Real-time 6 DOF Pose Estimation with Limited Priors

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Co Mentor: Dr. Ersin Das

Mentor: Prof. Joel Burdick

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Agenda

- Background and Motivation
- Objectives
- Methods
  - Simulation
  - Perception
- Results and Discussion
- Future Work
- Acknowledgements
- Q&A

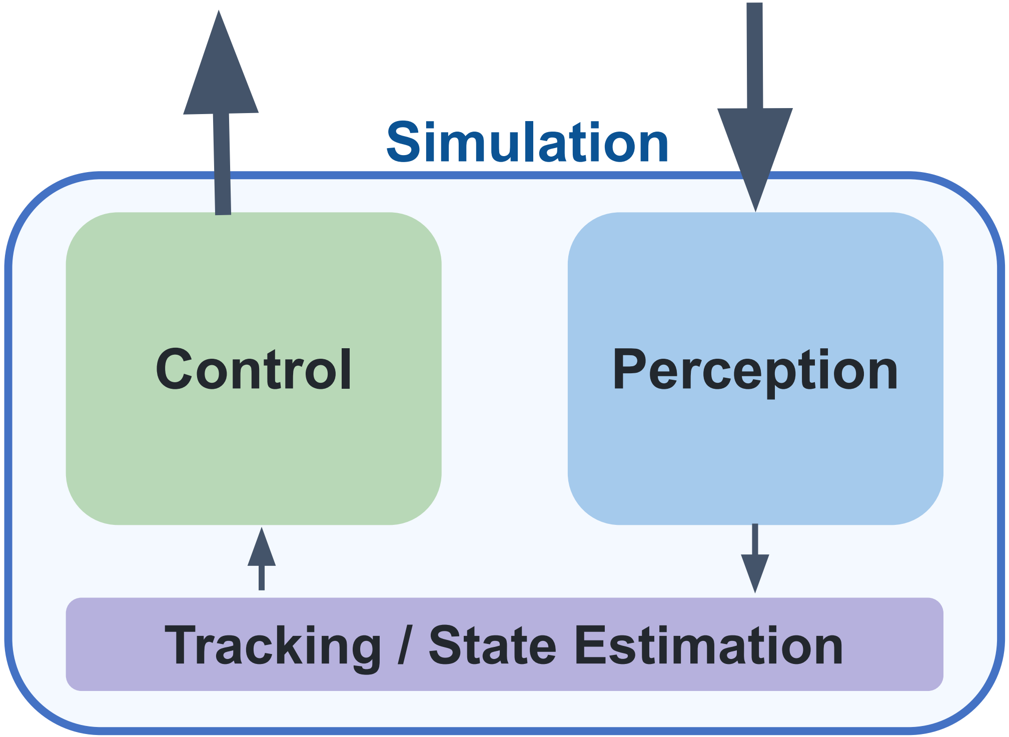
Background

tldr; this is a complex problem

DARPA LINC Phase 1

- Precise payload placement on ships
- Respond to events not predicted at design time
- Robustness to:
  - uncertain state estimates
  - perception error in dynamic environments
- Design ML models with **safety guarantees**

