

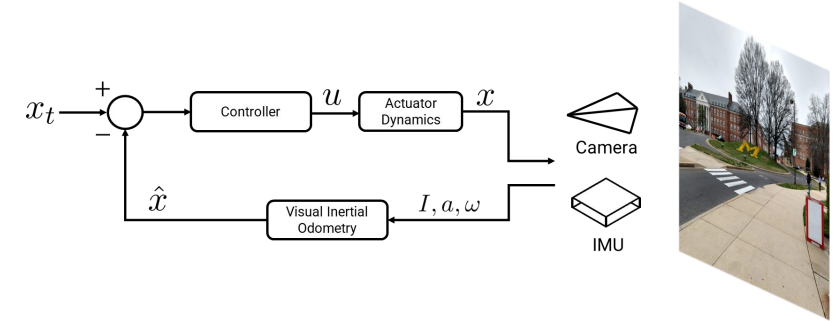
# **The Advantages of a Control Theoretic Approach to Monocular Computer Vision**

Levi Burner, PhD Student

Perception and Robotics Group  
Electrical & Computer Engineering Department  
University of Maryland, College Park

# Agenda

- Traditional Robot Control with Vision



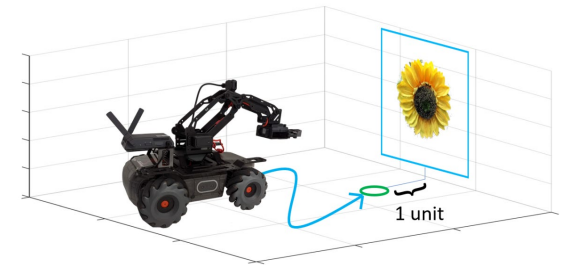
- Control Theoretic Approach

- Phi and Tau Constraints
- Stability Invariance

$$\mathbf{F} := \frac{\dot{\mathbf{X}}}{Z} \implies \mathbf{X}(t) = \underbrace{\begin{bmatrix} 1 & 0 & \int_0^t F_X(\lambda) \Phi_{F_Z}(\lambda) d\lambda \\ 0 & 1 & \int_0^t F_Y(\lambda) \Phi_{F_Z}(\lambda) d\lambda \\ 0 & 0 & \Phi_{F_Z}(t) \end{bmatrix}}_{\Phi(t) :=} \mathbf{X}_0$$

- Conclusion

- Summary of how to use in your own projects



- Full Paper: TTCDist: Fast Distance Estimation From an Active Monocular Camera Using Time-to-Contact, Levi Burner, Nitin J. Sanket, Cornelia Fermüller, Yiannis Aloimonos  
<https://arxiv.org/abs/2203.07530>

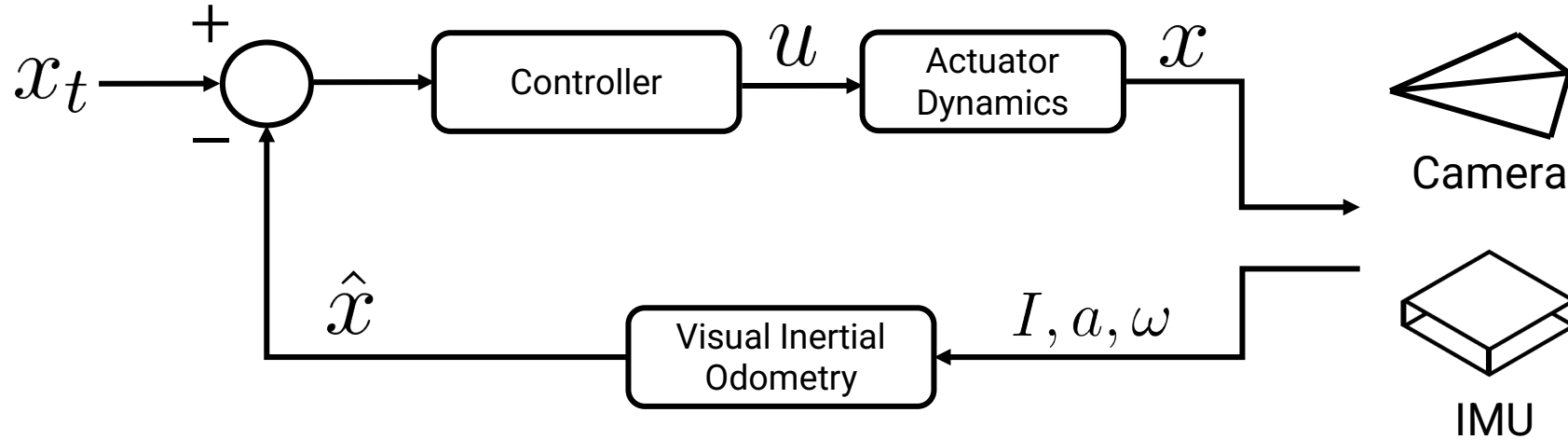


# Robots Tracking Trajectories with Cameras



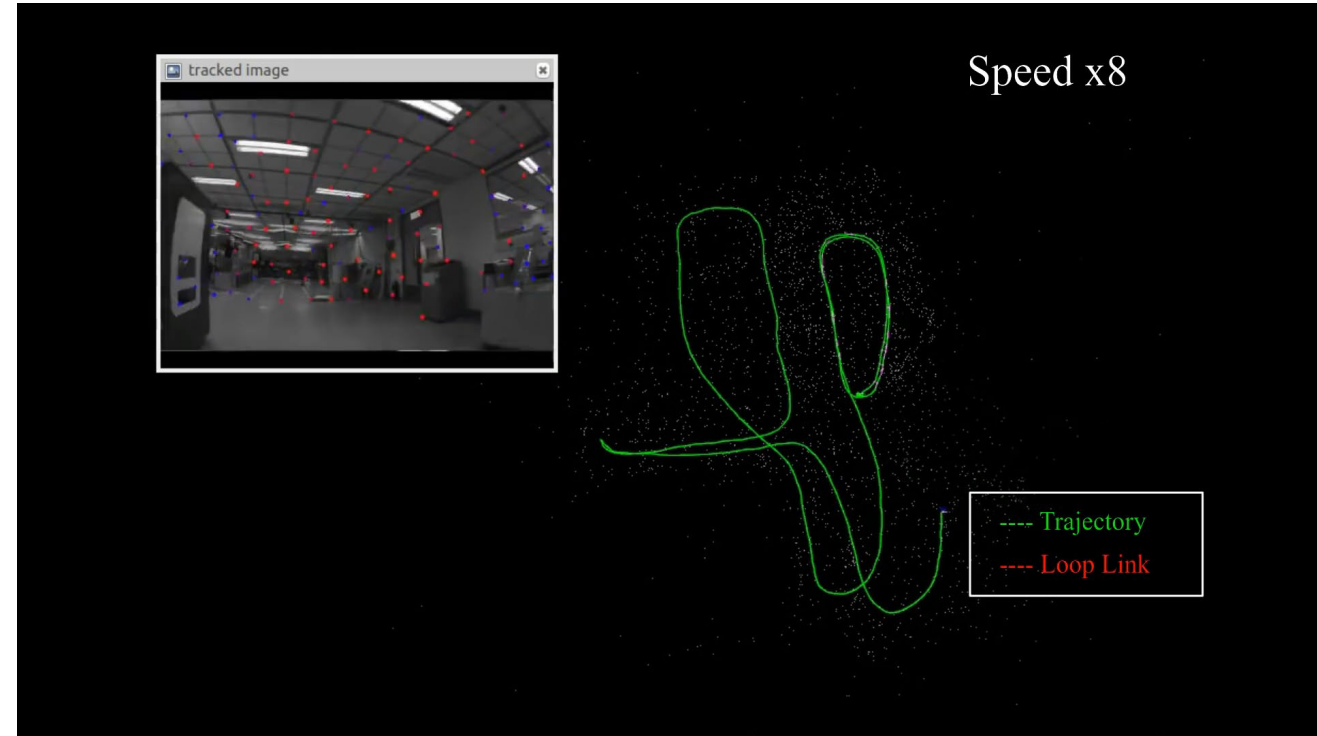
“Introducing Skydio 2” - <https://www.youtube.com/watch?v=imt2qZ7uw1s>  
“With you, Spot can” - <https://www.youtube.com/watch?v=VRm7oRCTkjE>

