

# Anytime Perception and Control for Safe and Intelligent Urban Air Mobility

**Heechul Yun**, Ahmet Soyyigit, Qitao Weng, Shawn Keshmiri

*University of Kansas*

Pavithra Prabhakar, *Kansas State University*

Nelson Brown, *NASA Armstrong Flight Research Center*

<https://www.ittc.ku.edu/~heechul>

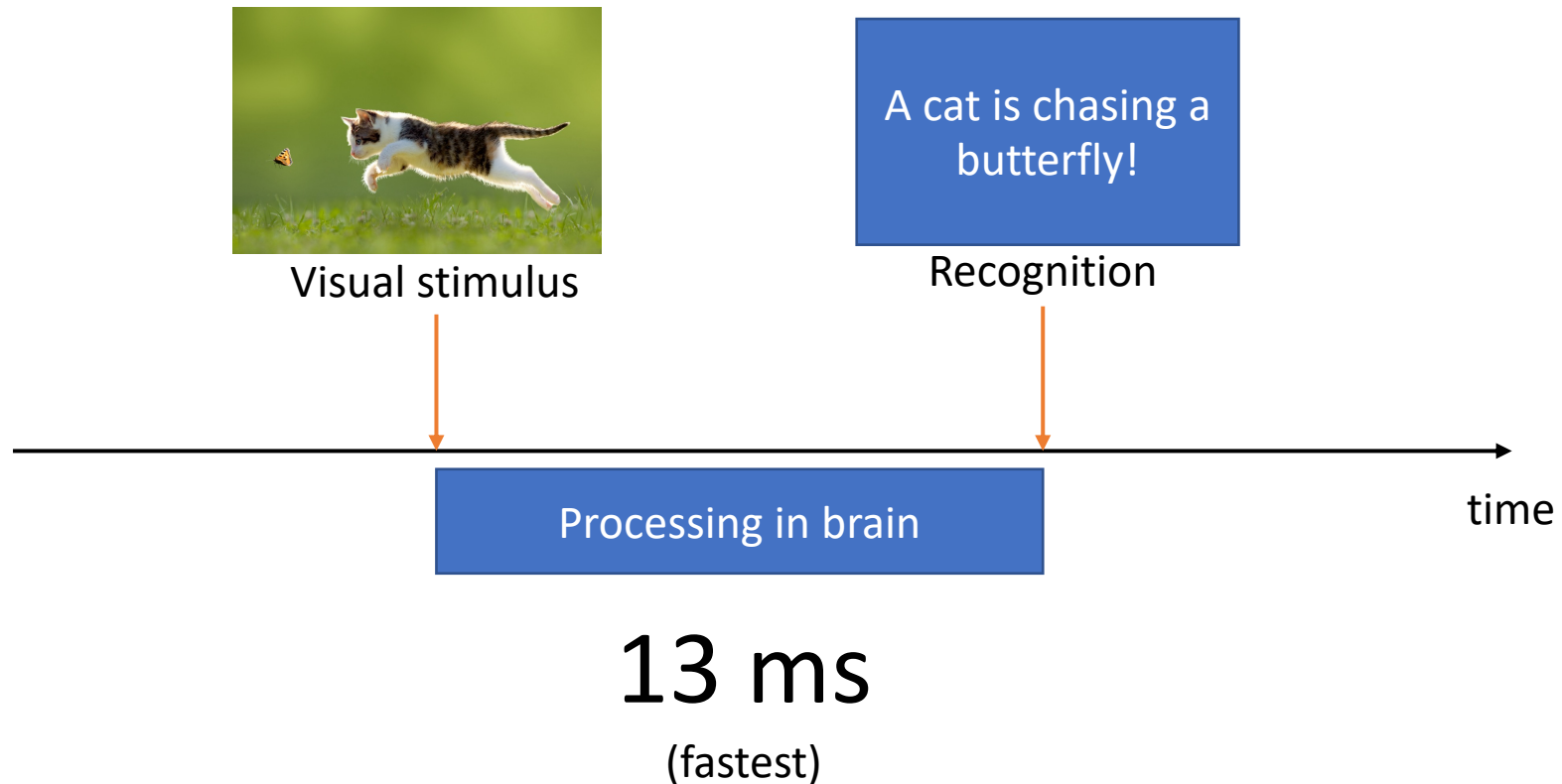


We need intelligent perception and control capabilities

blade runner 2049 concept art from  
<https://www.artstation.com/artwork/PxvJ1>

# Perception Latency

- Q. How fast can the human perceive images?

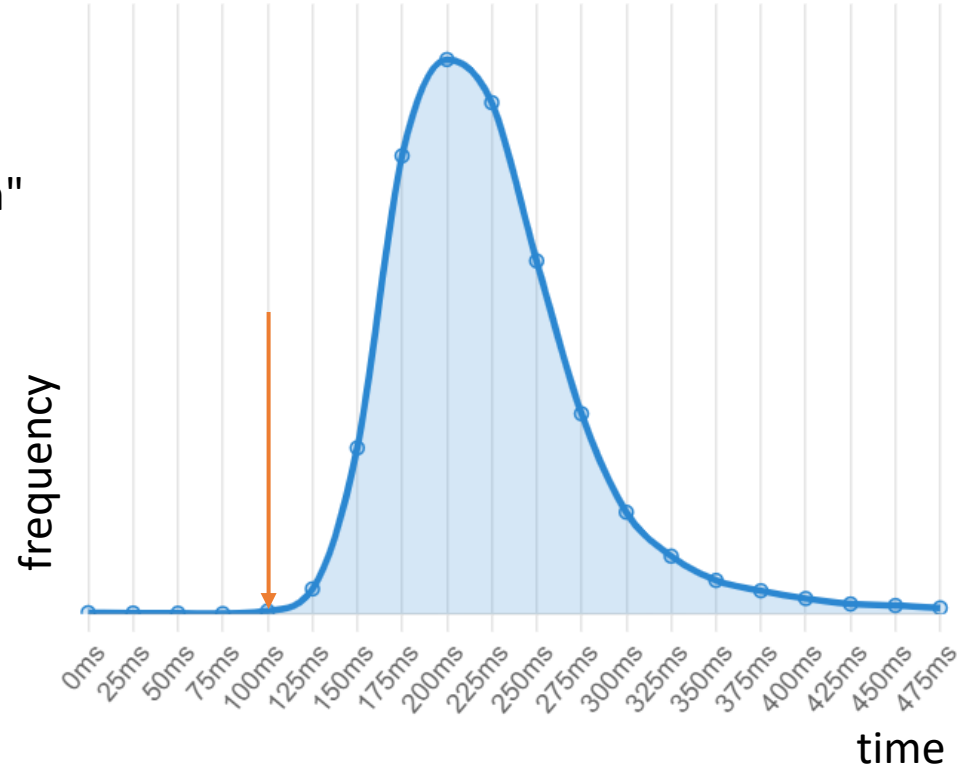


# Reaction (Perception and Control) Latency

- Q. How fast can the human react to a stimulus?

"when the red box turns green, click as quickly as you can"