from Burdick Lab slack



Simulation

Control

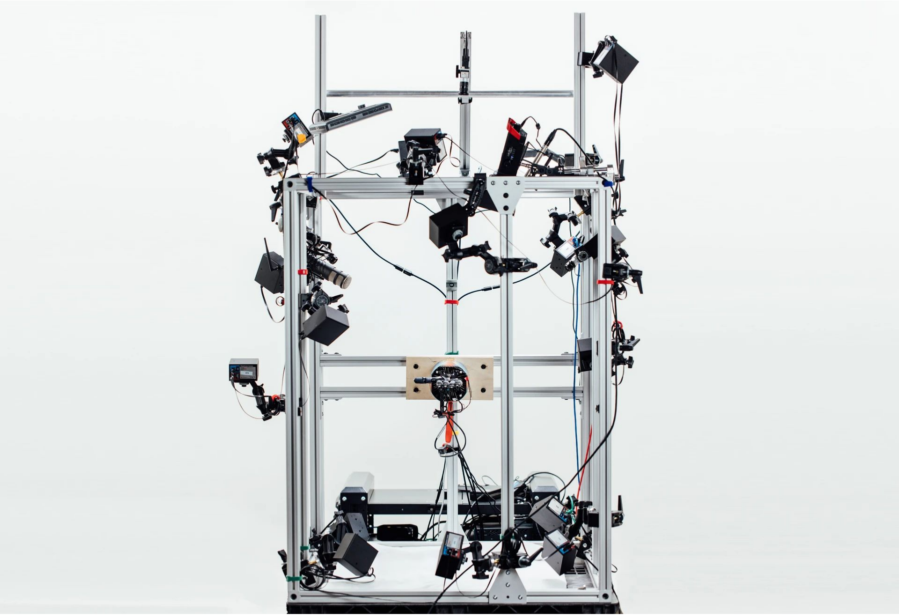
Perception

Tracking / State Estimation

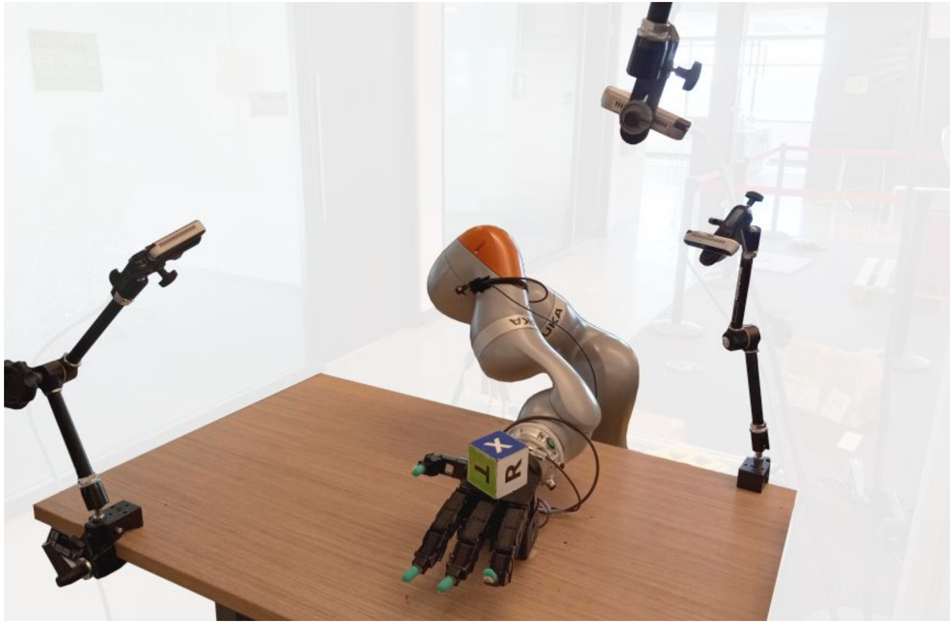
Project Objectives

- Implement a robust 6 DoF pose estimation method for objects with unknown geometry
  - Robust: Make it recover from errors in complete occlusion
  - Optimize: Make it run real time on AGX Orin with low compute
- Develop a high-fidelity simulation stack for testing control+perception
- Extend the algorithm to multiple cameras
- Create a ROS2 wrapper for plug and play support

Other Applications



Dactyl lab setup with Shadow Dexterous Hand, PhaseSpace motion tracking cameras, and Basler RGB cameras
OpenAI Dactyl Experiment, 2018



DeXtreme: Transfer of Agile In-Hand Manipulation from Simulation to Reality, 2024
OpenAI hand replication experiment

