Spiking Neural Network (SNN) Control of a Flapping Insect-scale Robot

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Introduction

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Overview

- Autonomous systems should be able to adapt to
  - Disturbances
  - Unmodeled dynamics
  - Environmental uncertainty

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Robot Miniaturization

$451\ mm$

$14\ mm$

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Miniaturization Advantages

- Physical robustness
- Agility
- Access to small spaces
- Discrete

RoboBee

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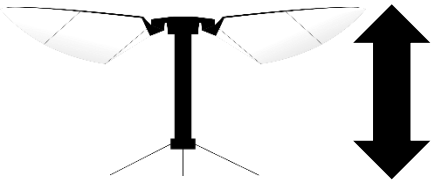
$80\ mg$



$14\ mm$

Credit: Ma, Kevin Y., et al. "Controlled flight of a biologically inspired, insect-scale robot." *Science* 340.6132 (2013): 603-607.

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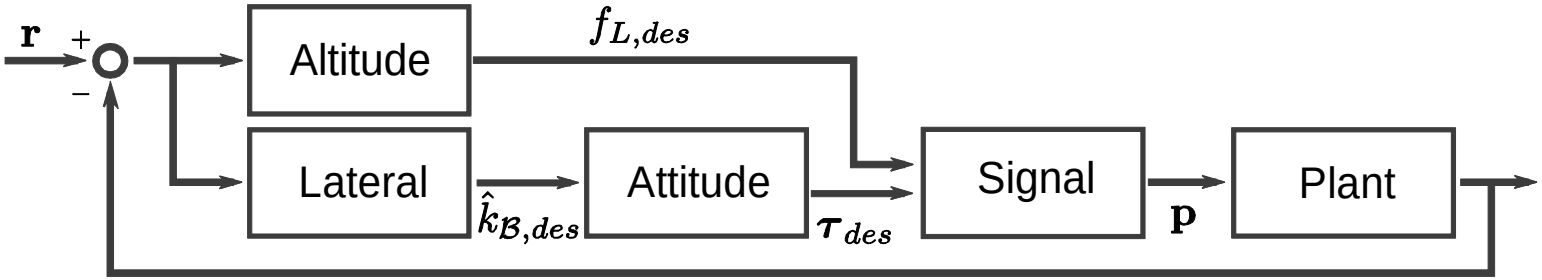
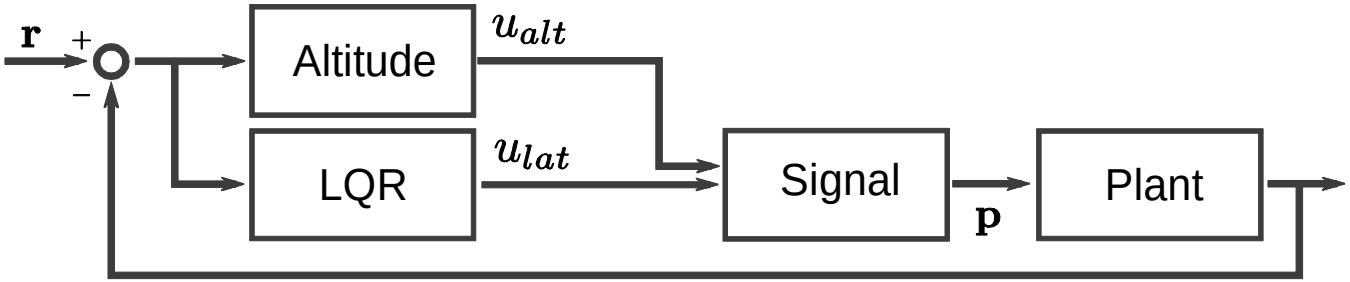
Existing RoboBee Controllers

- PID



- LQR (Planar Only)



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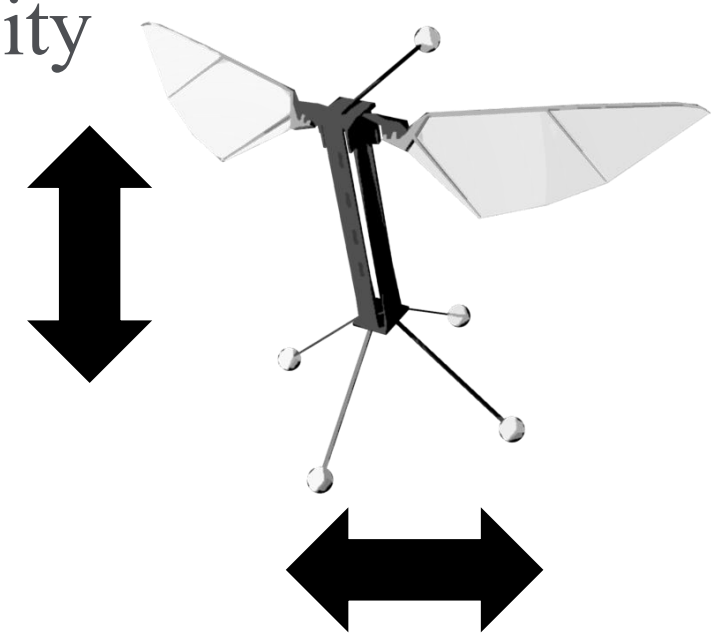
Existing Controller Limitations