# Typical Robot Visual Tracking Control (in academia)



# Visual Inertial Odometry

- Tracks points/patches scattered across FOV
- Combines IMU and tracked points through optimization
- Some methods use patches instead of points
  - Usually try to minimize a photometric loss with either an optimizer or iterative Extended Kalman Filter

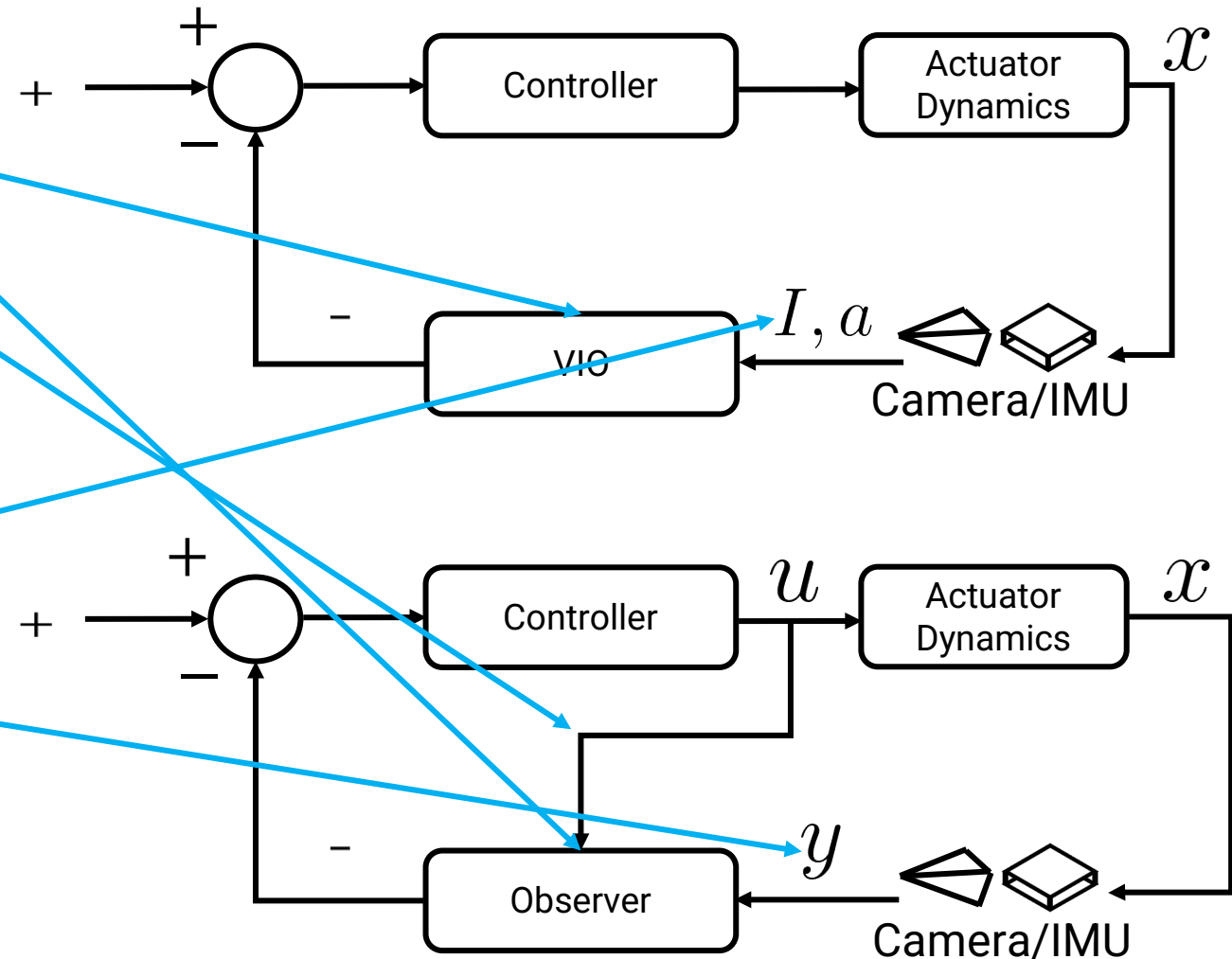


VINS-Mono: A Robust and Versatile Monocular Visual-Inertial State Estimator, Tong Qin, Peiliang Li, Zhenfei Yang, Shaojie Shen, *IEEE Transactions on Robotics*

# Control Theoretic Approach

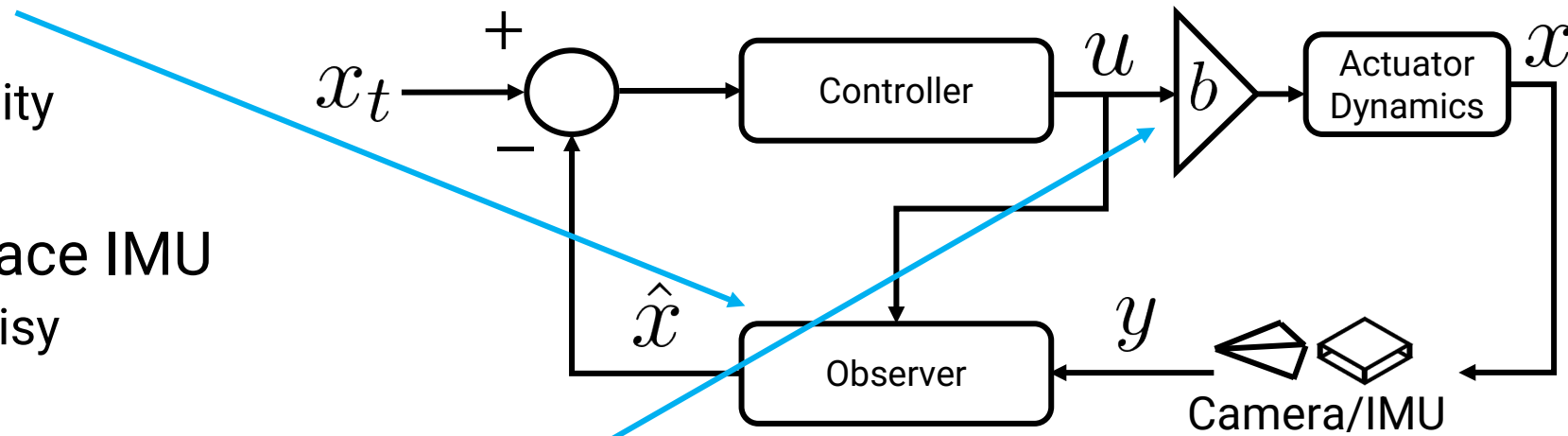
- Replace VIO with observer
- Send control signal to observer
- Treat camera as source of output feedback

$$y = h(x)$$



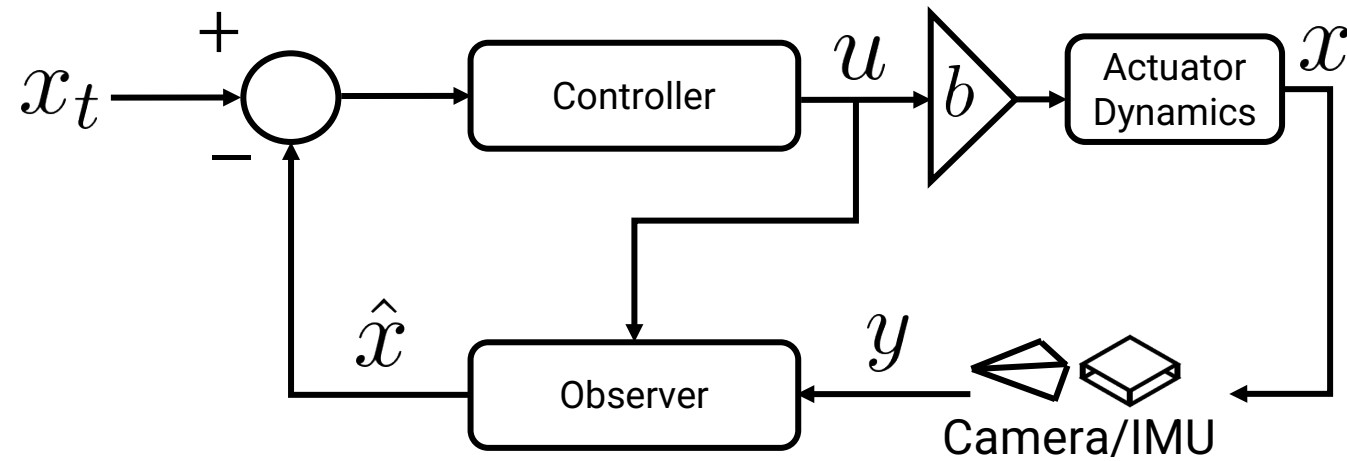
# Advantages of Control Theoretic Approach

