Reinforcement Learning for Unsteady Flow Control

Anthony Corso[1] – acorso@stanford.edu

[1] SISL Lab, Aeronautics and Astronautics, Stanford University

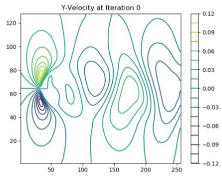
Stanford
CS 230

Objective

Goal: Apply deep reinforcement learning techniques to active flow control
Testcase: Suppress vortex shedding behind a 2D circular cylinder using rotation

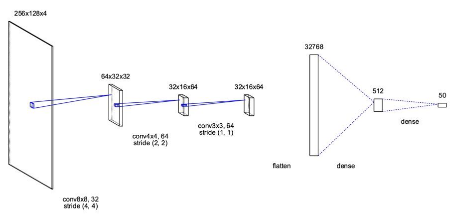
Data Generation and Simulation

Created OpenAI gym environment with PyFR[1] fluid simulator
States: 256x128x4 flow-field
Actions: Cylinder rotation (continuous or discrete)

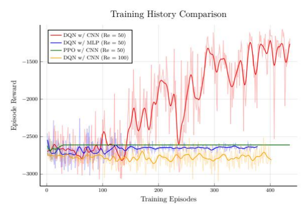


Algorithm and Architecture

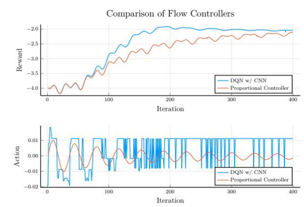
Algorithms: DQN[2], PPO[3]
Networks: MLP, CNN (pictured)



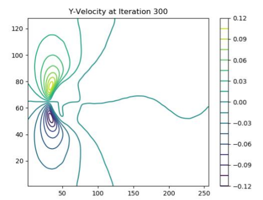
Results



- Trained with multiple architectures and algorithms
- DQN+CNN was the only successful configuration



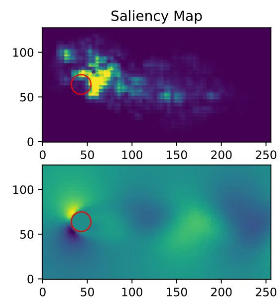
- RL approach outperforms existing proportional control policy
- Control approach is initially similar then qualitatively different



- Flow field snapshot after RL policy was applied demonstrates successful suppression

Further Analysis

- Saliency map demonstrates network focus for first action decision
- Near-wake region is most important
- Favors upper wake region when deciding to perform positive rotation



Future Work

- Use a different reward function such as the drag or vorticity of the flow field
- Use transfer learning from a linearization network[4] to accelerate the feature extraction process of the learning.
- Try other control techniques such as jets

References

[1] Witherden, F. D., Farrington, A. M., and Vincent, P. E. Pyfr: An open source framework for solving advection–diffusion type problems on streaming architectures using the flux reconstruction approach. Computer Physics Communications, 2014

[2] Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., et al. Human-level control through deep reinforcement learning. Nature, 2015

[3] Schulman, J., Wolski, F., Dhariwal, P., Radford, A., and Klimov, O. Proximal policy optimization algorithms, 2017

[4] Morton, J., Jameson, A., Kochenderfer, M. J., and Witherden, F. Deep dynamical modeling and control of unsteady fluid flows. In Advances in Neural Information Processing Systems, 2018