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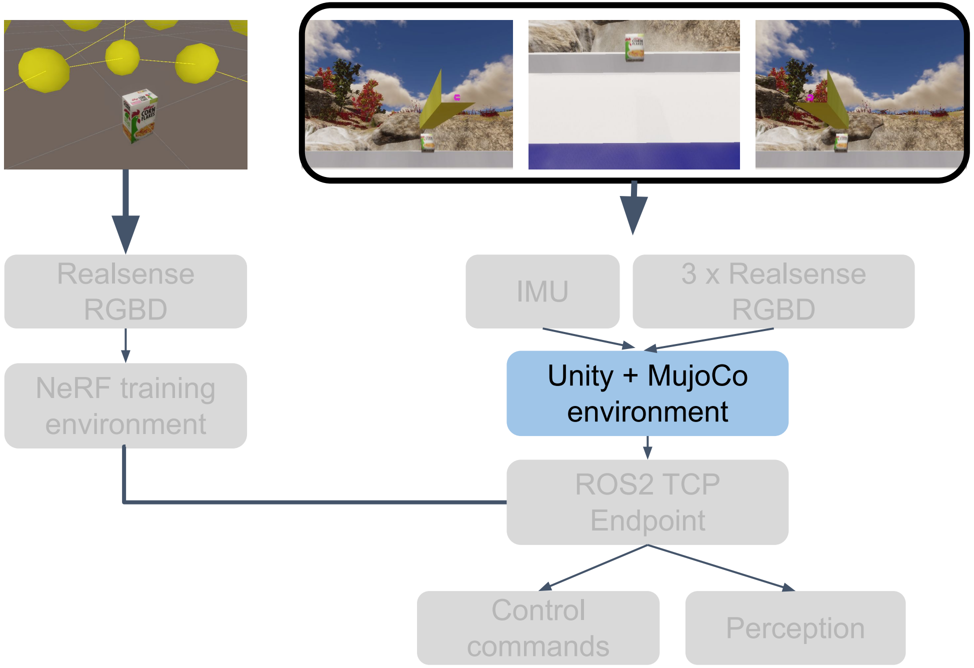
Methods

Simulation Stack

- High Fidelity environment replicating testbed
- Unity + MuJoCo integration
    - MuJoCo physics: control
    - Unity photorealism: perception



Realsense RGBD

NeRF training environment

IMU

3 x Realsense RGBD

Unity + MujoCo environment

ROS2 TCP Endpoint

Control commands

Perception

Simulation Stack

- High Fidelity environment replicating testbed
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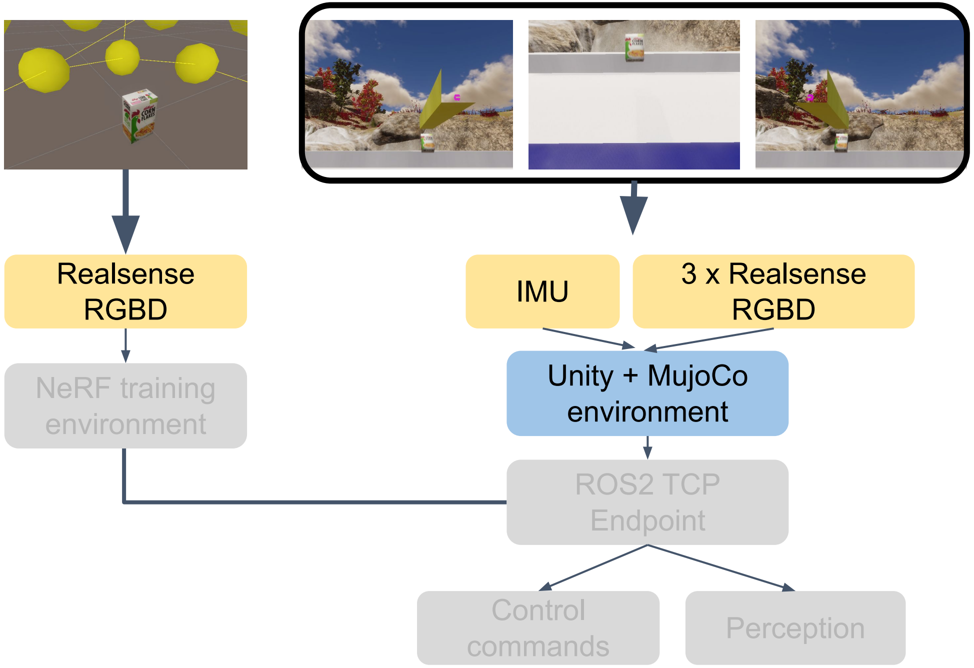
  - MuJoCo physics: control
  - Unity photorealism: perception
- RGBD + IMU sensor data integration for testing