- Careful choice of  $y$  allows observer to be linear
  - Due to two closely related linear equality constraints
    - Tau constraint
    - Phi constraint
  - Can easily prove stability
- Sometimes  $u$  can replace IMU
  - IMU acceleration is noisy
  - $u$  is not noisy
  - The closed loop dynamics become invariant to  $b$
  - Robot becomes “very stable”



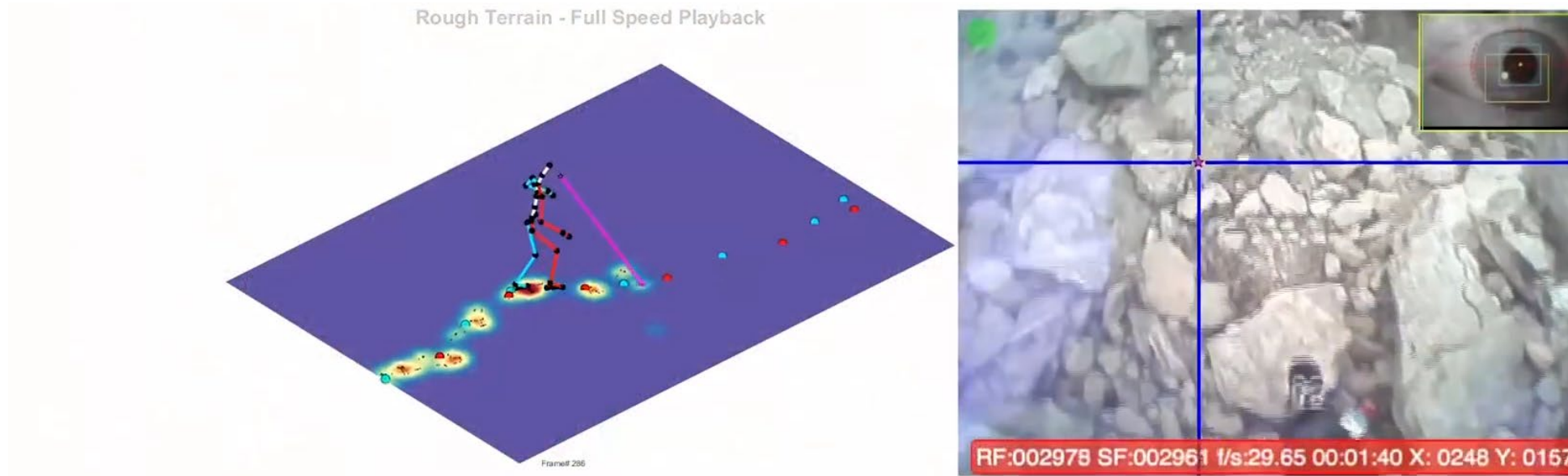
# What should $y$ be?

- $y = h(x)$
- We have the luxury of choosing  $h$
- Bio-inspiration?
  - What might humans measure?



# Mammalian Vision

- When human's walk they switch their gaze



Matthis, J.S., Yates, J.L., and Hayhoe, M.M. (2018), "Gaze and the control of the foot placement when walking in natural terrain". *Current Biology*

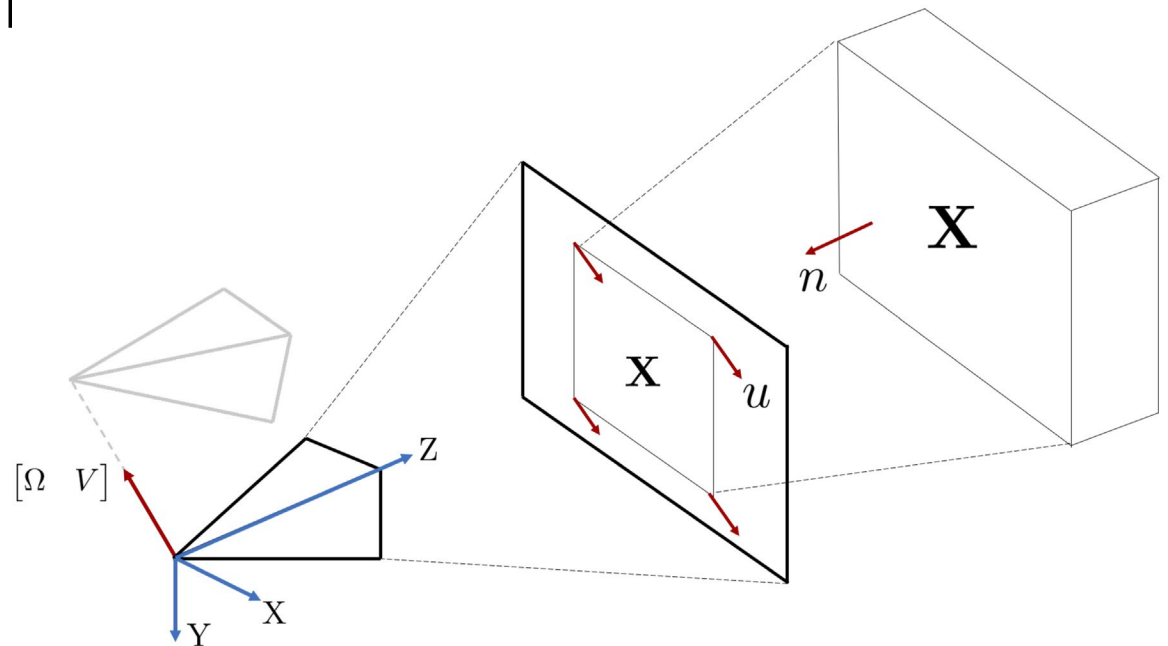
# Time to Contact



- Intuitively:
  - Rate of change of object size
  - Sense of when an object will hit

- Mathematically:

$$\tau(t) = \frac{Z(t)}{\dot{Z}(t)}$$





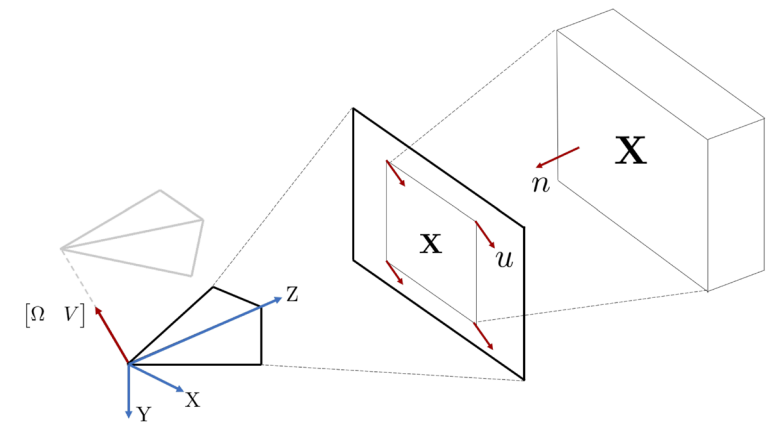
# Measuring Time to Contact

- We can describe where pixels in a patch with an affine “warp”
  - For those taking 733 one way to measure a warp is with the LK algorithm