- Require manual tuning
  - Manufacturing uncertainty causes wing torque variations
- Limited maneuvering capability
  - Hovering
  - Lateral maneuvering



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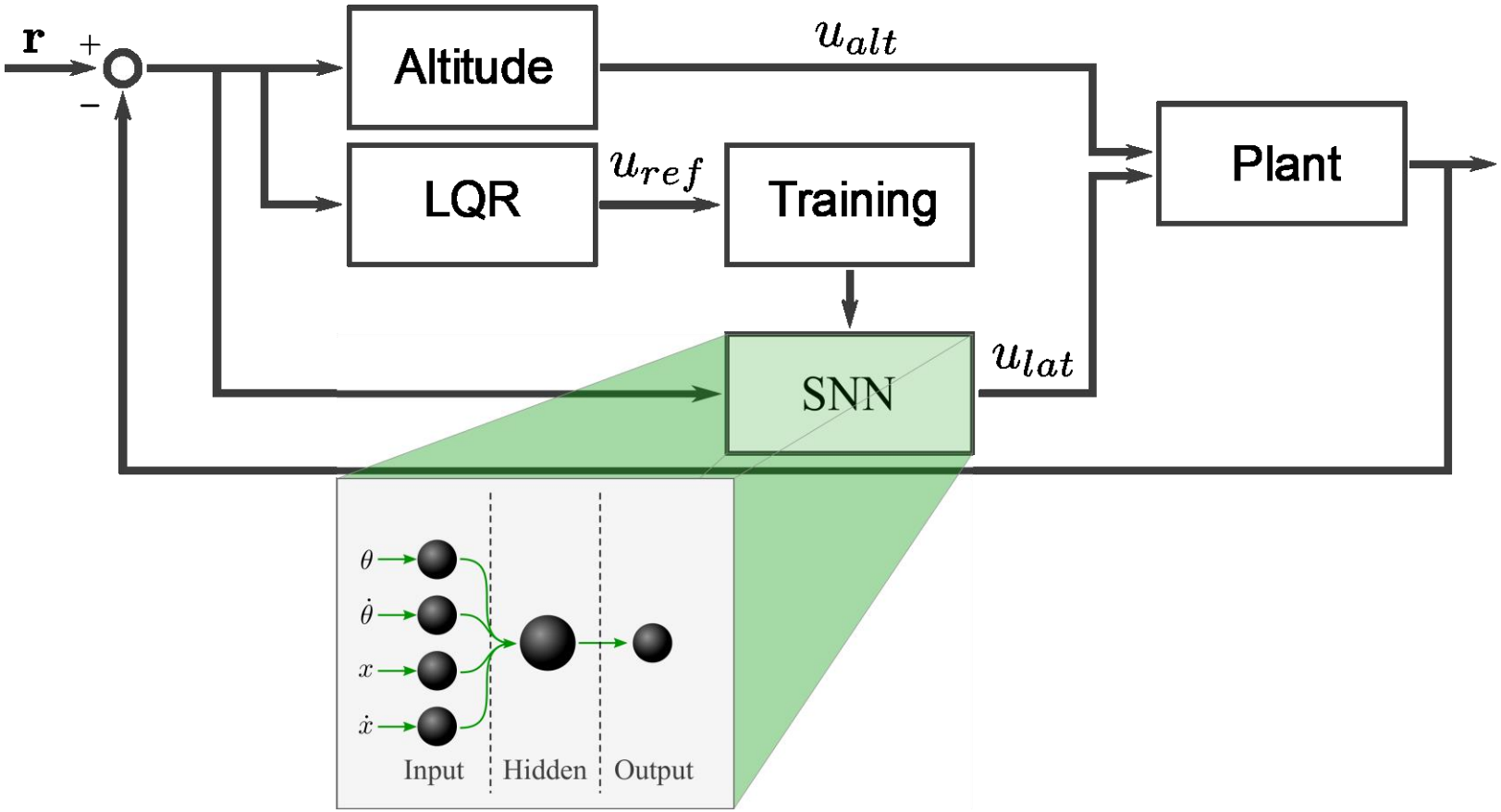
SNN Control Structure