**100 ms**  
(fastest)





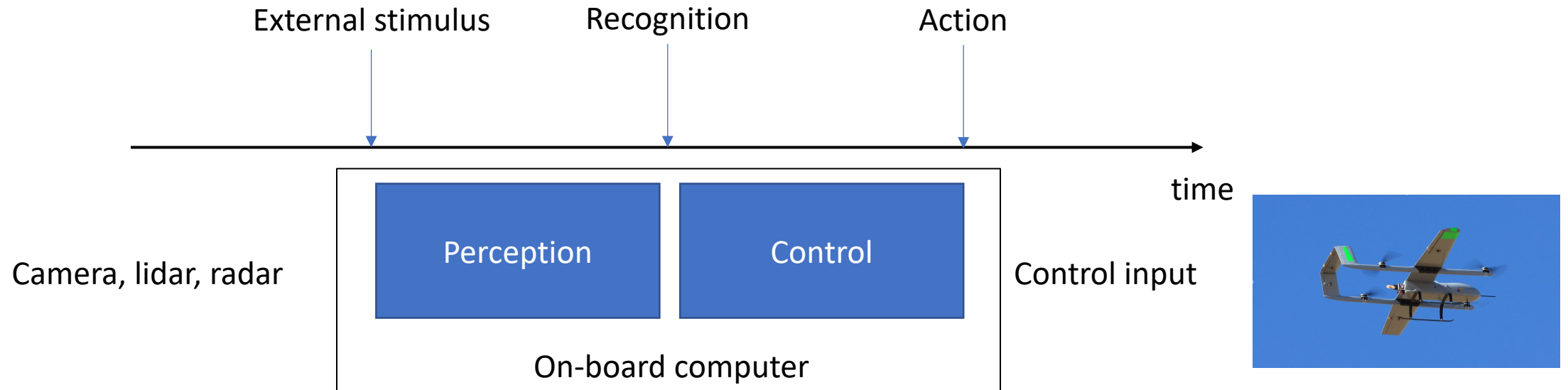




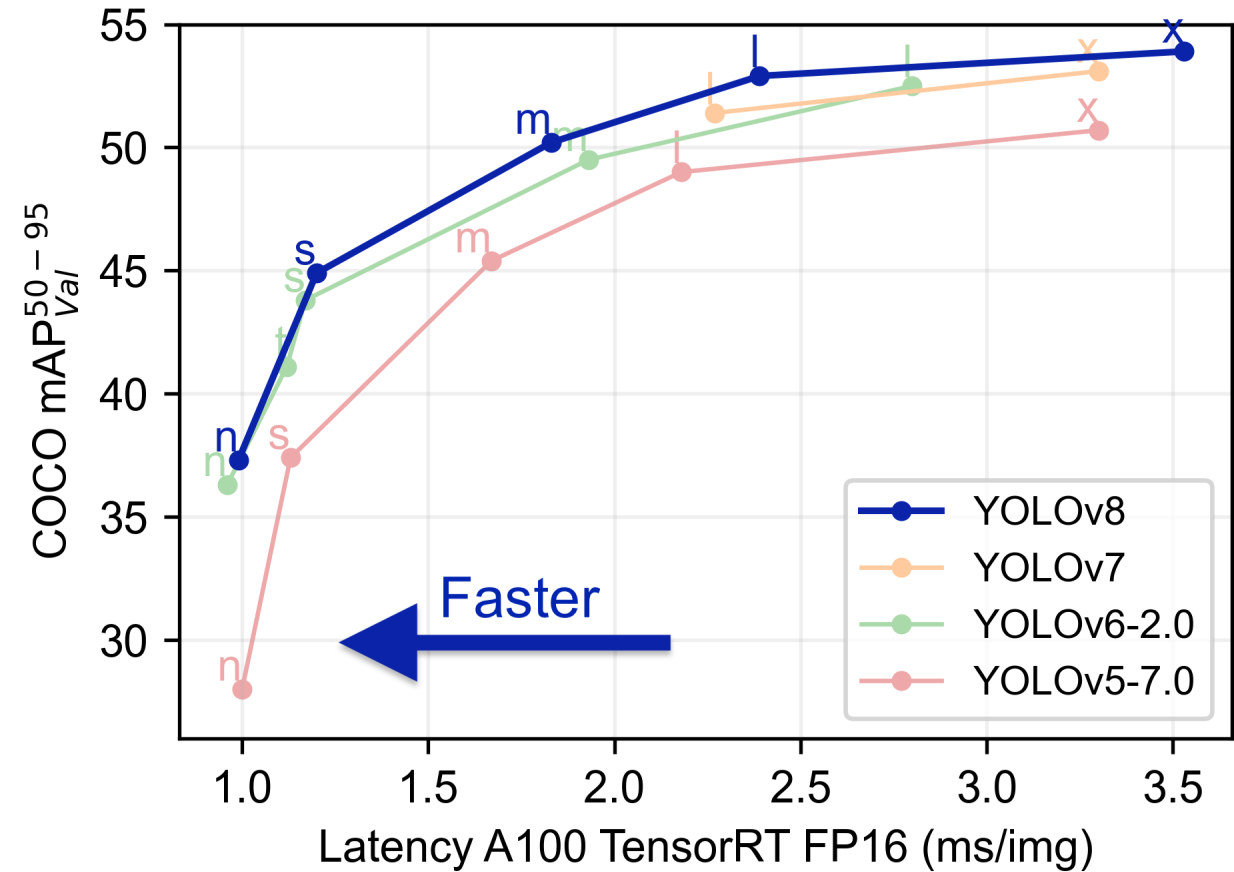
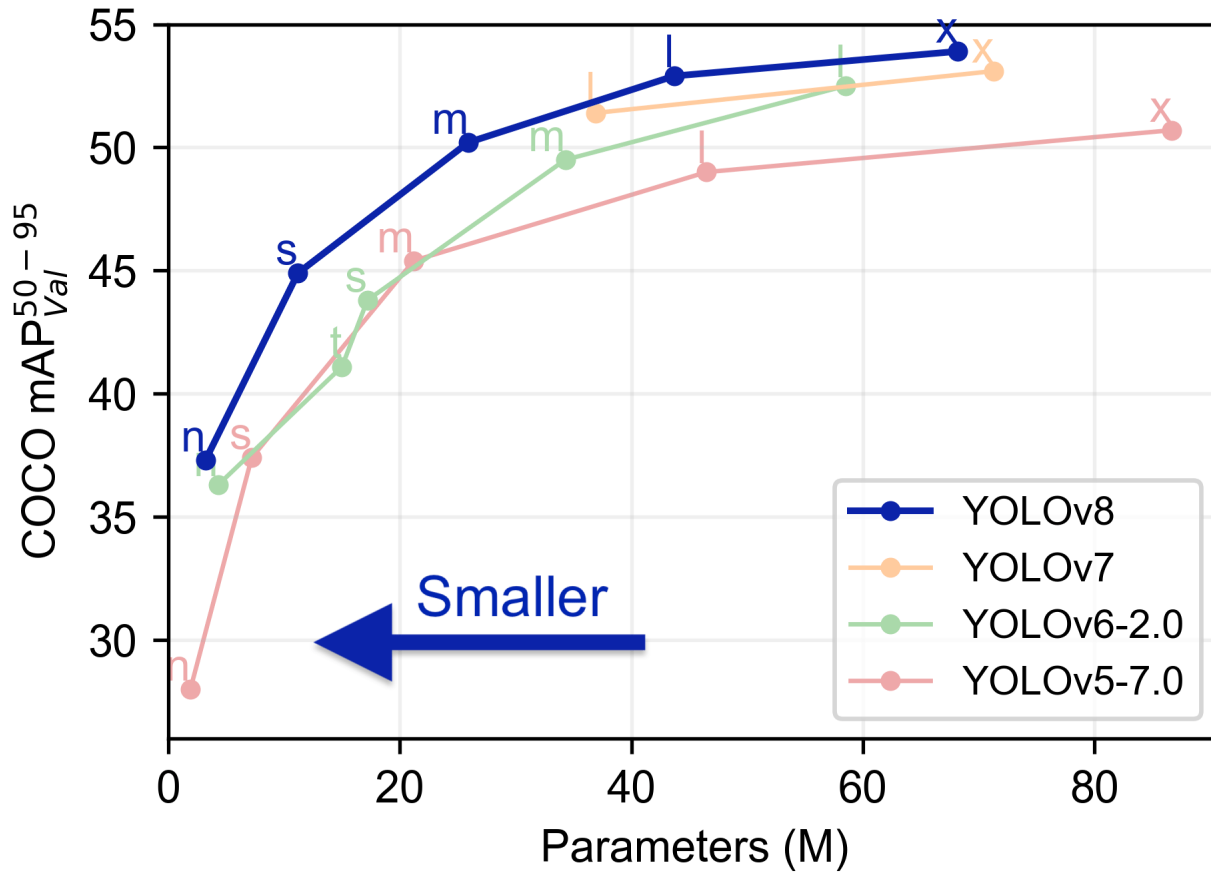


# Artificial Perception & Control Systems

- Use on-board sensors and computers for perception and control
- Advanced perception (e.g., DNN) systems can achieve human-like accuracy
- **But are they flexible and adaptable as humans?**