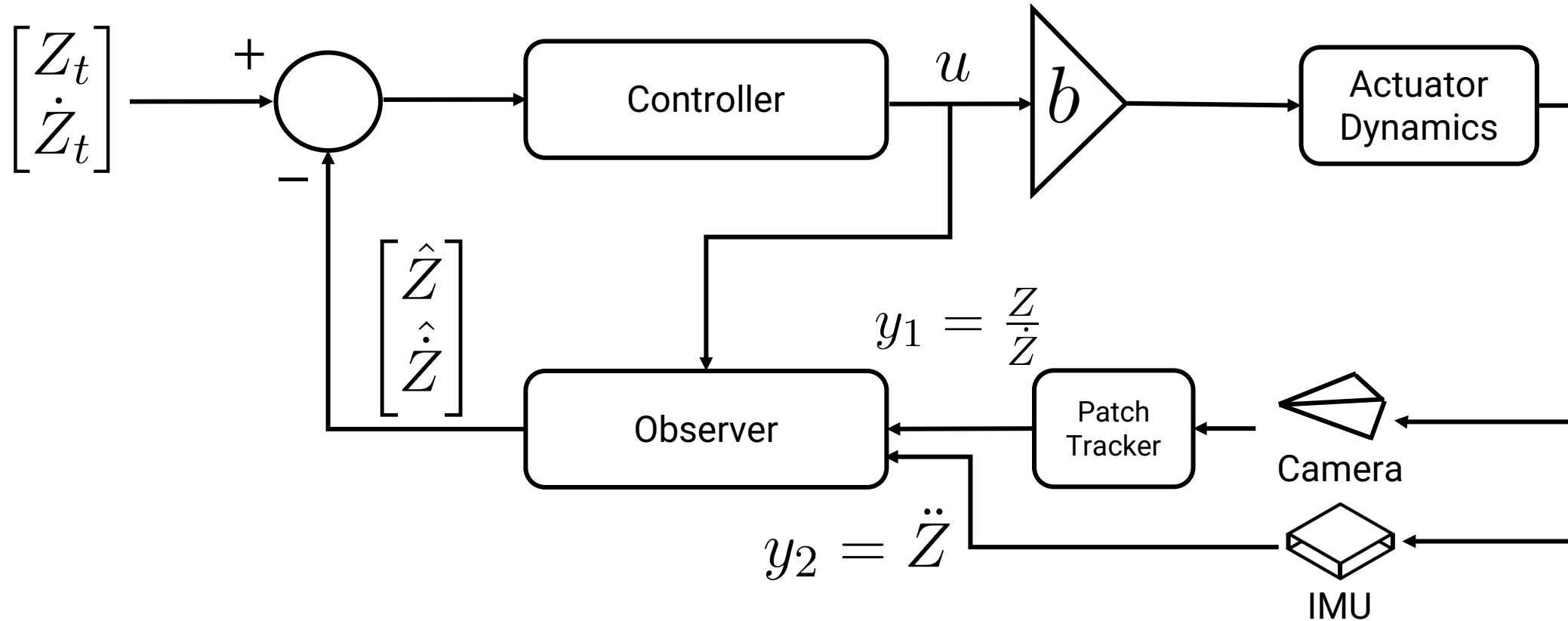
$$\mathbf{x}(t) = \underbrace{\begin{bmatrix} Z_0/Z & 0 & (X - X_0)/Z \\ 0 & Z_0/Z & (Y - Y_0)/Z \\ 0 & 0 & 1 \end{bmatrix}}_{A:=} \mathbf{x}(0)$$

- Differentiating gives optical flow
  - But the affine terms are time-to-contact!

$$\mathbf{u}_x = \frac{d\mathbf{x}(t)}{dt} = \dot{A}A^{-1}\mathbf{x} = - \begin{bmatrix} \dot{Z}/Z & 0 & \dot{X}/Z \\ 0 & \dot{Z}/Z & \dot{Y}/Z \\ 0 & 0 & 0 \end{bmatrix} \mathbf{x}$$



# Simplified Case – Z Only



# Full Case – Tau/Phi Constraint

- Generalize to frequency of contact

$$\mathbf{F} := \frac{\dot{\mathbf{X}}}{Z} \implies \dot{\mathbf{X}} = \mathbf{F}Z$$

- Recognize F defines an ODE

$$\mathbf{X}(t) = \underbrace{\begin{bmatrix} 1 & 0 & \int_0^t F_X(\lambda)\Phi_{F_Z}(\lambda)d\lambda \\ 0 & 1 & \int_0^t F_Y(\lambda)\Phi_{F_Z}(\lambda)d\lambda \\ 0 & 0 & \Phi_{F_Z}(t) \end{bmatrix}} \mathbf{X}_0$$

- ODE has closed form solution

- Linear Time Varying System
- Covered in ENEE660

$$\Phi_{F_Z}(t) = \exp\left(\int_0^t F_Z(\lambda)d\lambda\right)$$

- Write X as function of acceleration

$$\mathbf{X}(t) - \mathbf{X}_0 = t\dot{\mathbf{X}}_0 + \underbrace{\int_0^t \left( \int_0^\lambda \ddot{\mathbf{X}}(\lambda_2)d\lambda_2 \right) d\lambda}_{\mathcal{J}\{\ddot{\mathbf{X}}\}(t) :=}$$

- Set both sides equal to each other!

# Full Case – Phi/Tau Constraint

- Setting both sides equal results in Phi-constraint

$$\underbrace{(\Phi(t) - I)}_{\text{}} \underbrace{\begin{bmatrix} 0 \\ 0 \\ Z_0 \end{bmatrix}}_{\text{}} - t\dot{\mathbf{X}}_0 = \mathcal{J}\{\ddot{\mathbf{X}}\}(t)$$

(Phi-constraint)

- Substitute  $\dot{\mathbf{X}} = \mathbf{F}Z_0$  to get Tau-constraint

$$\underbrace{(\Phi(t) - I - t \begin{bmatrix} 0 & 0 & \mathbf{F}(0) \end{bmatrix})}_{E(t) :=} \begin{bmatrix} 0 \\ 0 \\ Z_0 \end{bmatrix} = \mathcal{J}\{\ddot{\mathbf{X}}\}(t).$$

( $\tau$ -constraint)

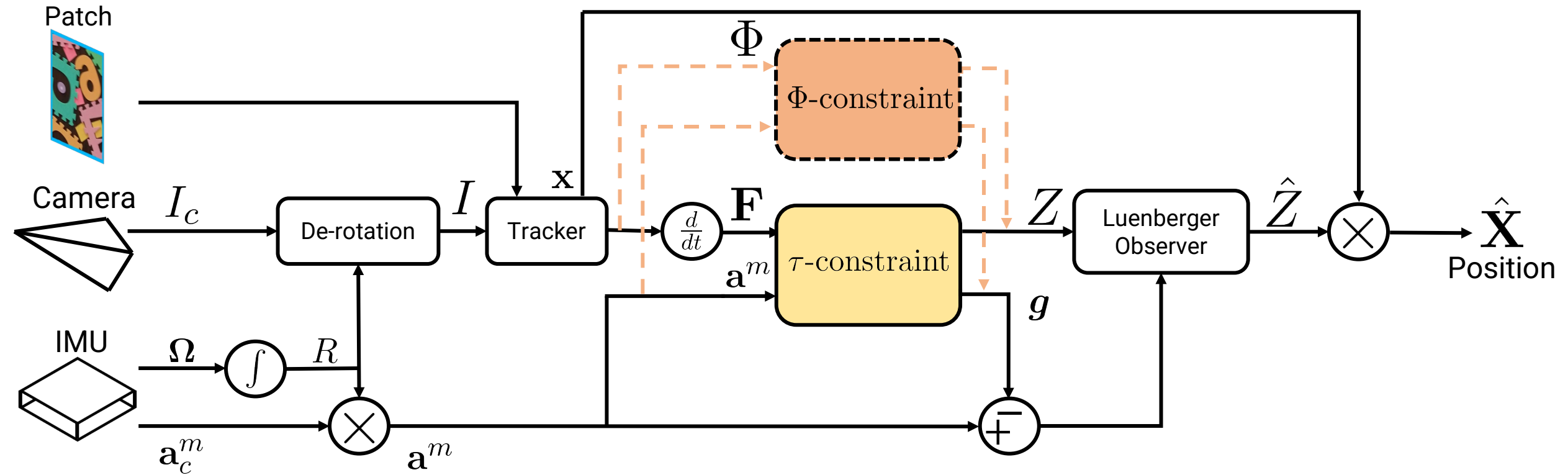
# Estimating Distance Becomes a Linear

- Suppose acceleration with an unknown gravitational bias is available
- Can do linear least squares over time

$$\operatorname{argmin}_{Z_0, \dot{Z}_0, g_Z} \left\| (\Phi_{F_Z} - 1) Z_0 - r \dot{Z}_0 + \mathcal{J}\{a_Z^m + g_Z\} \right\|_2^2 \quad (\Phi\text{-constraint})$$

$$\operatorname{argmin}_{Z_0, g_Z} \|E_Z Z_0 + \mathcal{J}\{a_Z^m + g_Z\}\|_2^2 \quad (\tau\text{-constraint})$$

$$\tau := \frac{Z}{\dot{Z}} \quad \Rightarrow \quad \mathbf{F} := \frac{\dot{\mathbf{X}}}{Z}$$