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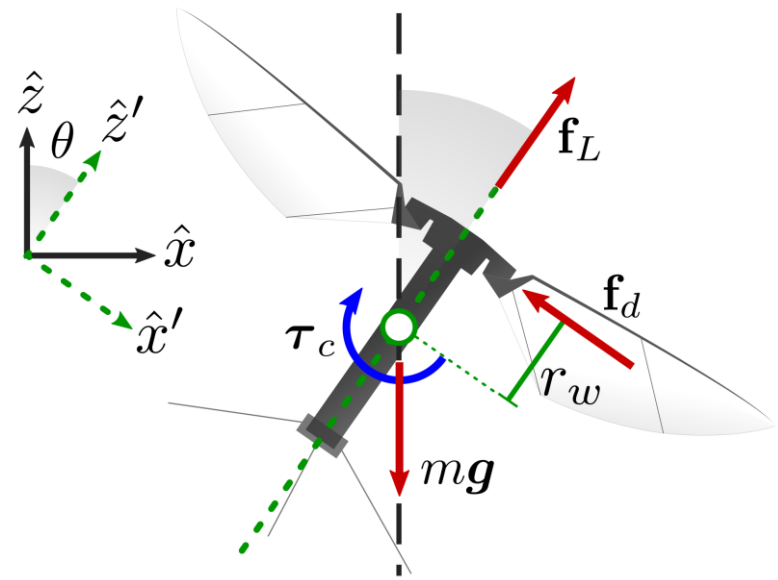
Planar RoboBee Dynamics

Linear Momentum Balance

$$m\dot{\mathbf{v}} + \boldsymbol{\omega} \times m\mathbf{v} = \mathbf{f}_d + m\mathbf{g} + \mathbf{f}_L$$

Angular Momentum Balance

$$I_y\dot{\boldsymbol{\omega}} + \boldsymbol{\omega} \times I_y\boldsymbol{\omega} = \boldsymbol{\tau}_c + (\mathbf{r}_{w/G} \times \mathbf{f}_d)$$



I_y	Inertia	$\boldsymbol{\omega}$	Rotation rate
m	Mass	$\boldsymbol{v}$	Velocity
$\boldsymbol{f}_d$	Drag force	$\boldsymbol{g}$	Gravity
$\boldsymbol{f}_L$	Lift force	$\boldsymbol{\tau}_c$	Control torque

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Maneuvers

Credit: Ma, Kevin Y., et al. "Controlled flight of a biologically inspired, insect-scale robot." *Science* 340.6132 (2013): 603-607.

Spiking Neural Network (SNN) Controller

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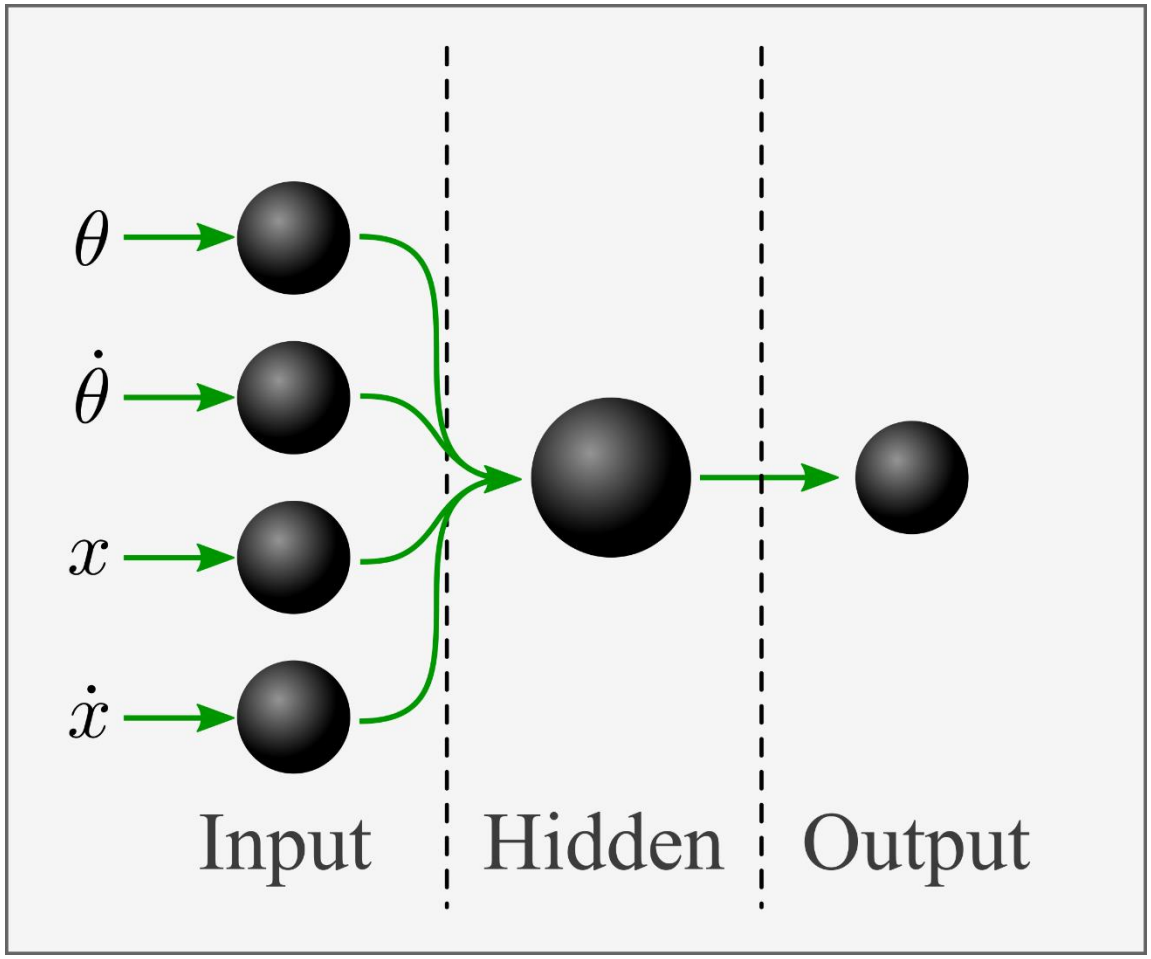
Overview