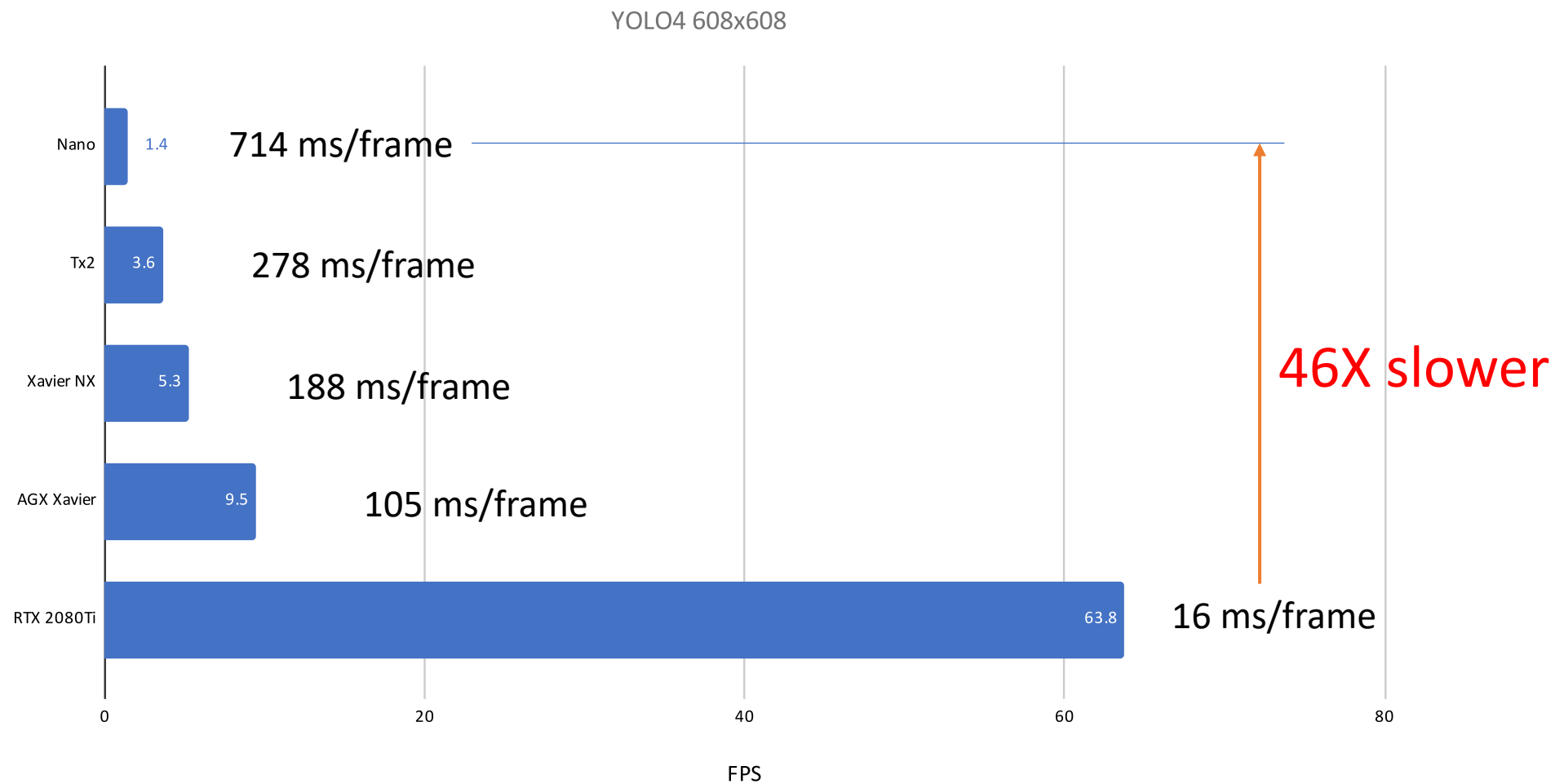
# Accuracy vs. Latency



<https://github.com/geoffrey-g-delhomme/yolov8-lard>



# Latency vs. GPU



Data source: <https://github.com/ceccocats/tkDNN>

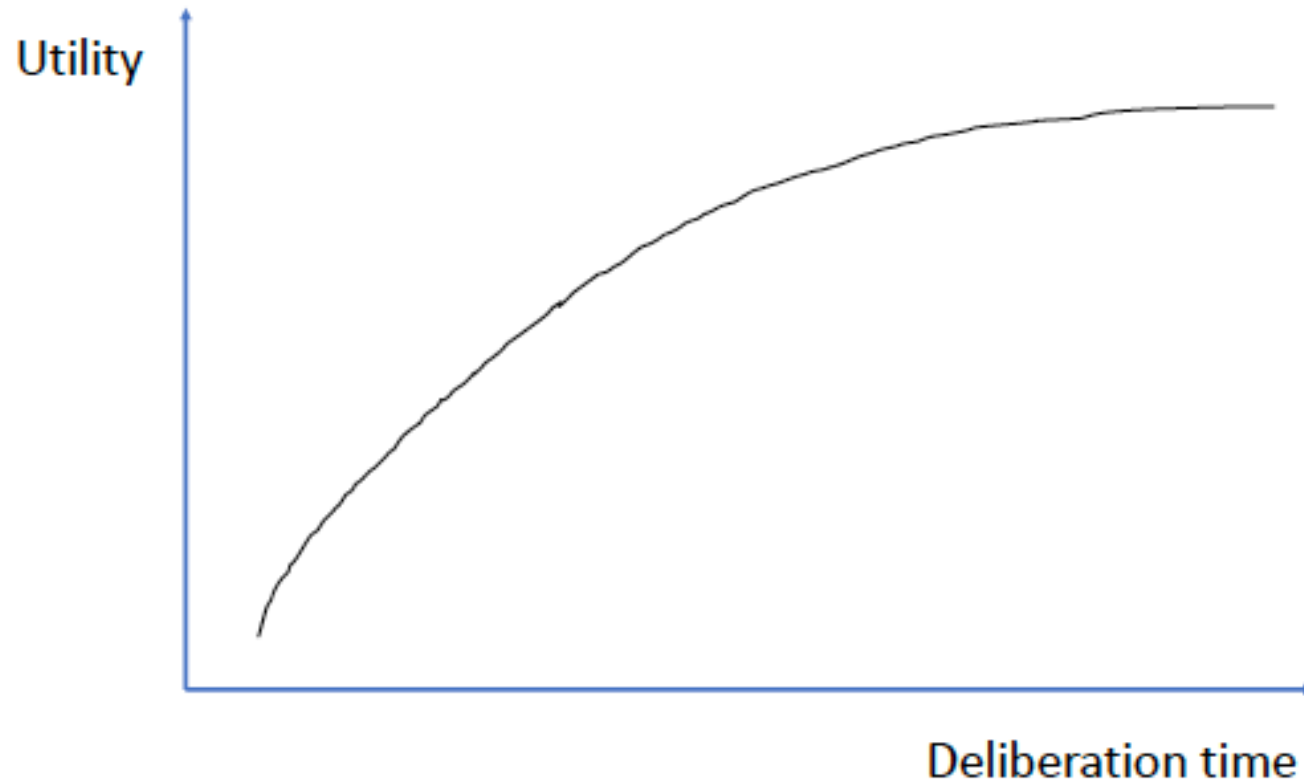
# Challenges

- Which perception model to use may depend on:
  - Speed of the vehicle (affect needed perception and reaction time)
  - Surrounding environment (e.g., urban vs. rural)
  - On-board computing capability
- On-board computing capability is limited
  - Due to size, weight, and power (SWaP) constraints and cost

Can we *dynamically* and *automatically* adapt our perception and control systems to find right latency, accuracy, and performance trade-offs on the fly just as humans do?