# Sequence 2

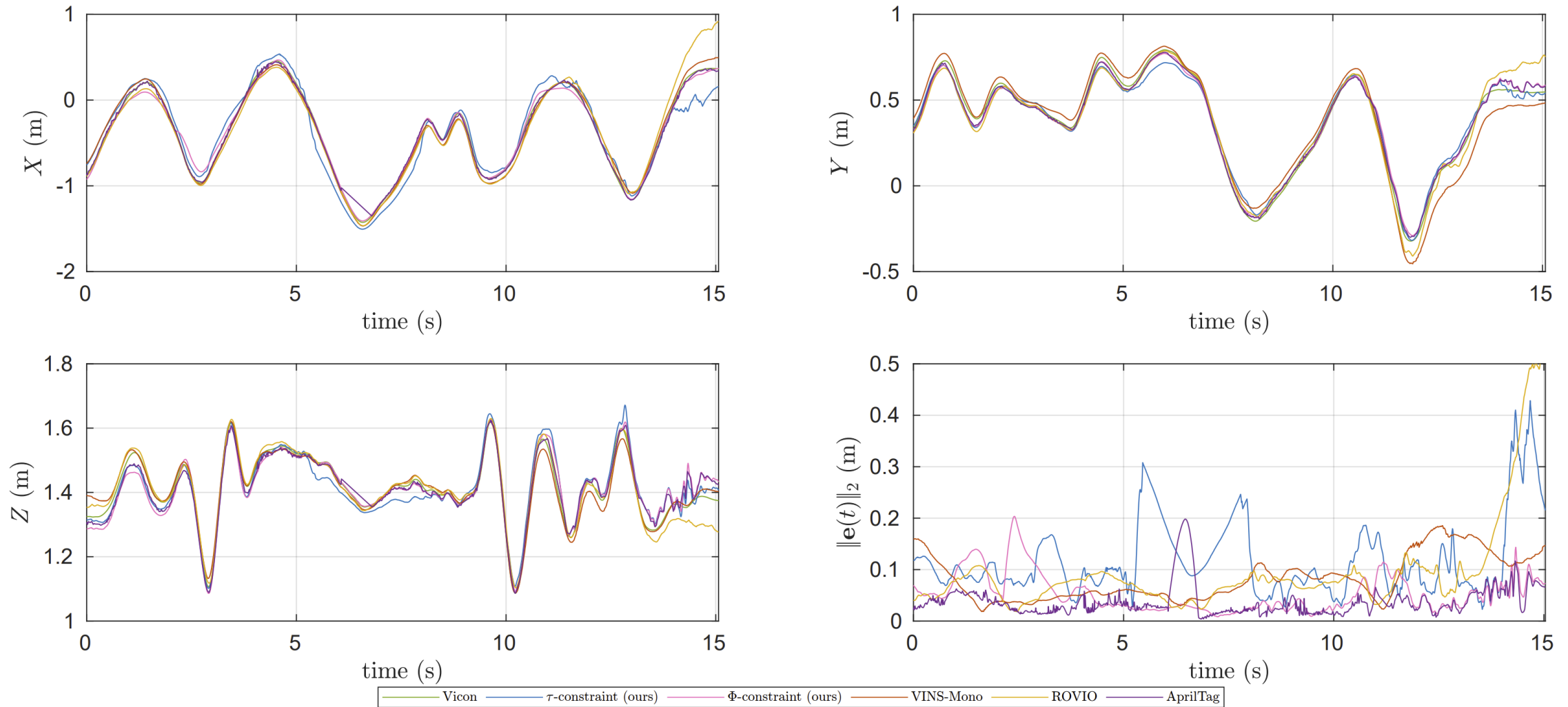


# Sequence 4

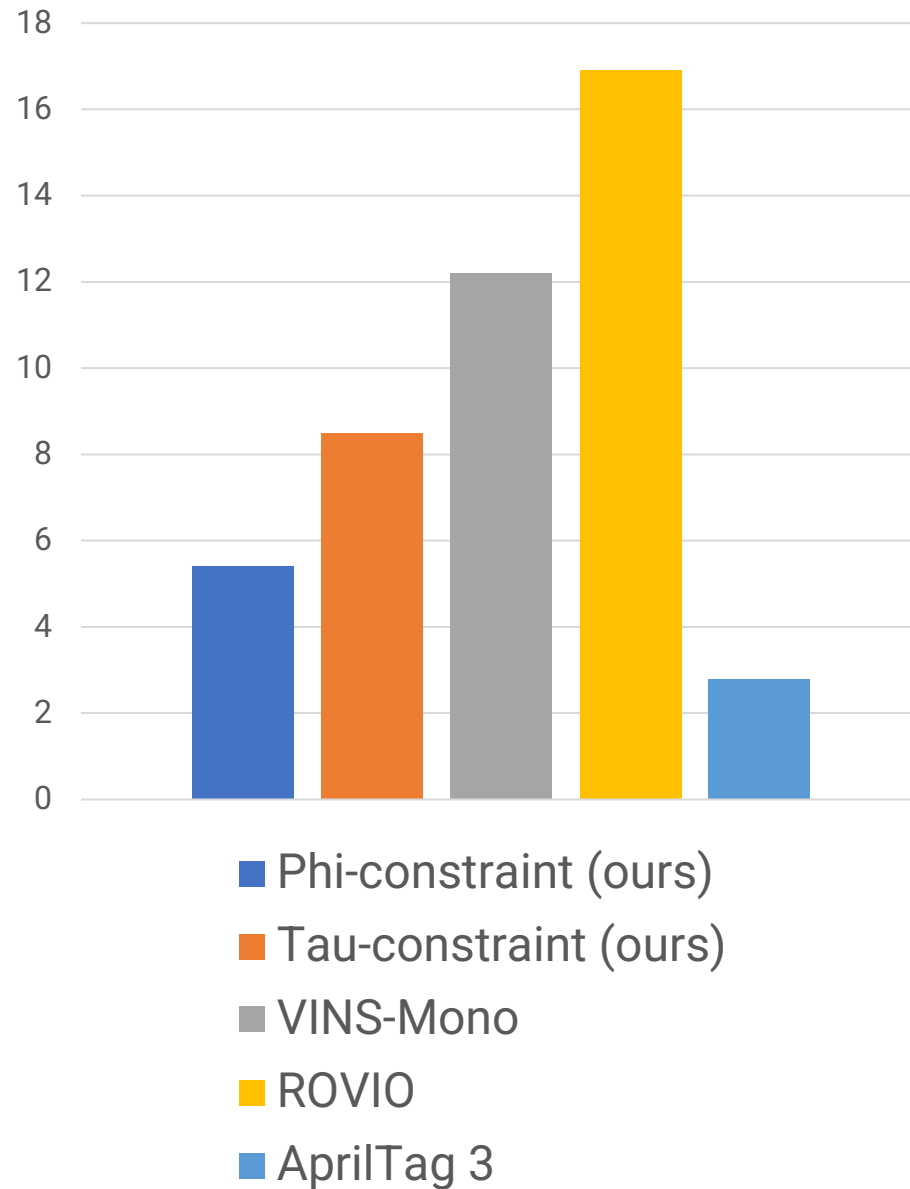




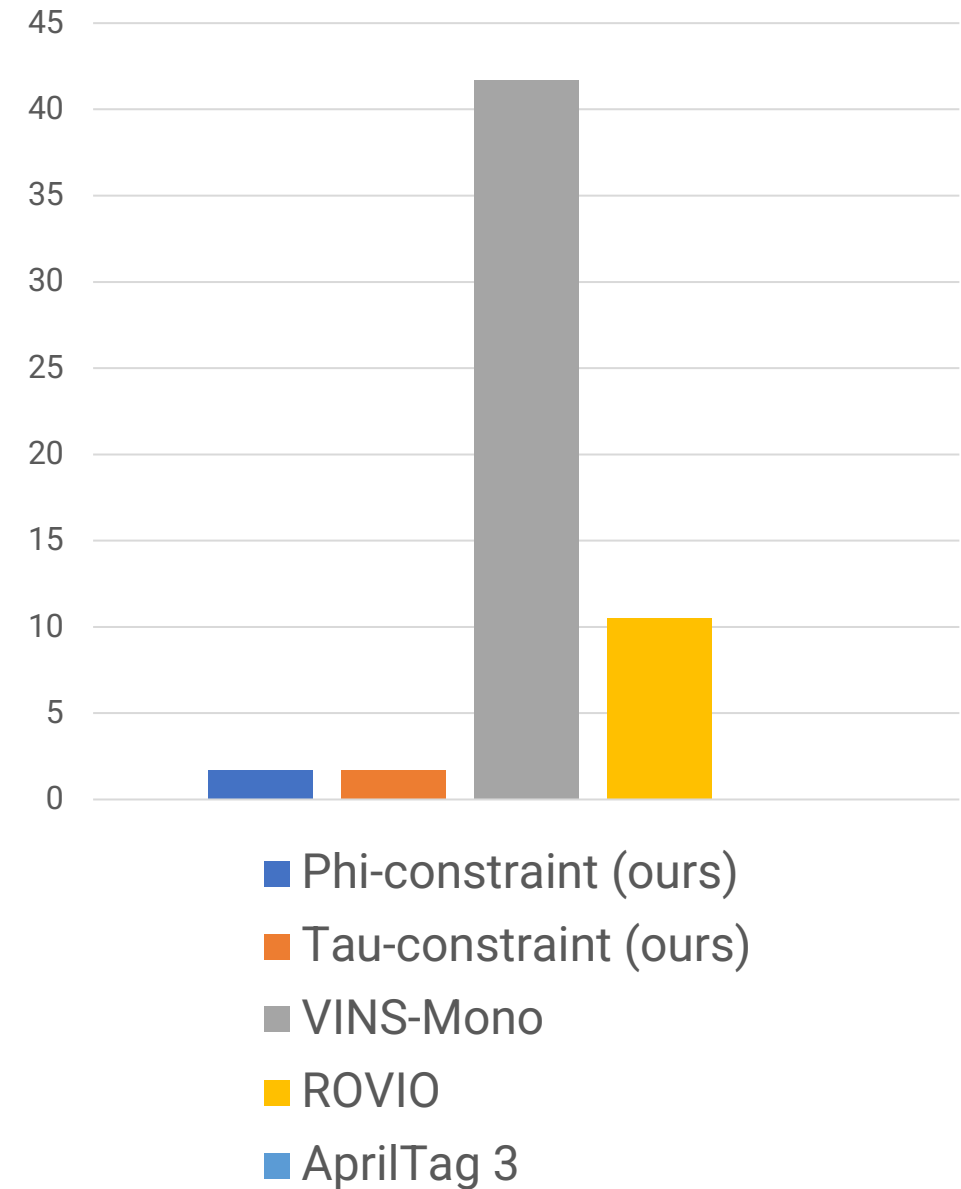
# Sequence 1 Trajectory/Error



### Average Trajectory Error (cm)

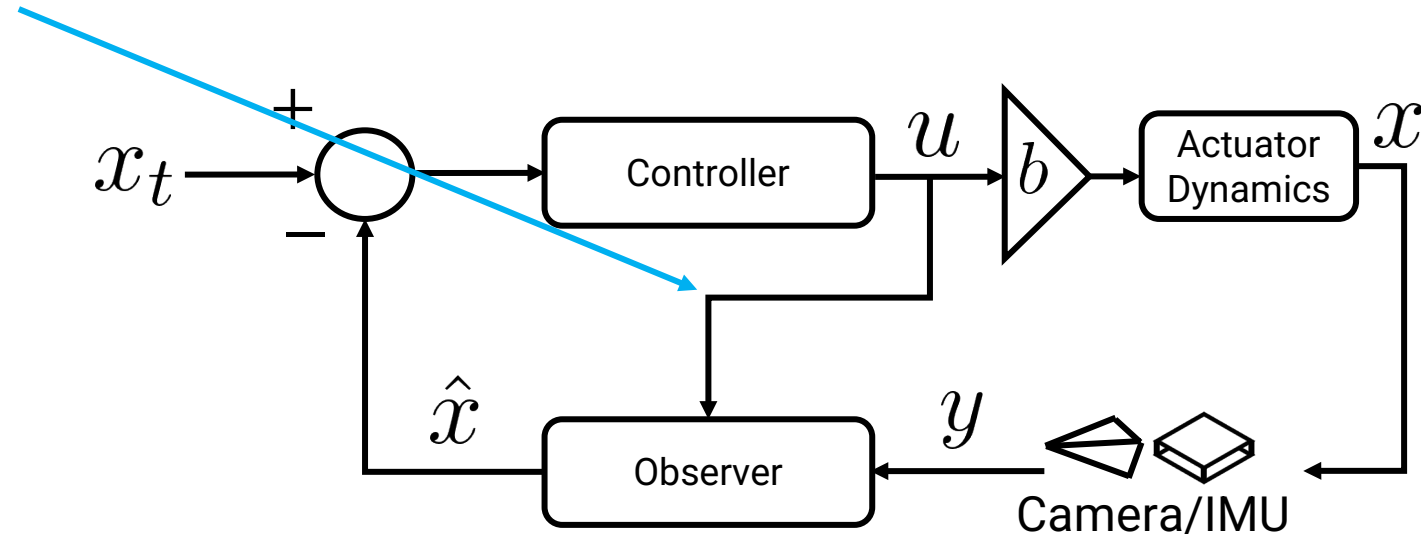


### Time-per-frame (milliseconds)



# Stability Invariance

- We still have not used control effort in observer



# Control effort and acceleration

$$\ddot{x} = \frac{1}{100} u$$



$$\ddot{x} = \frac{1}{200} u$$