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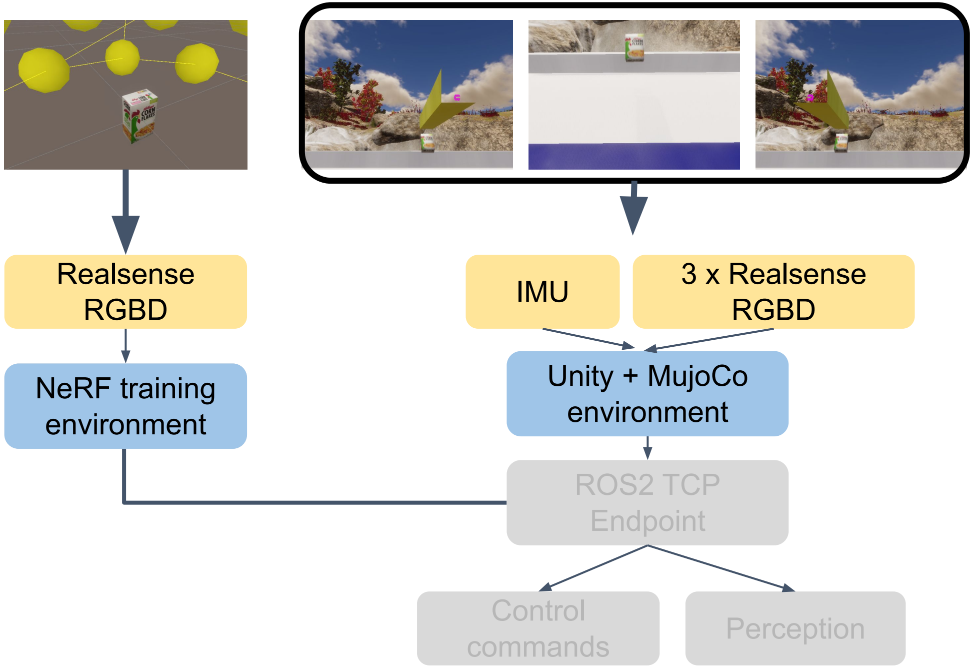
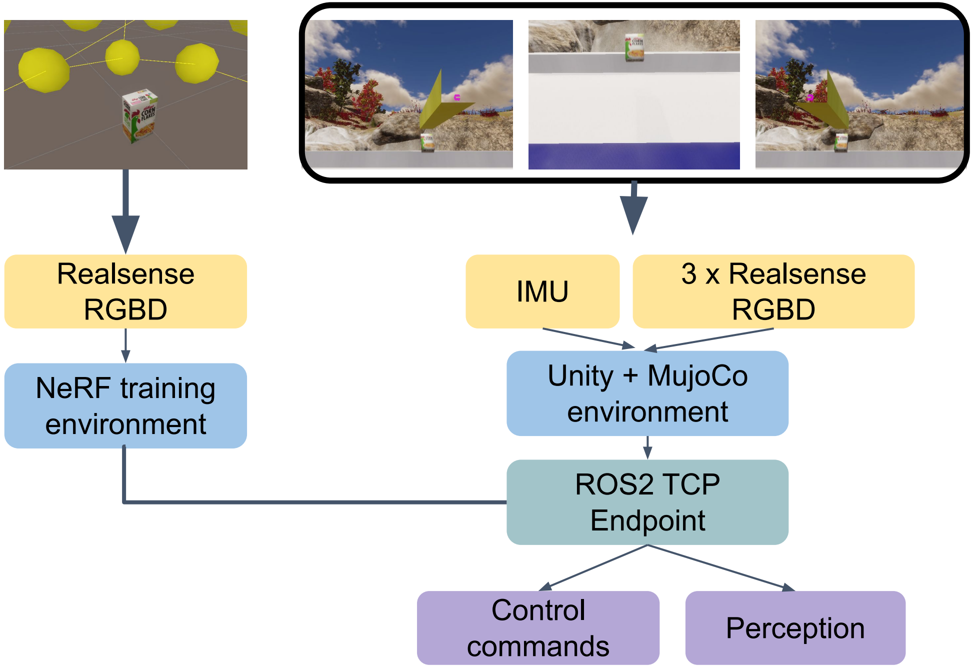


