



האוניברסיטה העברית בירושלים THE HEBREW UNIVERSITY OF JERUSALEM

ביה״ס להנדסה ולמדעי המחשב ע״ש רחל וסלים בנין

The Rachel and Selim Benin School of Computer Science and Engineering

Deep Learning Approach to Flapping Wing Flight Control: Leveraging Reinforcement and Imitation Learning from Fruit Flies

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Under the supervision of **Prof. Tsevi Beatus**

IAAC, April 2025



Introduction - Flapping Wing MAVs Are Coming!

- Inefficient aerodynamic setup of current MAV
- Improvements in robotics and avionics
- We need good controllers







Robobee X-Wing (Jafferis et al, 2019)

Introduction - Biomimicry can help?

- Current models of flies are PID based
- Address only angular control but are highly coupled with velocities
- Hard to find actual parameters







Beatus 2015, Whithead & Beatus 2015

Introduction - What is our goal?

- Stable controller for all axes combined
- Robust
- Adaptive
- Efficient

What do we need?

• Simulation

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- Data acquisition system
- Algorithm



6-DOF simulation of a flying fruit fly with control input

Prescribed wing motion



6-DOF simulation of a flying fruit fly with control input

- Prescribed wing motion
- Quasi-steady aerodynamic force model



 $L = \frac{1}{2}\rho V^2 S C_L(\alpha)$



6-DOF simulation of a flying fruit fly with control input

- Prescribed wing motion
- Quasi-steady aerodynamic force model
- EOM + Solver (RK45)



Single Stroke

6-DOF simulation of a flying fruit fly with control input

- Prescribed wing motion
- Quasi-steady aerodynamic force model
- EOM + Solver (RK45)



Single Stroke

Data Acquisition System and Hull Reconstruction



estimation of free-flying fruit flies. J Exp Biol

Imitation Learning Algorithm



Imitation Learning Algorithm

Proximal Policy Optimization

(Schulman et al 2017)

Generative Adversarial Imitation Learning



Imitation Learning Algorithm

Proximal Policy Optimization

(Schulman et al 2017)

Generative Adversarial Imitation Learning



Results - Learning from a PID "Expert"

- Using trajectories from PID controlled simulated flies
- Hyper Parameter tuning
- Time to convergence ~70-120 epochs

Agent sample trajectories while training (Pitch) Epoch 40 Epoch 80



pitch



Results - Learning from a PID "Expert"

- Testing the trained agent under pitch perturbations
- Comparing performance to PID "expert"



PID vs RL effect on perturbation in pitch

Results - Measured Raw Data

• Data Collected for the MFL Dataset: >1000 Trajectories >41K Individual wingbeats



Results - Learning from the raw data

- Convergence at 120-140
- Controller was able to sustain stable flight



Results - Learning from the raw data

- Stabilizes Pitch and Roll
- Dampens yaw
- Maintains velocity and altitude



Results - Learning from the raw data: Unseen Conditions

Pitch perturbation

(Beatus et al 2015)





Results - Learning from the raw data





Results - Learning from the raw data

- GAN collapses at ~240
- Hyper-Parameter tuning has no effect







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Thank You **Questions**?

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