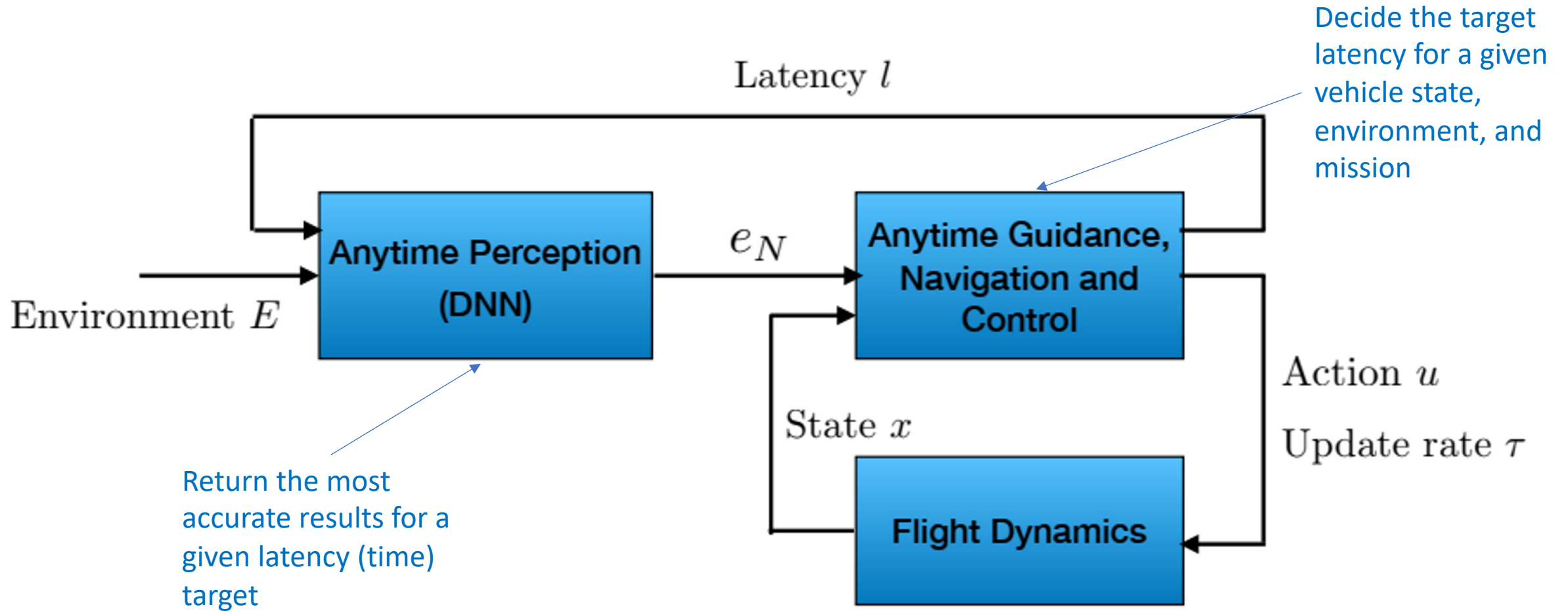


# Anytime Algorithms



Boddy, M., and Dean T. L. "Solving Time-Dependent Planning Problems." *In Proceedings of the Eleventh International Joint Conference on Artificial Intelligence*, 1989.

# Our Vision: Anytime Perception and Control



# Outline

- Introduction
- **A case study**
- Anytime perception and control for UAM/UAS
- Conclusion

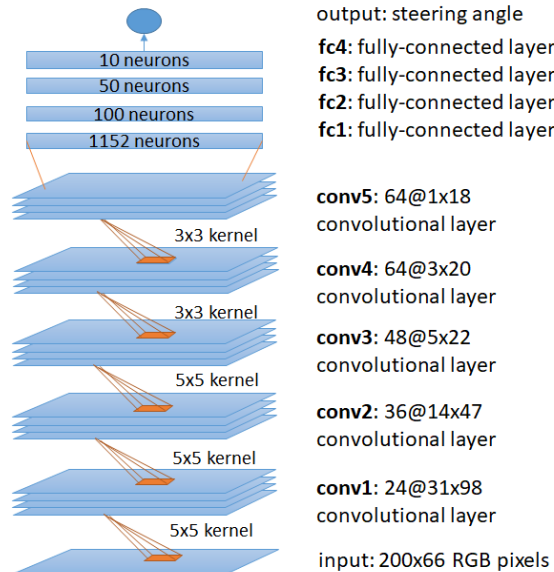


# DeepPicar

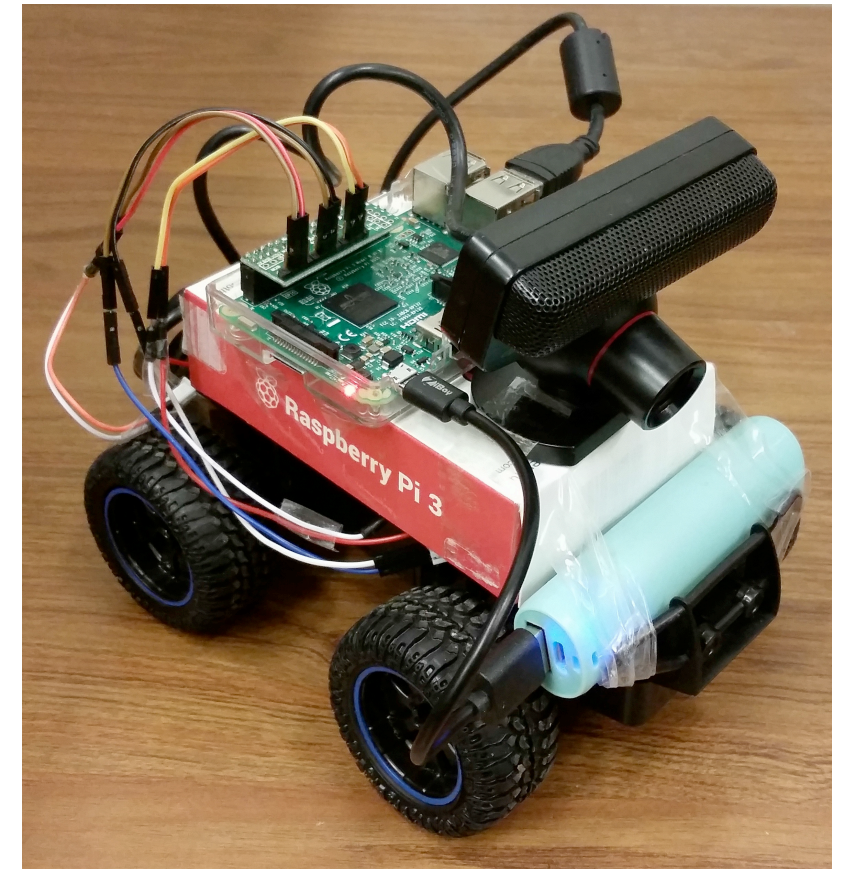
- End-to-end deep learning: *pixels to steering*
- Using identical CNN with NVIDIA's DAVE-2



DAVE-2



PilotNet



DeepPicar

# DeepPicar



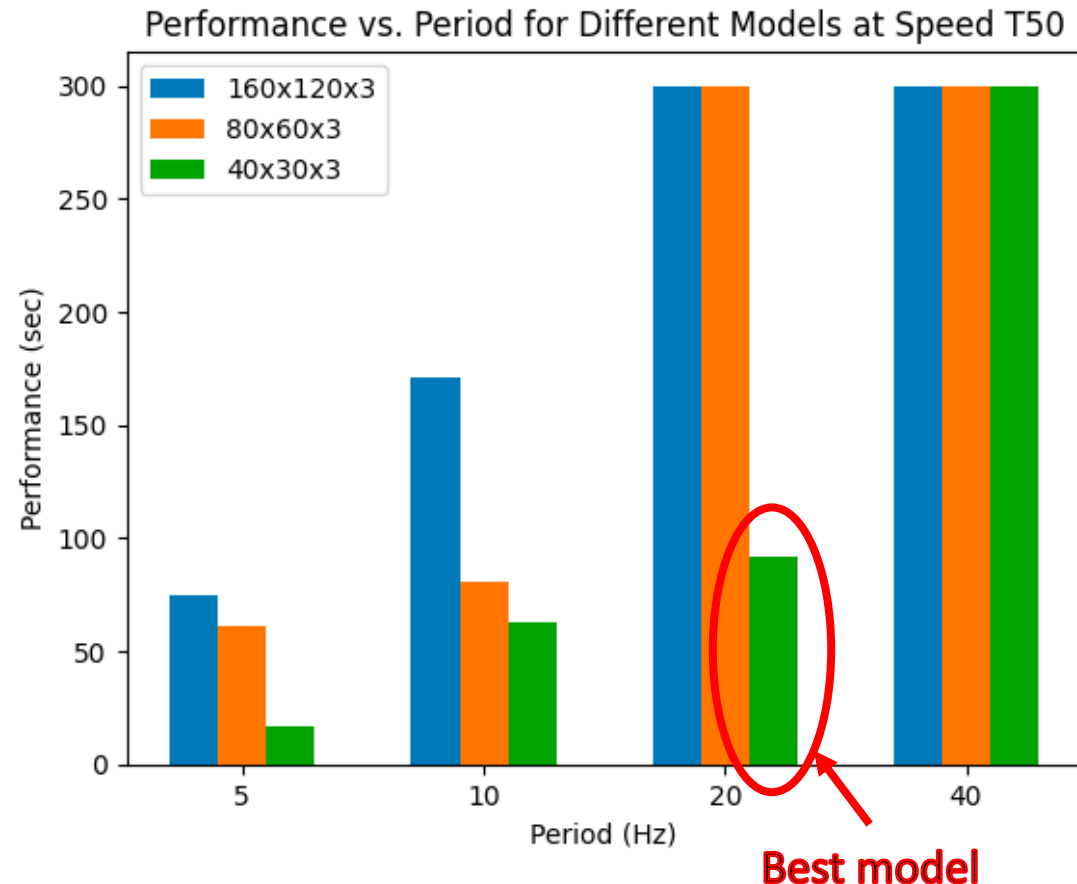
# Big, Medium, Small PilotNet Variants

Model (input res.)	MACs	Params
160x120x3	47186K	802K
80x60x3	14202K	367K
40x30x3	7230K	175K