# Scaled State Estimates Using “u”

- Recall the Phi/Tau constraints result in linear least squares problems
- Using control effort in place of acceleration results in scaled state estimate

$$\operatorname{argmin}_{Z_0, \dot{Z}_0, g_Z} \left\| (\Phi_{F_Z} - 1) Z_0 - r \dot{Z}_0 + \mathcal{J}\{a_Z^m + g_Z\} \right\|_2^2$$

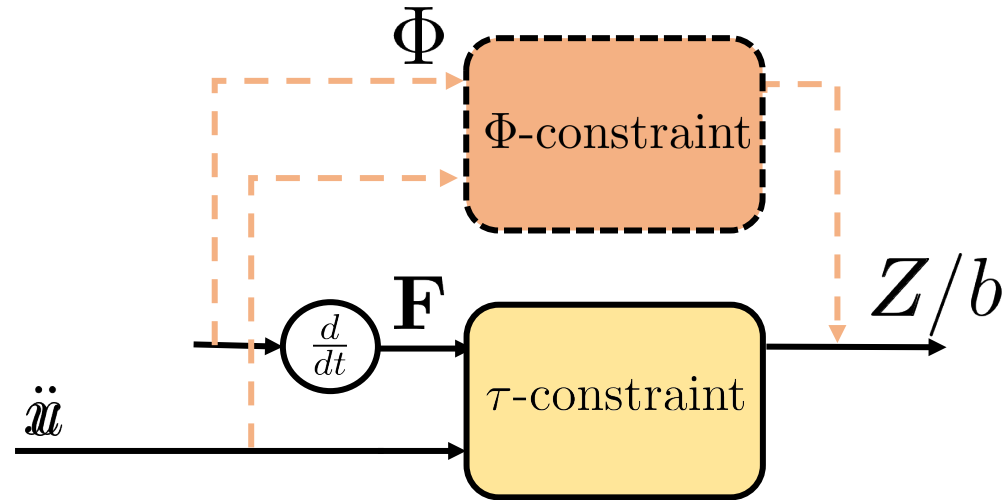
$$\Rightarrow \begin{bmatrix} Z \\ \dot{Z} \\ g_Z \end{bmatrix} = (A^T A)^{-1} A^T \ddot{x}$$