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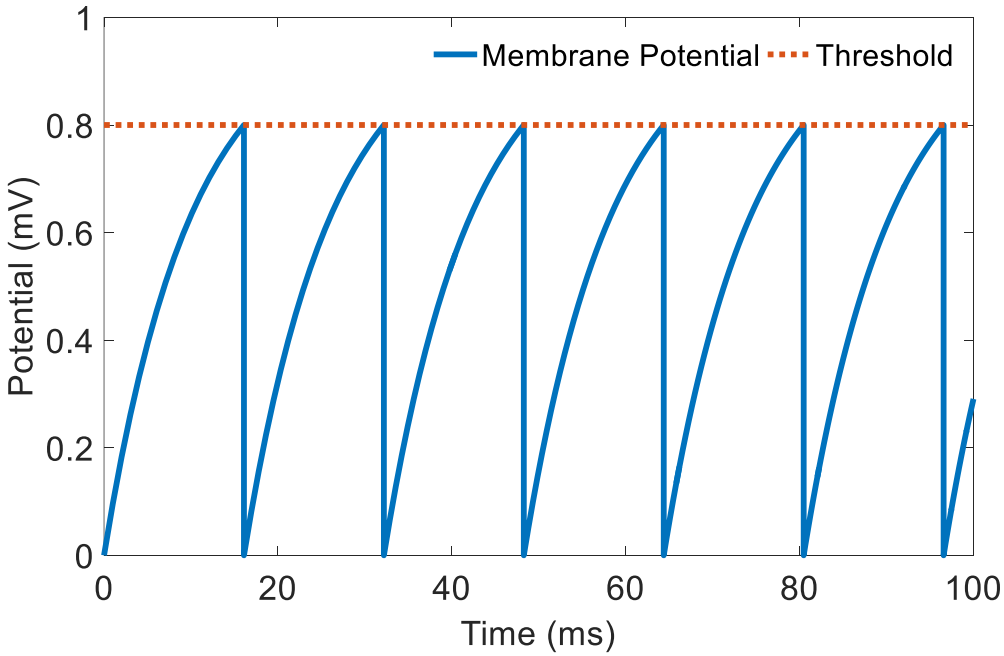
Neuron Model

