_{t=1}^{t_f}|e_t|$$

$$ACR = \frac{1}{N}\Sigma_{i=1}^{N}\Sigma_{t=1}^{t_f}|\dot{u}_t|$$

$$CTE = \Sigma_{j=1}^{M} ATE$$

$$CCR = \Sigma_{j=1}^{M} ACR$$

TABLE II

CUMULATIVE ERROR (CTE), CONTROL RATE (CCR), AND FINAL COST

	CTE	CCR	Cost
3-Layer RNN/GRU	339.15	100.16	1.0438
2-Layer RNN	359.28	313.64	2.4970
GS	1000.21	1180.04	-

DLC Performance: 66% reduction in CTE, 91.5% reduction in CCR

N number of trajectories for each analysis model
t_f is the duration of each sampled trajectory
CTE is the cumulative tracking error
CCR is the cumulative control rate

DLC - Results

Flight Condition:

Mach	α (deg)	q (deg/sec)	Altitude (km)
1.7	0	0	14

Initial Conditions:

	MIN	MAX
α_0(deg)	-30	30
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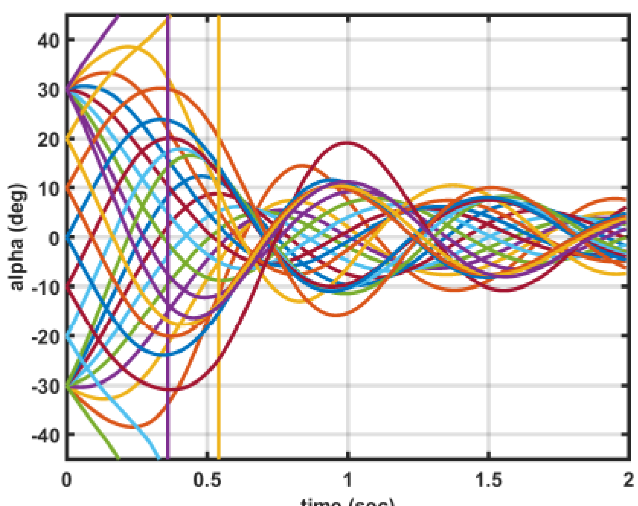
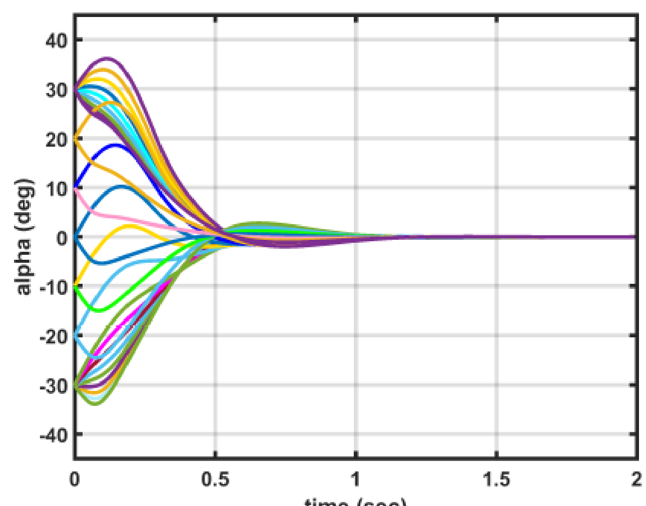
Augmented polynomial short period model:

$$
\begin{aligned}
\dot{e}_I &= \alpha - \alpha_{cmd} \\
\dot{\alpha} &= f(\alpha,\, q,\, \delta_e,\, \rho_\alpha,\, \rho_q,\, \rho_u,\, \lambda_u) \\
\dot{q} &= f(\alpha,\, q,\, \delta_e,\, \rho_\alpha,\, \rho_q,\, \rho_u,\, \lambda_u)
\end{aligned}
$$