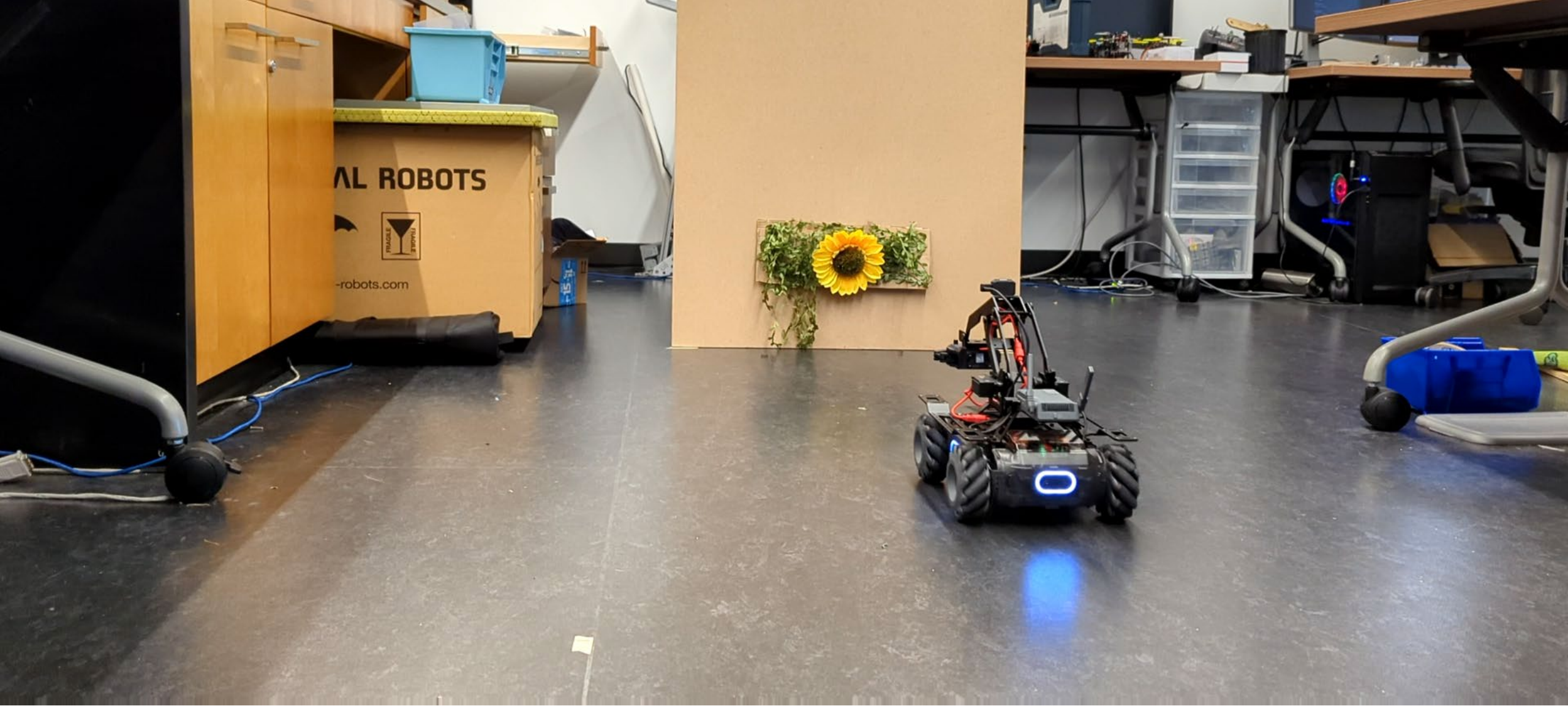
$$\ddot{x} = bu \Rightarrow \ddot{x}/b = u$$

$$\Rightarrow \begin{bmatrix} Z/b \\ \dot{Z}/b \\ g_Z/b \end{bmatrix} = (A^T A)^{-1} A^T u$$