- Leaky Integrate and Fire

$$\frac{dv}{dt} = \frac{RI - v}{\tau} + \xi$$

v	Membrane potential
I	Input current
R	Resistance
τ	Time constant
ξ	Noise



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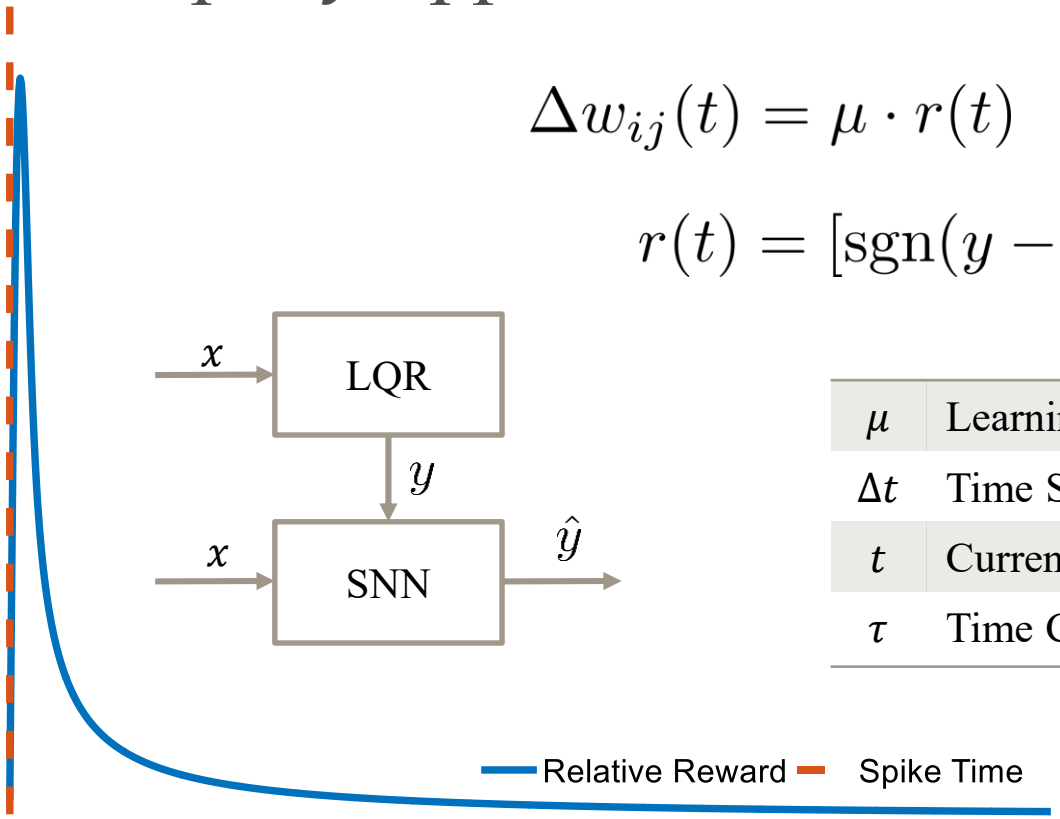
Training Algorithm

- Network weights adjusted by Δw_{ij} so that SNN output $\hat{y}$ approaches reference control y

$$\Delta w_{ij}(t) = \mu \cdot r(t)$$

$$r(t) = [\mathrm{sgn}(y - \hat{y}) + r(t - \Delta t)] \cdot e^{(\hat{t}_i - t)/\tau}$$

μ	Learning Rate	$\hat{y}$	Actual Output
Δt	Time Step	y	Target Output
t	Current Time	$\hat{t}_i$	Spike Time
τ	Time Constant	Δw_{ij}	Weight Change



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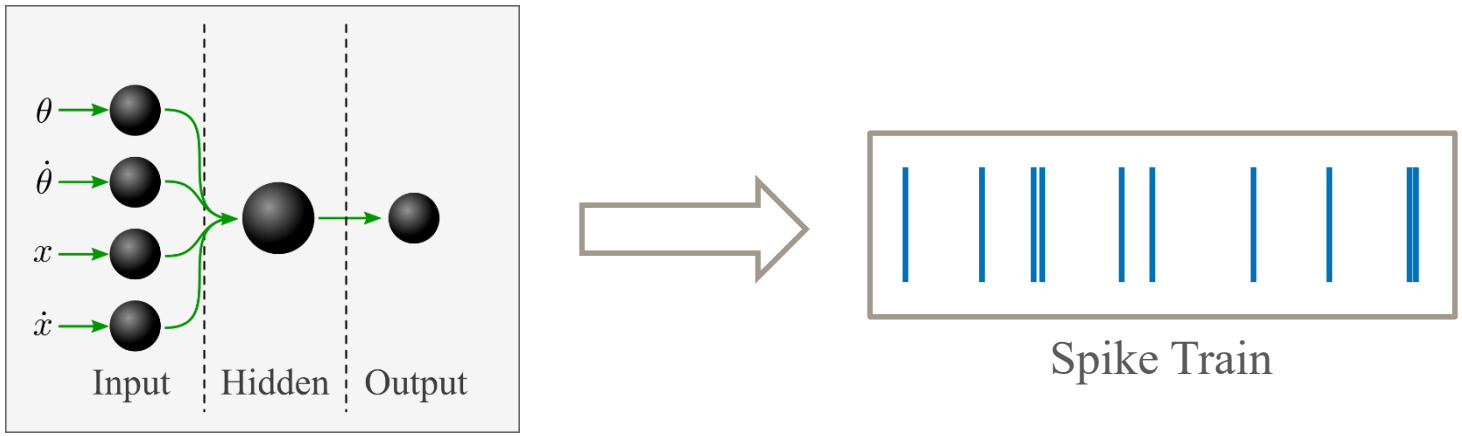
Spike Train Decoding