Gain Scheduled Controller



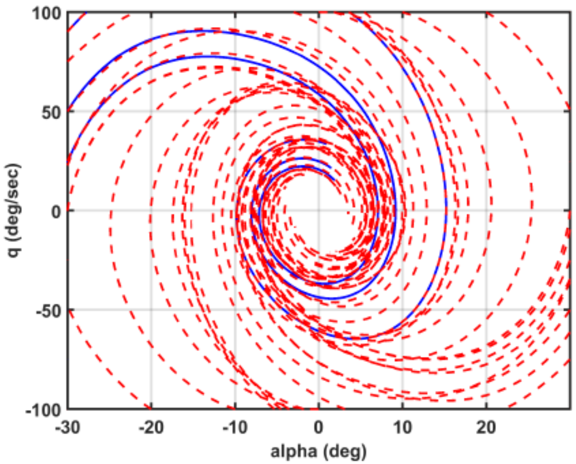
Deep Learning Controller



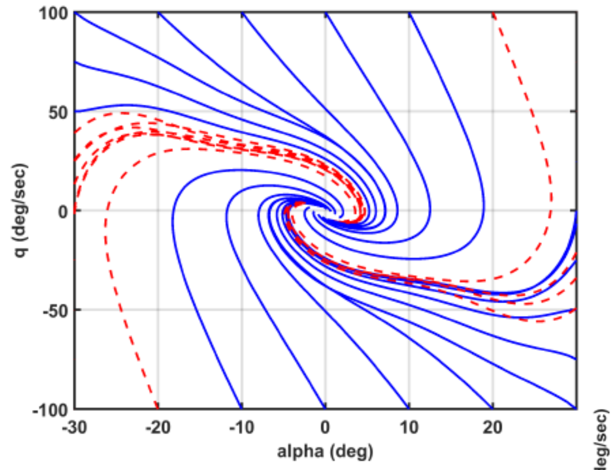
$\lambda_u = 0.5,\ \rho_u = 0,\ \rho_\alpha = 0.05$, and $\rho_q = 2.5$

DLC - Results

Gain Scheduled Controller

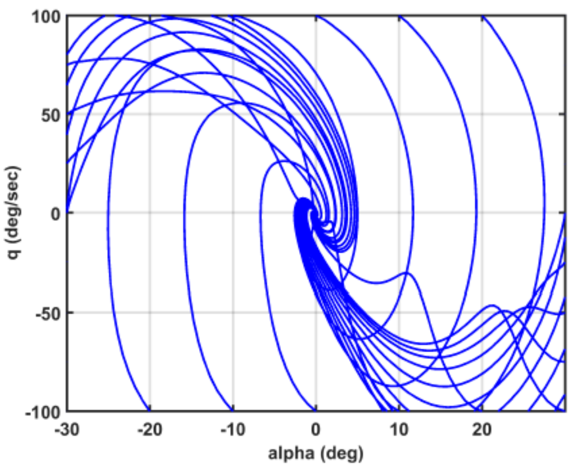


$\lambda_u = 0.75,\ \rho_u = 0,\ \rho_\alpha = 0.025, \text{ and } \rho_q = 5$

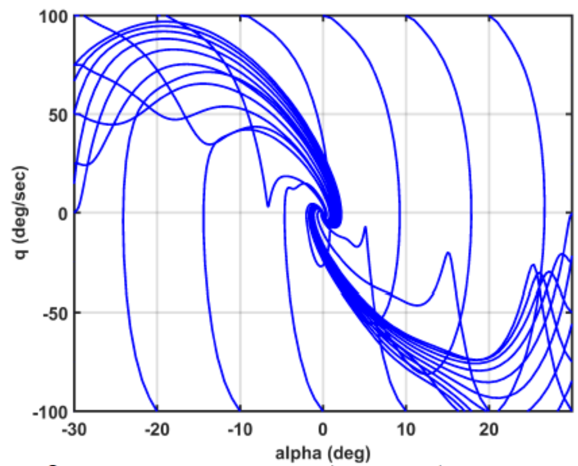


$\lambda_u = 0.5,\ \rho_u = 0,\ \rho_\alpha = 0.05, \text{ and } \rho_q = 2.5$

Deep Learning Controller

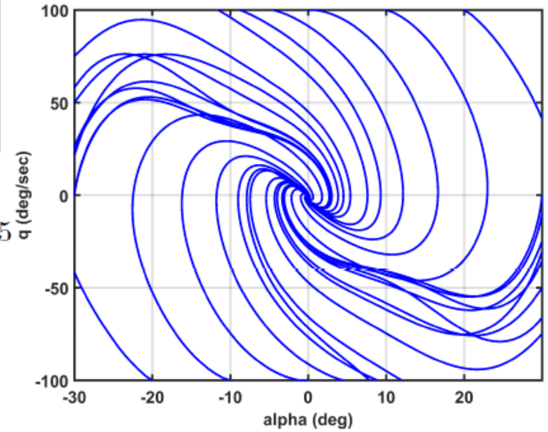


$\lambda_u = 0.75,\ \rho_u = 0,\ \rho_\alpha = 0.025, \text{ and } \rho_q = 5$



$\lambda_u = 0.5,\ \rho_u = 0,\ \rho_\alpha = 0.05, \text{ and } \rho_q = 2.5$

Gain Scheduled Controller



No uncertainty or disturbances

Contribution and Conclusion

- Created a novel training procedure focused on bringing deep learning benefits to flight control.
- Trained controller using a set of sample trajectories that contain disturbances, aerodynamic uncertainties, and significant control attenuation/amplification in the plant dynamics during optimization.
- We found benefits of using a piecewise cost function that allows the designer to solve both robustness and performance criteria simultaneously.
- We utilized an incremental initialization training procedure for deep recurrent neural networks.

Future Work

- Pursue a vehicle model with flexible body effects, time delays, controller effectiveness, center of gravity changes, and aerodynamic parameter variations.
- Explore improving parameter convergence and analytic guarantees: Kullback-Leibler (KL) divergence, importance sampling, etc.
- Pursue development/use of robustness analysis tools for deep learning controllers to provide region of attraction estimates and time delay margins: sum-of-squares programming etc.

Questions?