# Scaled State Estimates Using “u”

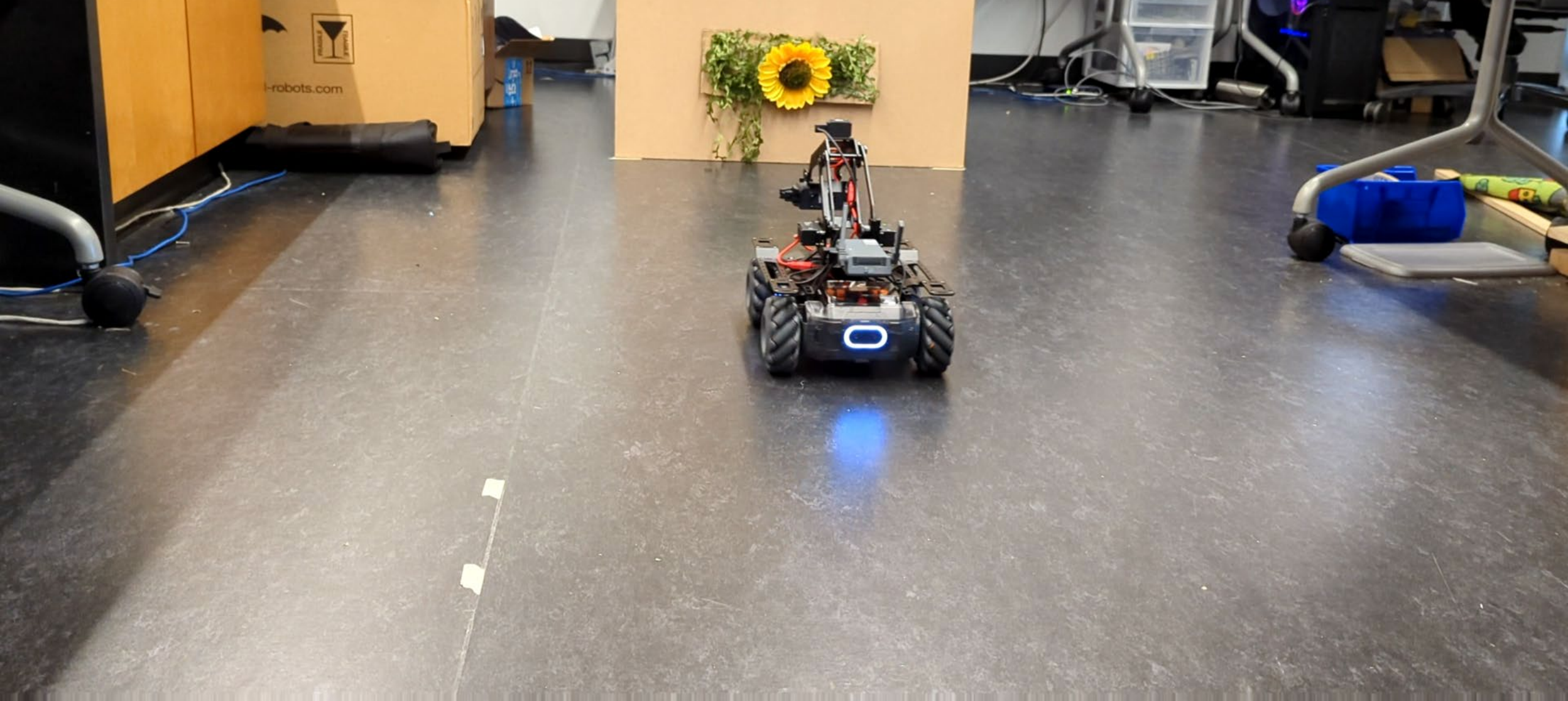
$$\ddot{x} = bu = \cancel{bkZ/b}$$





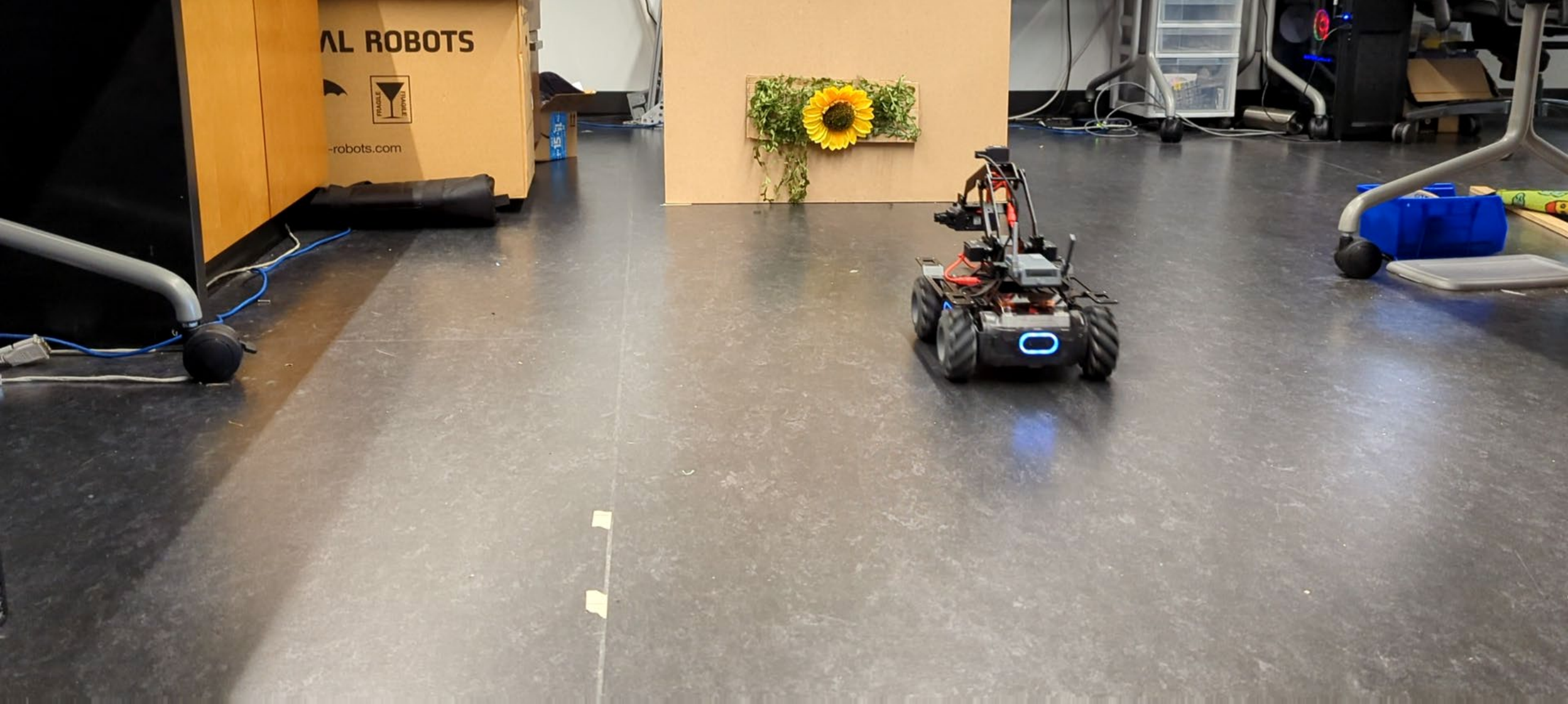
$b = 1$ , measured acceleration





$b = 1$ , efference copy





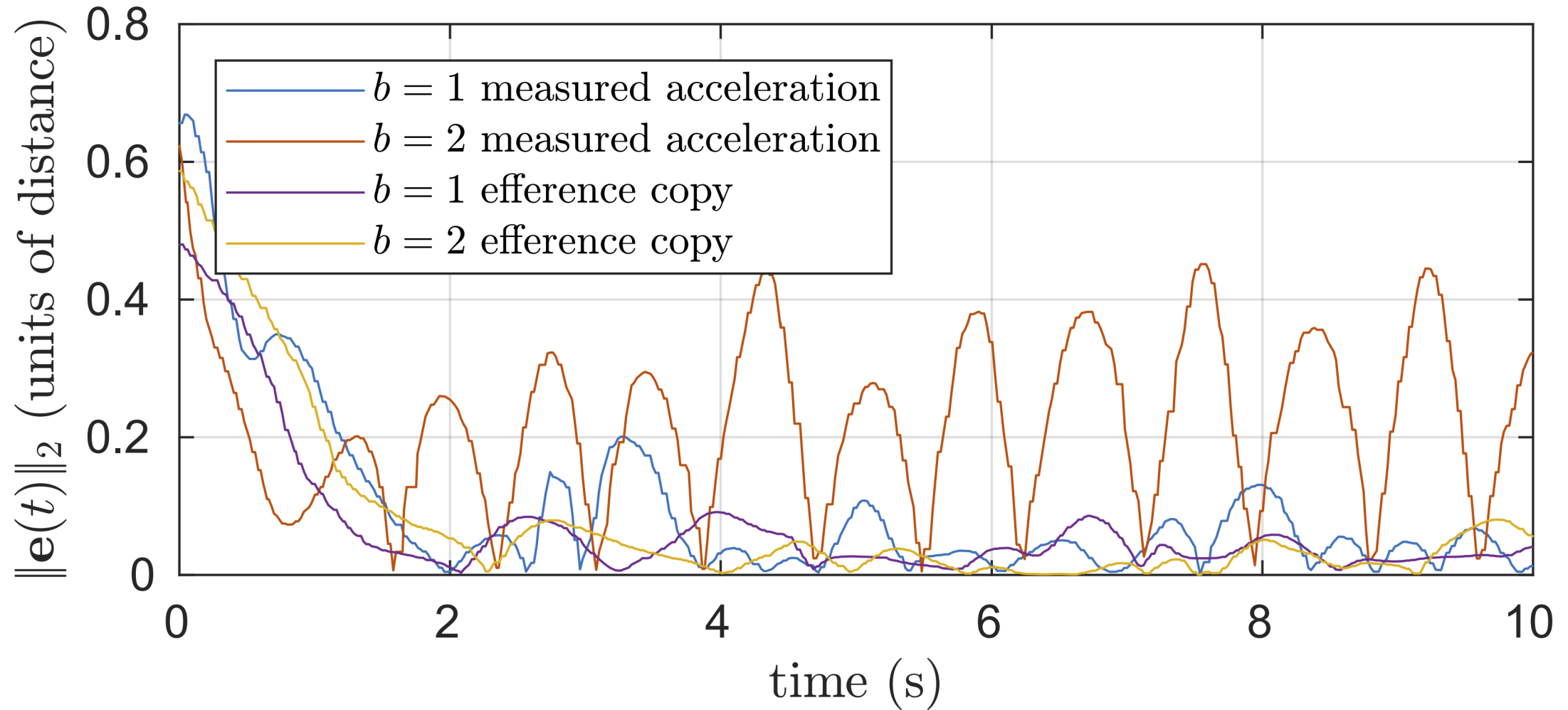
$b = 2$ , measured acceleration





$b = 2$ , efference copy

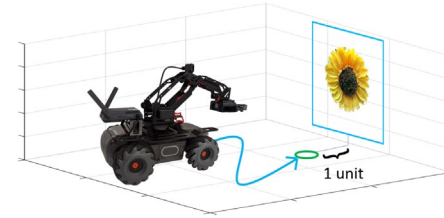
# Oscillations



# How to Use This Approach?

- Three Easy Steps

- Measure a bounding box with a camera
  - Bounding box will give you  $\Phi$  or  $F$



$$\implies \mathbf{X}_c = \Phi_c(t) \mathbf{X}_0$$

- Relate bounding box params to motion model

$$\begin{aligned} \dot{\mathbf{X}}_m &= f(t, \mathbf{X}_m, u) \\ \implies \mathbf{X}_m &= \Phi_f(t, \mathbf{X}_0, u) \end{aligned}$$

- Apply optimization to a window of time

- Can use a recursive observer, pure optimization, etc
- Feedback linearized models will result in linear problems

$$\min_{\mathbf{X}_0} \|\mathbf{X}_m - \mathbf{X}_c\|$$

- Full Paper: TTCDist: Fast Distance Estimation From an Active Monocular Camera Using Time-to-Contact, Levi Burner, Nitin J. Sanket, Cornelia Fermüller, Yiannis Aloimonos  
<https://arxiv.org/abs/2203.07530>

# Conclusion

- Took a control theoretic approach to monocular distance estimation
- Found a linear equality constraint that allows fast and accurate estimation of distance
  - Achieved competitive trajectory estimation performance
  - 6.2x and 25x faster than ROVIO and VINS-Mono
  - 30-70% less centimeters of average trajectory error
- Found that in certain cases, stability margins become invariant
  - Idea should be more fully developed into a form of adaptive control

# Thanks to my Collaborators and Sponsors!



Prof. Nitin Sanket



Dr. Cornelia Fermüller



Prof. Yiannis Aloimonos