Used a same dataset to train all three models



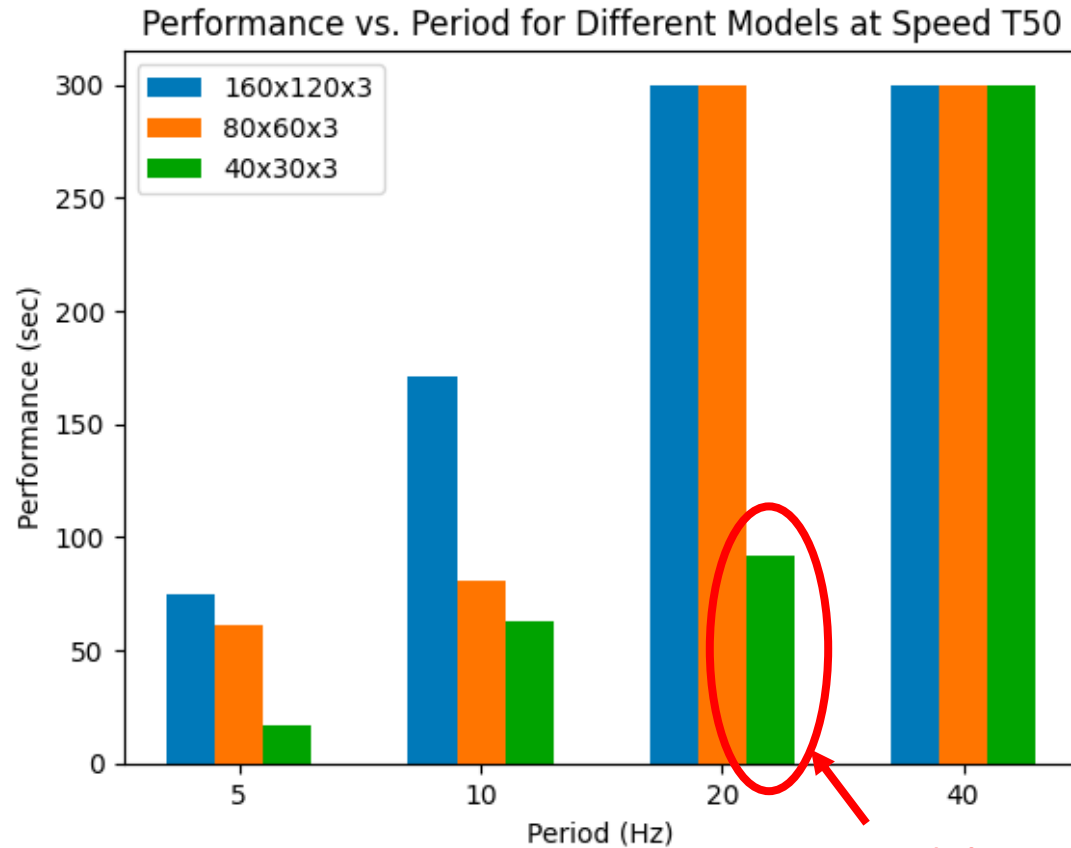
# Accuracy, Latency, and Performance



- Bigger model performs better (drive longer w/o crash)
- Lower latency (higher update rate) improves performance
- Ideally, bigger & faster model performs better
- But, you cannot have both at the same time in practice!

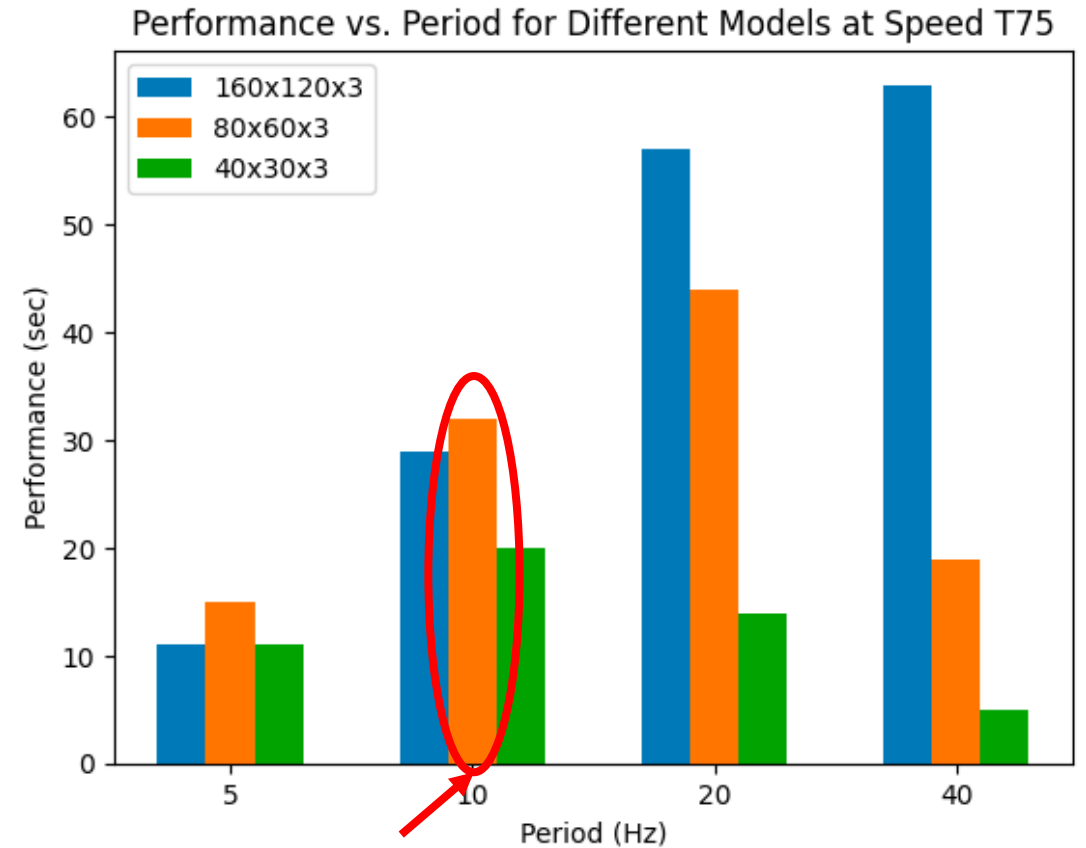
# Accuracy, Latency, *Speed* and Performance

Throttle = 50%



Best model

Throttle = 75%



Best model

# Takeaways

- In a modern perception system

Performance =  $f$  (accuracy, latency, environment)

- Anytime perception enables runtime adaptation to maximize performance on limited on-board embedded computing resources
- Co-designing anytime perception and control can further improve intelligence and safety of urban mobility vehicles



# Outline

- Introduction
- A case study
- **Anytime perception and control for UAM/UAS**
- Conclusion

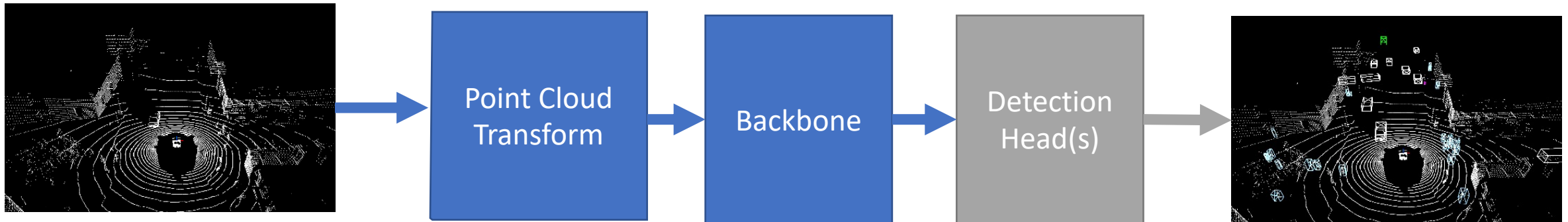
# Anytime Perception

- Target applications
  - Sense and avoid (bird, other UAM/UAS, buildings, trees, etc.)
  - Agile navigation/planning
  - Autonomous takeoff/landing
- Target sensor types
  - Camera, lidar
- Target perception tasks
  - Object detection/classification
  - Odometry/SLAM

# Lidar-based 3D Object Detection

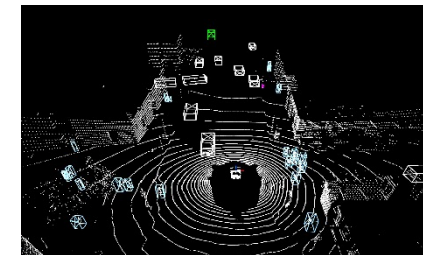
- Point cloud to 3D bounding boxes and classifications
  - Examples: Voxelnet, SECOND, PointPillars, CenterPoint
- High computational cost, **deadline-unaware**