Simulation Stack

- High Fidelity environment replicating testbed
- Unity + MuJoCo integration
  - MuJoCo physics: control
  - Unity photorealism: perception
- RGBD + IMU sensor data integration for testing
- NeRF training environment
- ROS2 wrapper
  - communication with sim
  - swapping with hardware



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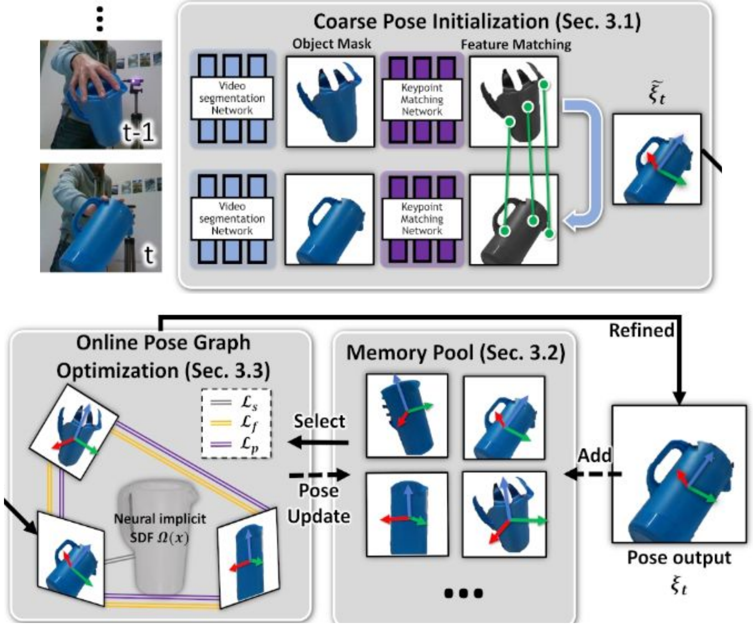
Perception

Perception Stack

Previous Methods

- Feature Tracking approaches
  - Classical Approaches:
    - Inverse SLAM
    - LoFTR feature tracking
  - Deep Learning:
    - BundleSDF
- Transformer approaches:
  - FoundationPose
    - Not suited for longer videos


t-1
t
Coarse Pose Initialization (Sec. 3.1)
Object Mask
Feature Matching
Video segmentation Network
Keypoint Matching Network
Video segmentation Network
Keypoint Matching Network
$\tilde{\xi}_t$
Refined
Online Pose Graph Optimization (Sec. 3.3)
$\mathcal{L}_s$
$\mathcal{L}_f$
$\mathcal{L}_p$
Neural implicit SDF $\Omega(x)$
Select
Pose Update
Memory Pool (Sec. 3.2)
Add
Pose output
ξ_t