- SNN output is a series of discrete events
- Convert into continuous control signal

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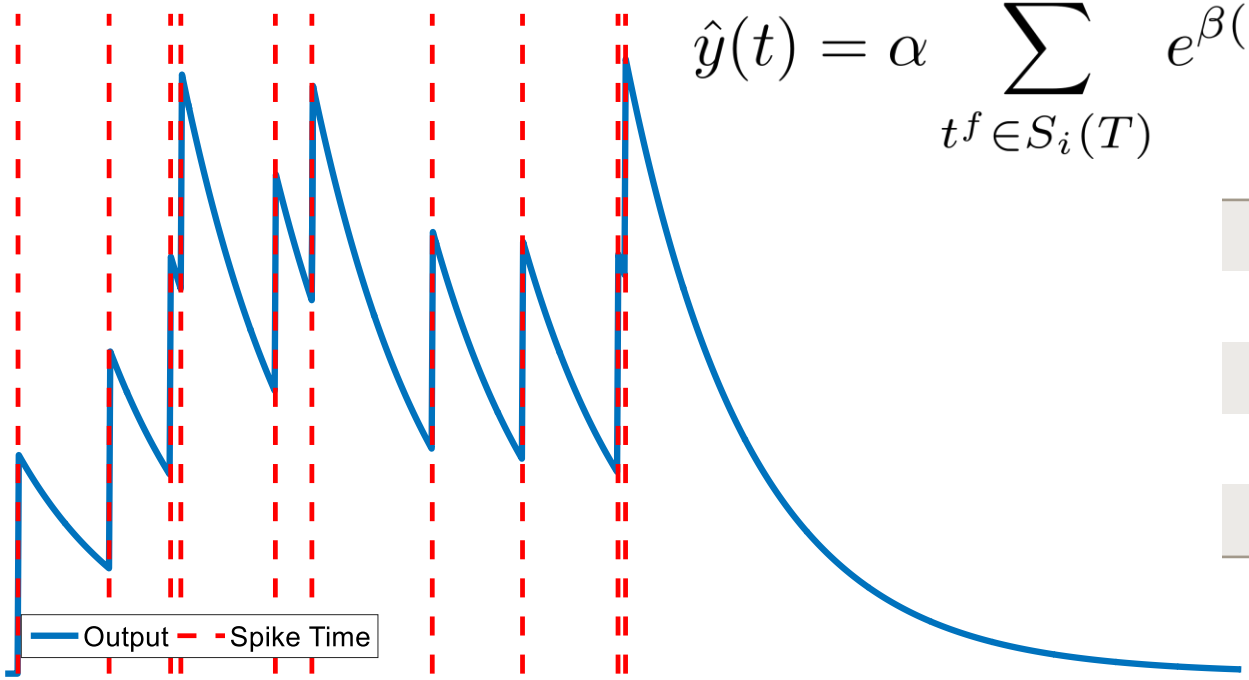
Spike Train Decoding



$$\hat{y}(t) = \alpha \sum_{t^f \in S_i(T)} e^{\beta(t^f - t)} - \gamma, \quad \forall t^f < t$$

$\hat{y}$	Decoded output
α	Scaling factor
β	Decay factor
γ	Offset factor
t^f	Spike time