250 ~ 330 ms

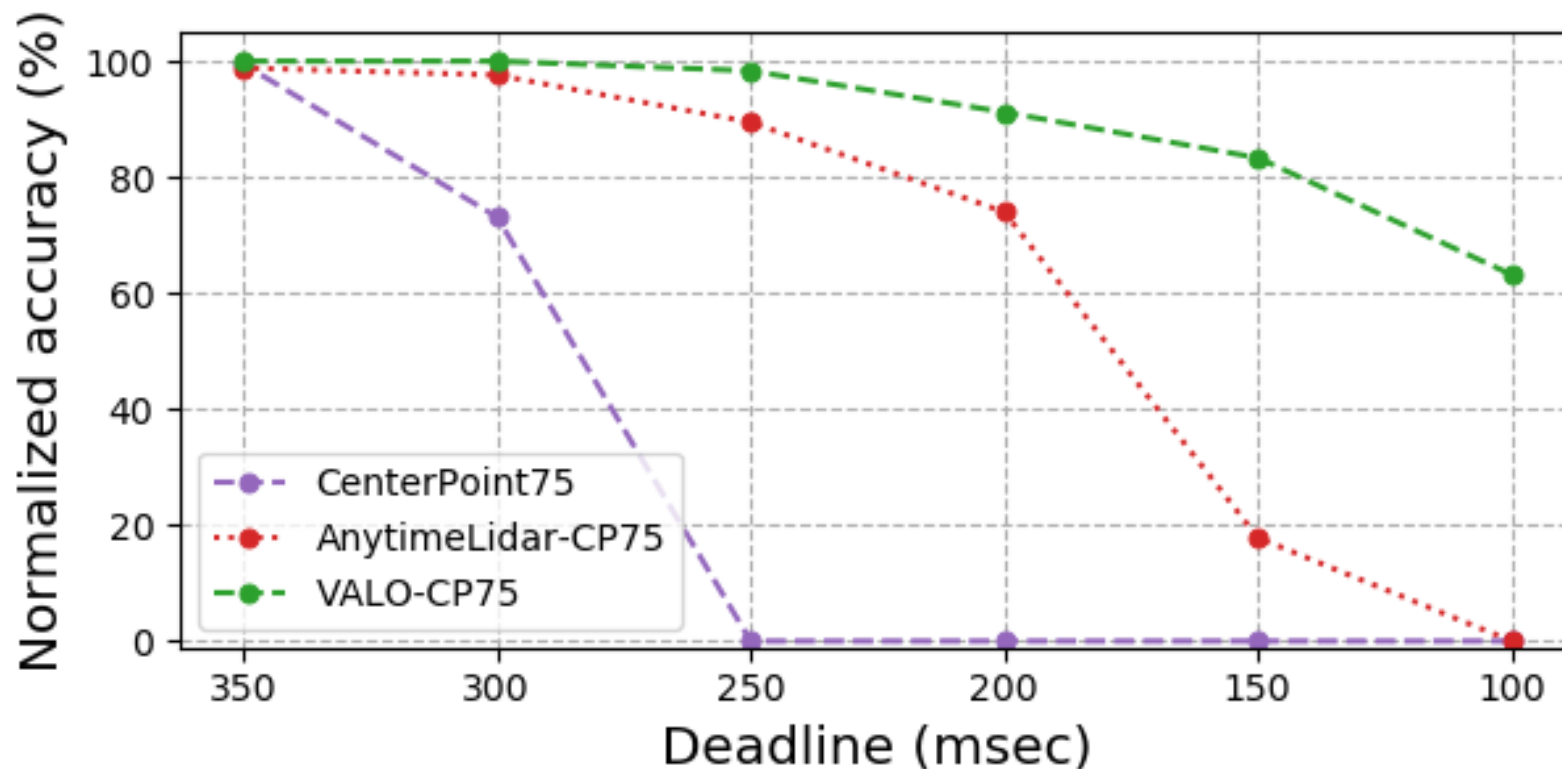


NVIDIA Jetson AGX Xavier  
512 core GPU, 8-core CPU, 16G RAM

# Anytime 3D Object Detection



- maximize detection accuracy for a given (arbitrary) computing budget



CenterPoint:  
SOTA 3D object detector

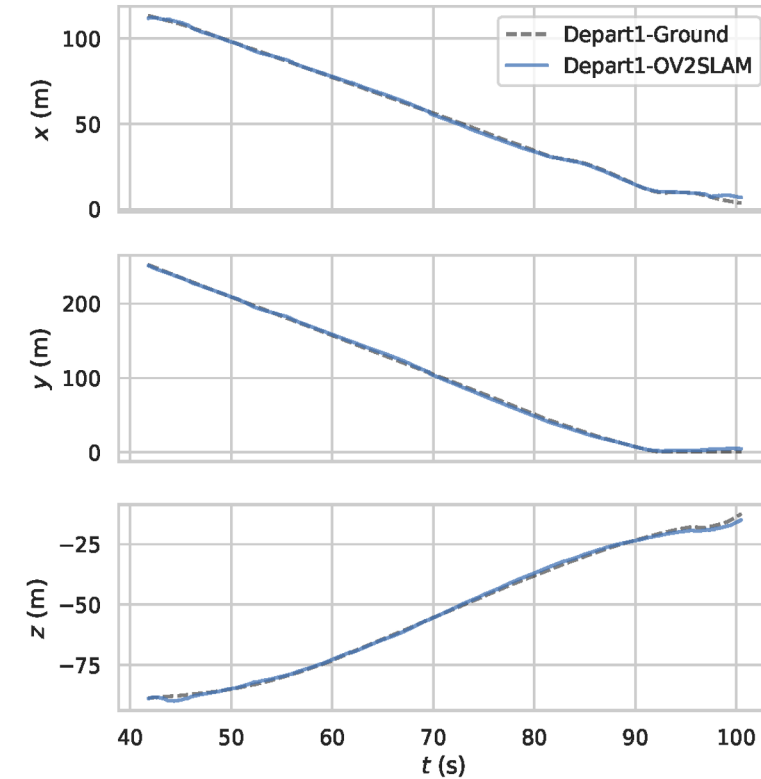
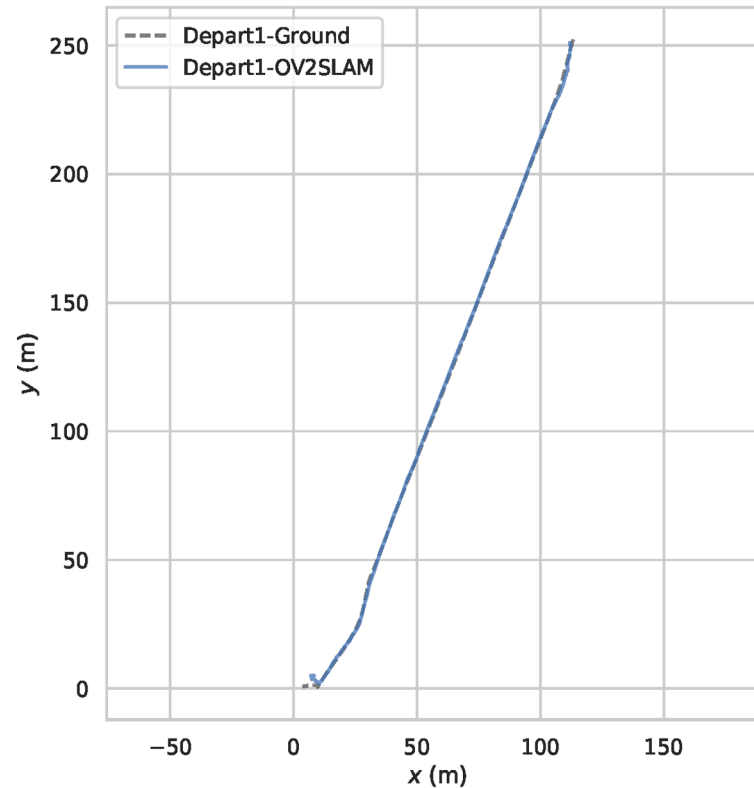
Anytime-Lidar:  
our prior work