BundleSDF: Neural 6-DoF Tracking and 3D Reconstruction of Unknown Objects
NVIDIA, 2023

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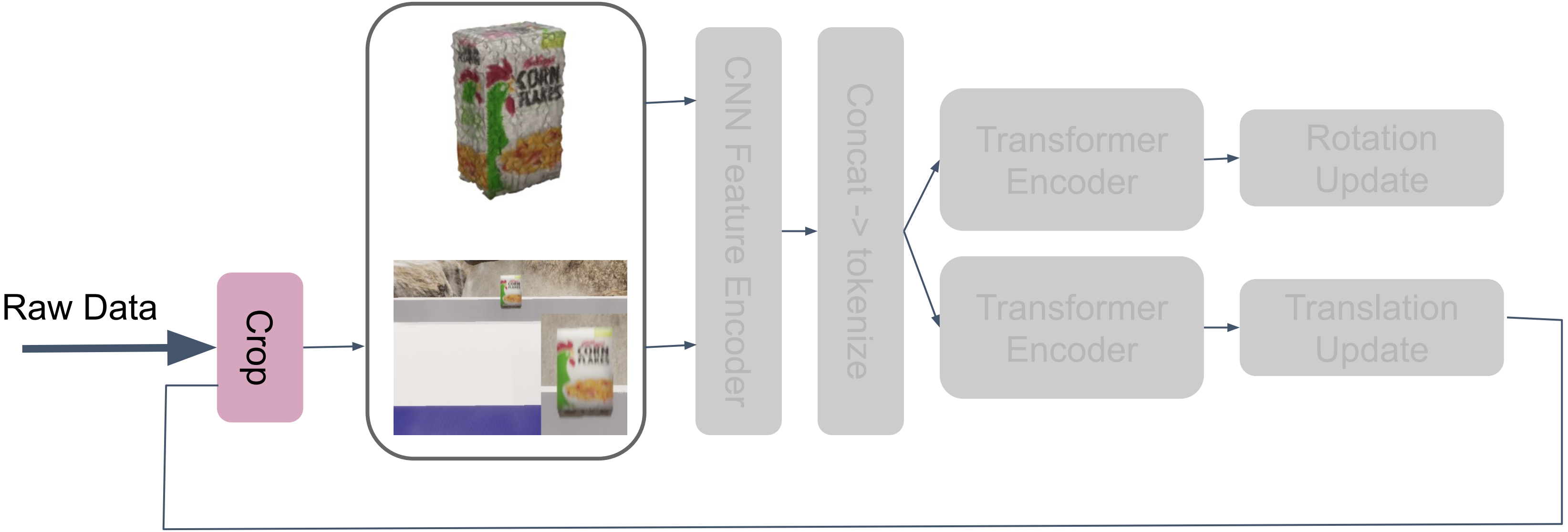
Perception Stack