- Convolve spike train with an exponential window

Simulation Results

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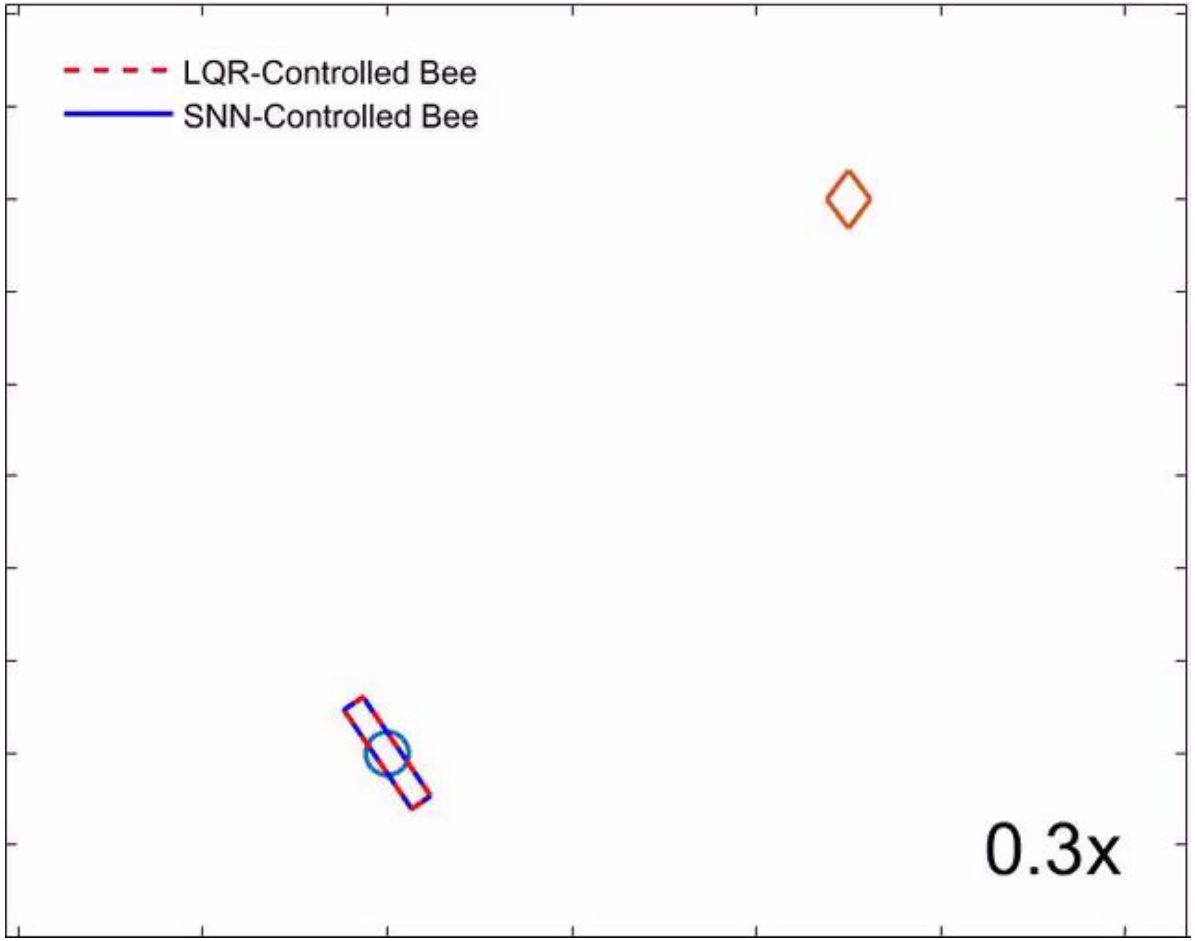
Trajectory Comparison



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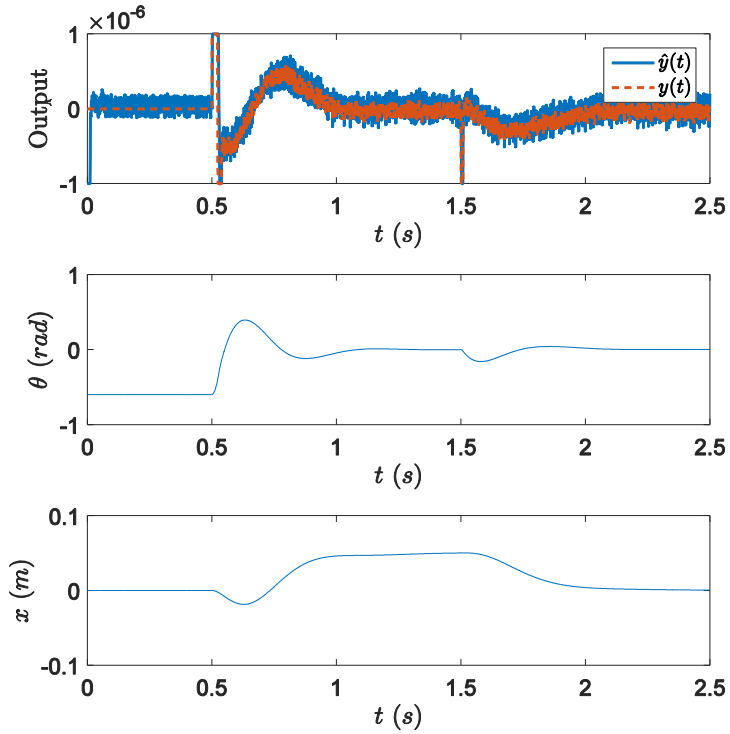
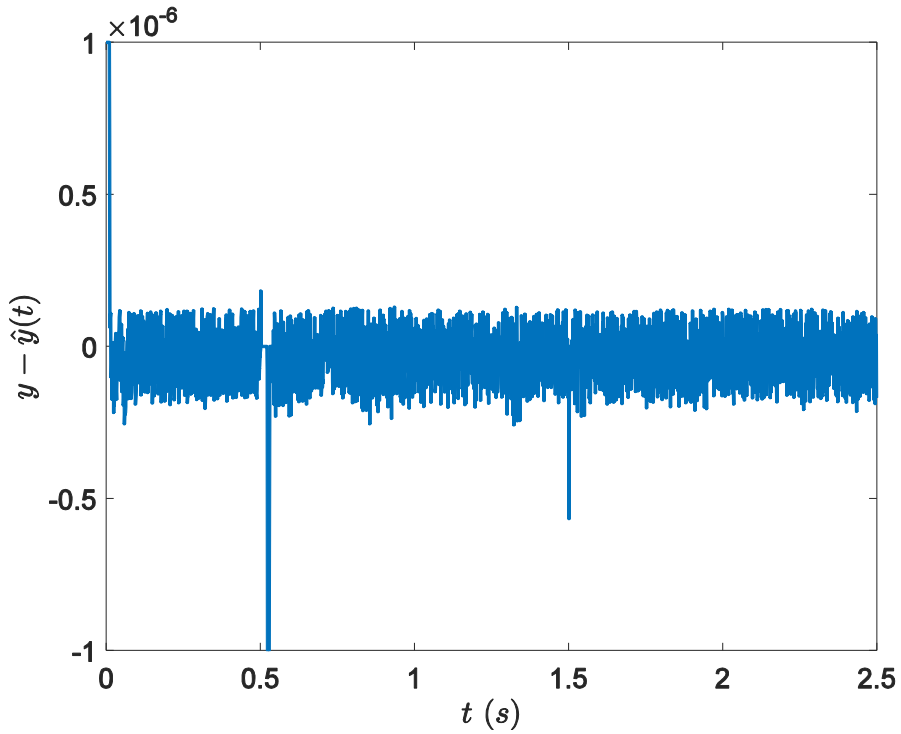
Error