VALO:  
our approach



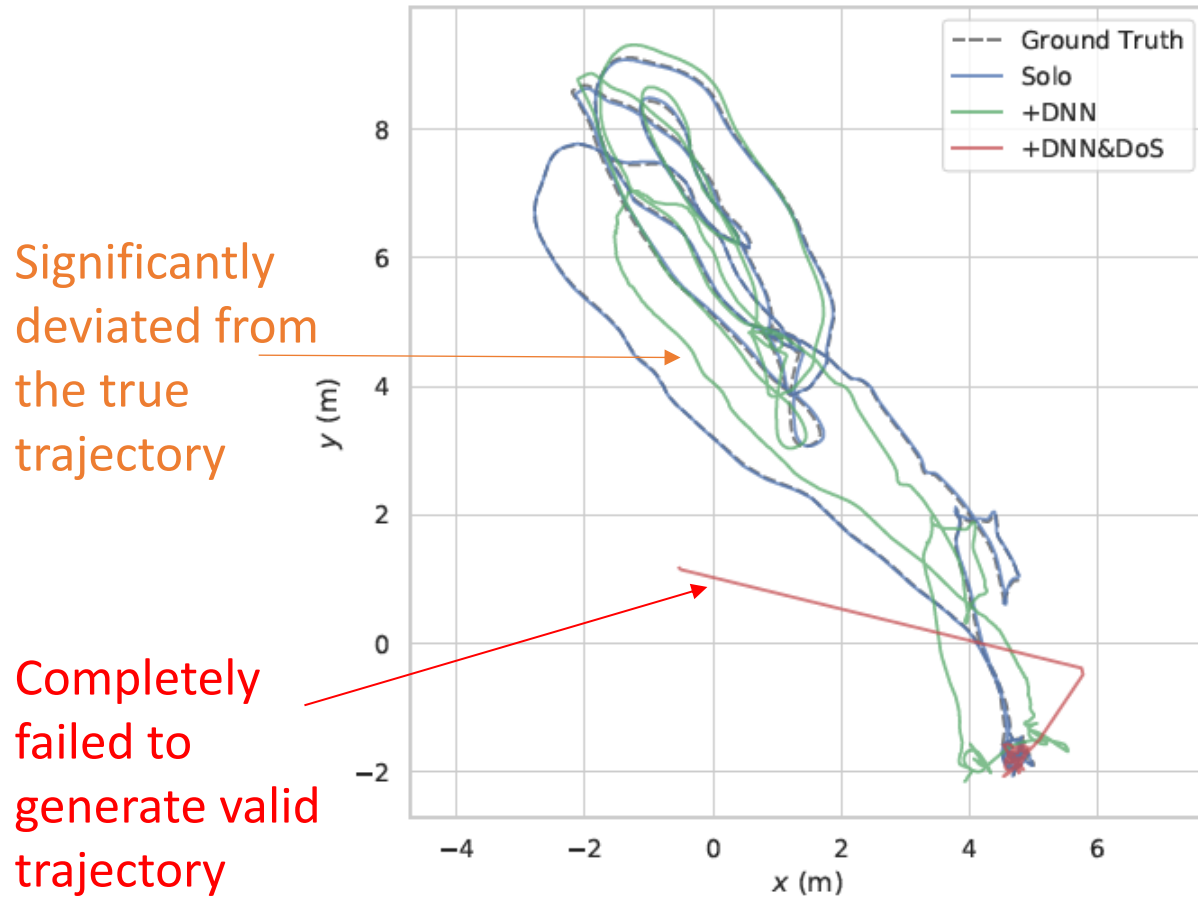
# Visual Odometry

- Estimate position and pose from the camera input in real-time

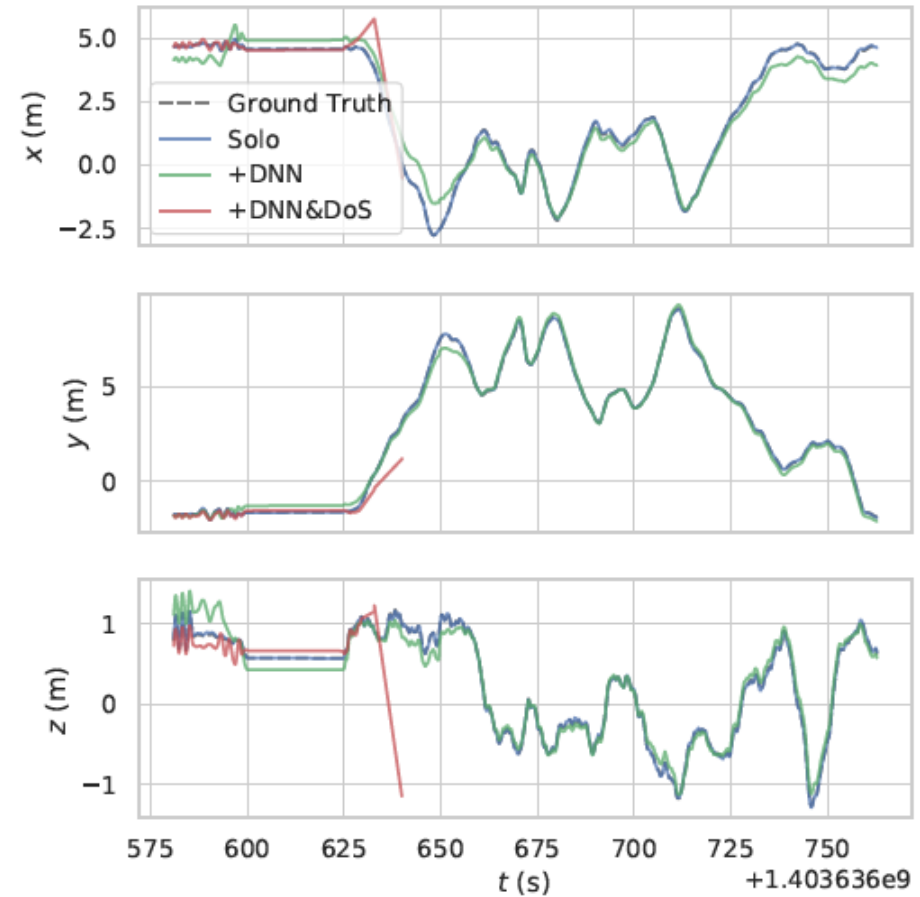


OV<sup>2</sup>SLAM on NASA Alta8 Dataset

# Impact of DNN and DoS attacks on OV<sup>2</sup>SLAM



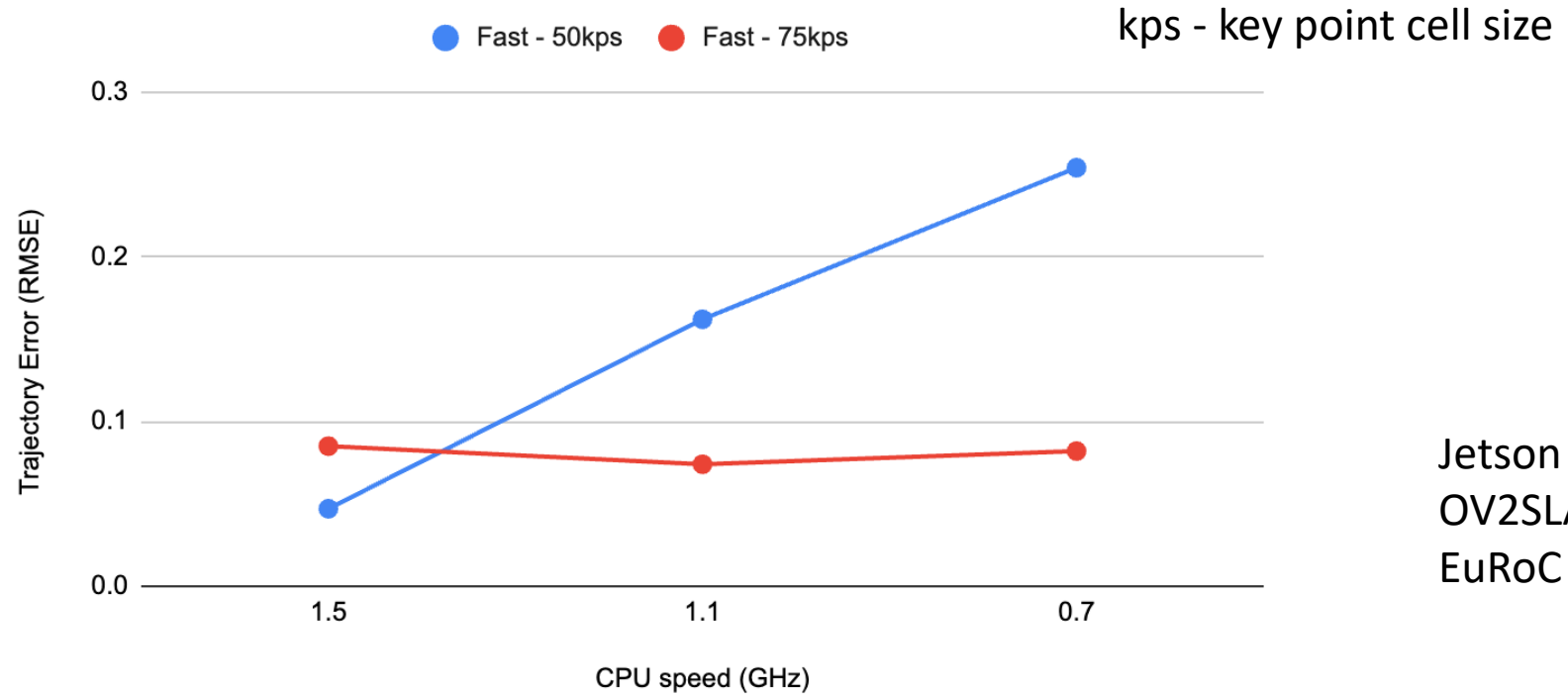
(a) Trajectory in XY plane



(b) X, Y and Z positions over time

# Anytime Visual SLAM

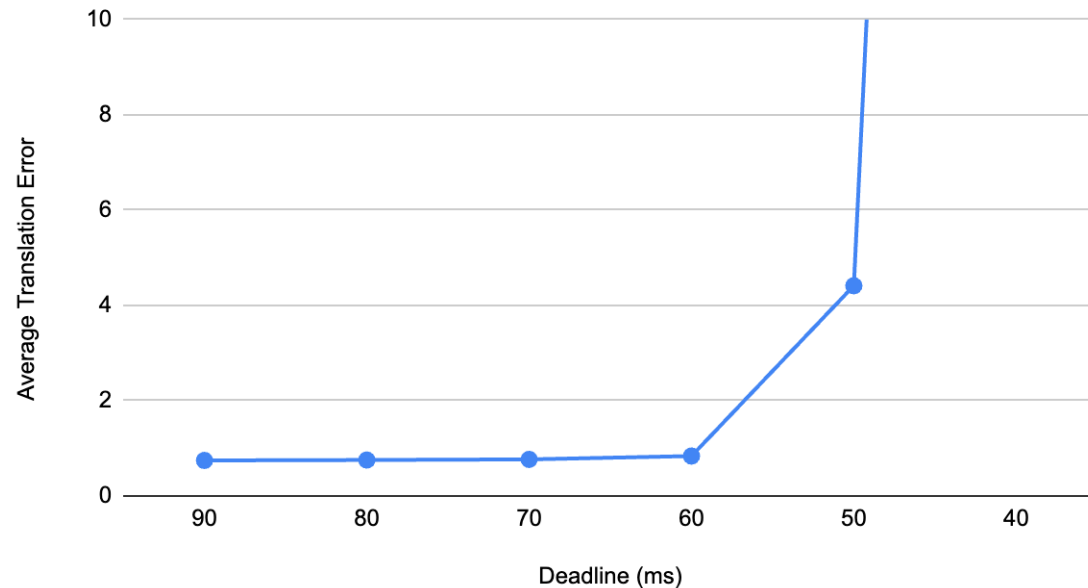
CPU speed vs. Trajectory Error



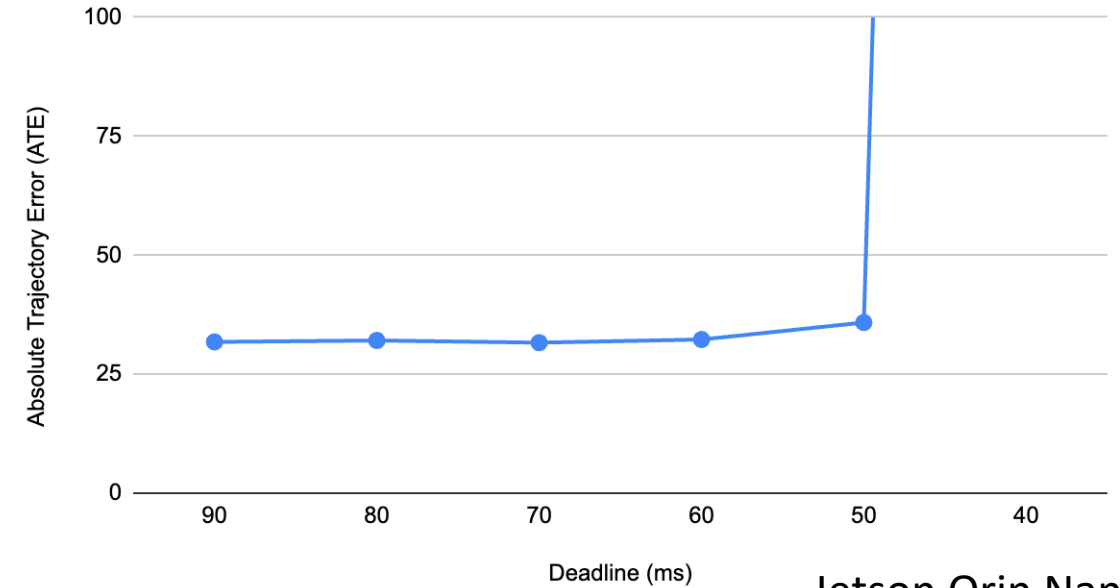
- Depending on available computing speed, the optimal algorithm varies

# Anytime Lidar Odometry

Average Translation Error vs. Deadline (ms)



Absolute Trajectory Error (ATE) vs. Deadline (ms)



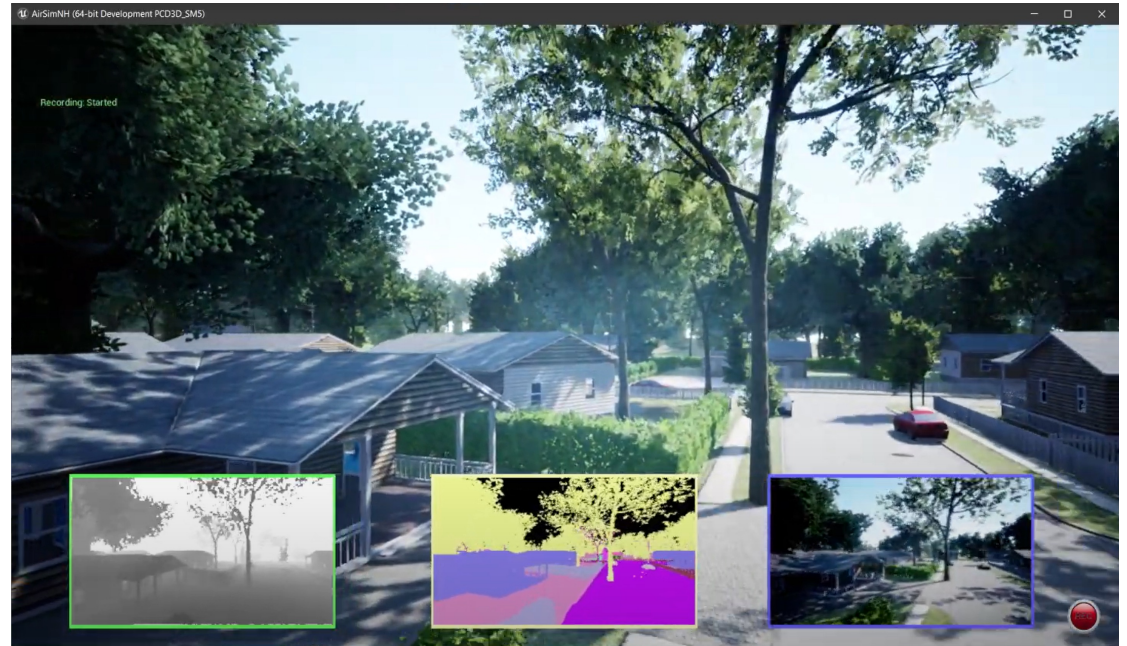
Jetson Orin Nano,  
KISS-ICP (modified)  
KITTI Dataset

- Finishing early (up to a point) did not significantly impact accuracy



# Evaluation Methods

- NASA sUAS dataset and others
- AirSim simulator
- Aurelia X4 VTOL testbed





# Outline

- Introduction
- A case study
- Anytime perception and control for UAM/UAS
- **Conclusion**

# Conclusion

- UAM requires powerful perception and control for high intelligence and safety
- Sophisticated perception and control algorithms are computationally expensive and require trade-offs in time, accuracy, and performance.
- Anytime perception and control enables runtime adaptation to maximize system performance on limited on-board computing resources

# Thank You!

Acknowledgements:

*This research is supported in part by  
NSF CNS-1815959, CPS-2038923, FAA  
A54\_A11L.UAS.97, NASA KNEP PDG  
grants*