Comparing the lateral control signals



Lateral control signal error



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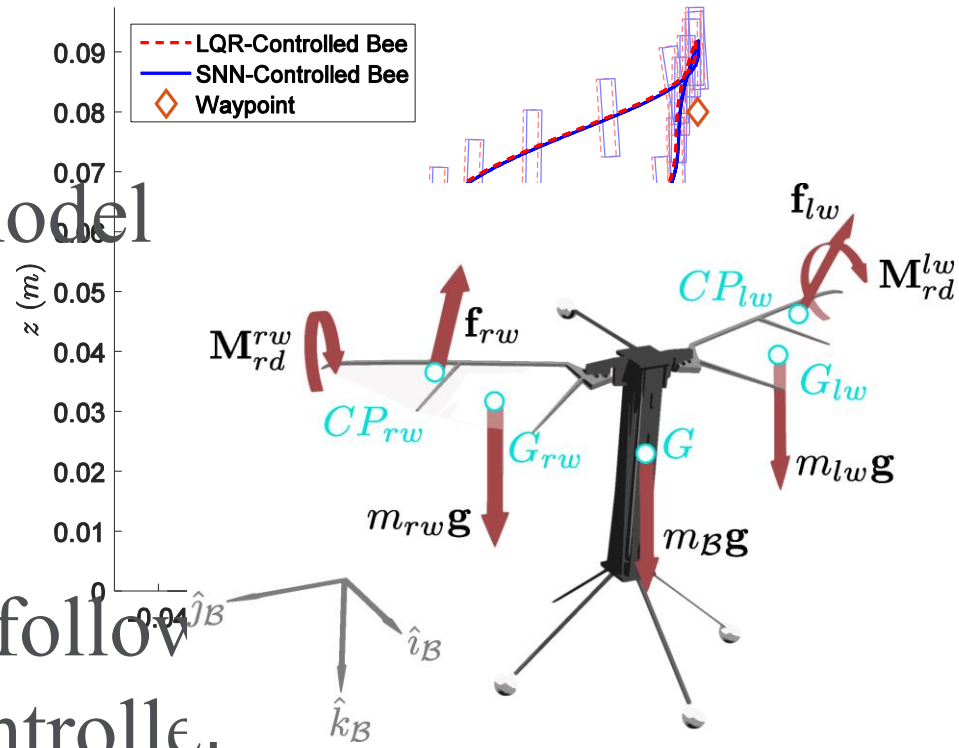
Conclusions and Future Work

- SNN effectively matched 2D LQR Controller
- Implement on 3D model
- Use implicit model follow beyond classical controller



LABORATORY FOR INTELLIGENT SYSTEMS AND CONTROLS

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