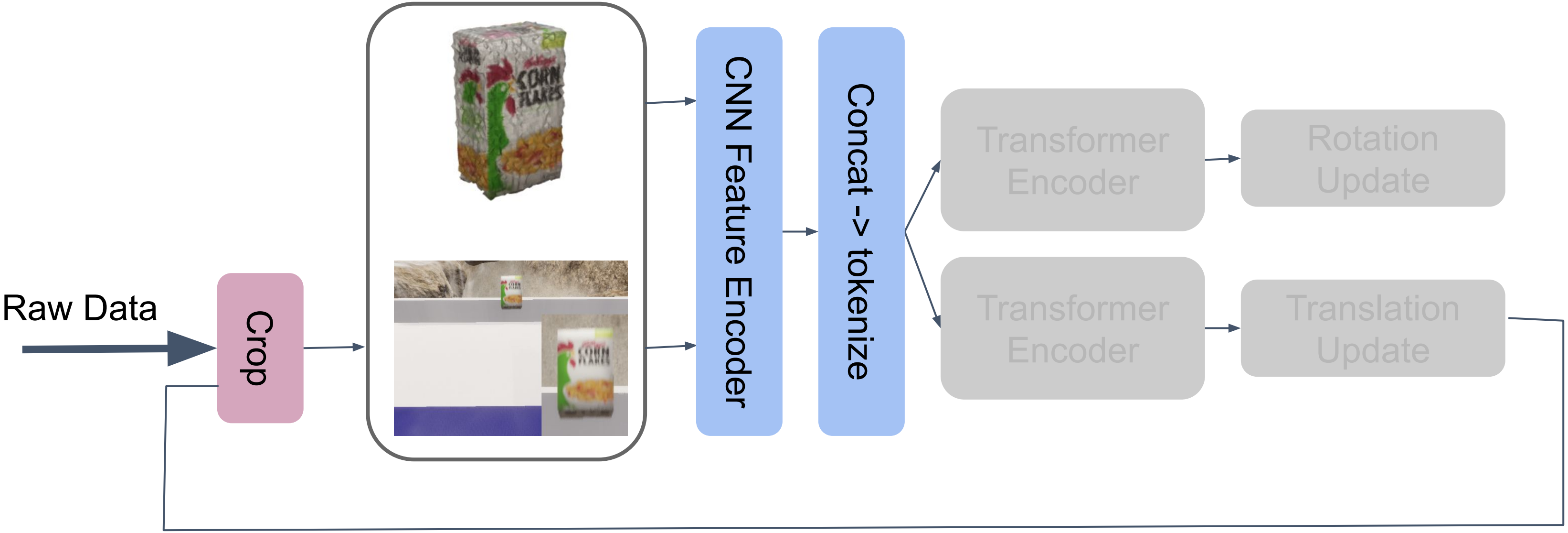
FoundationPose



FoundationPose Architecture

Perception Stack

FoundationPose



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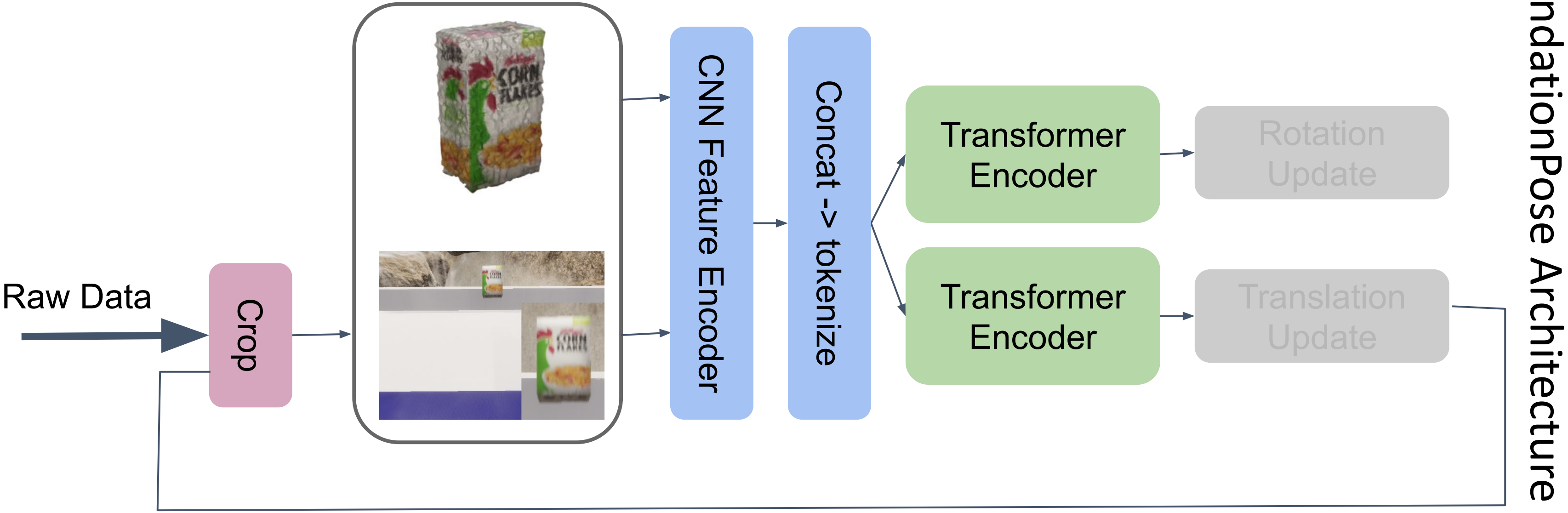
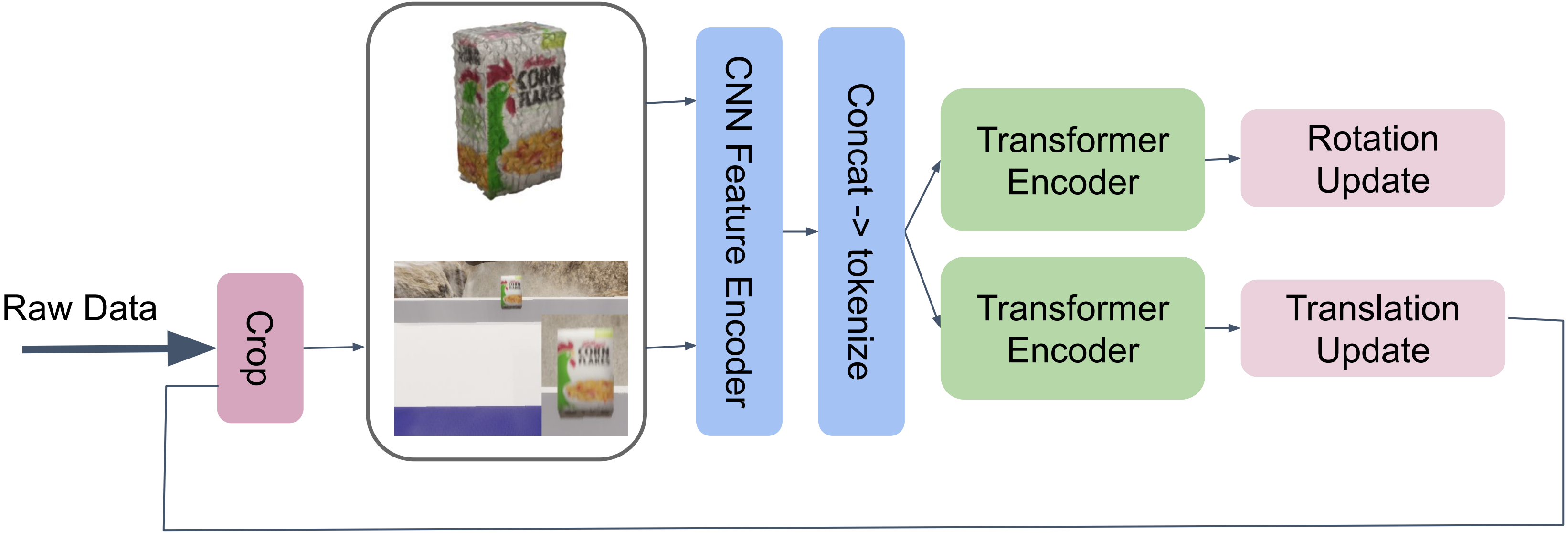
Perception Stack

FoundationPose



Perception Stack

FoundationPose



FoundationPose Architecture

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Perception Stack

Video Object Segmentation

- Cutie: Putting the Object Back Into Video Object Segmentation
- Why segmentation?
  - 2D data is easier than 3D data
  - Current 2D models outperform 3D
  - Provides a good coarse input

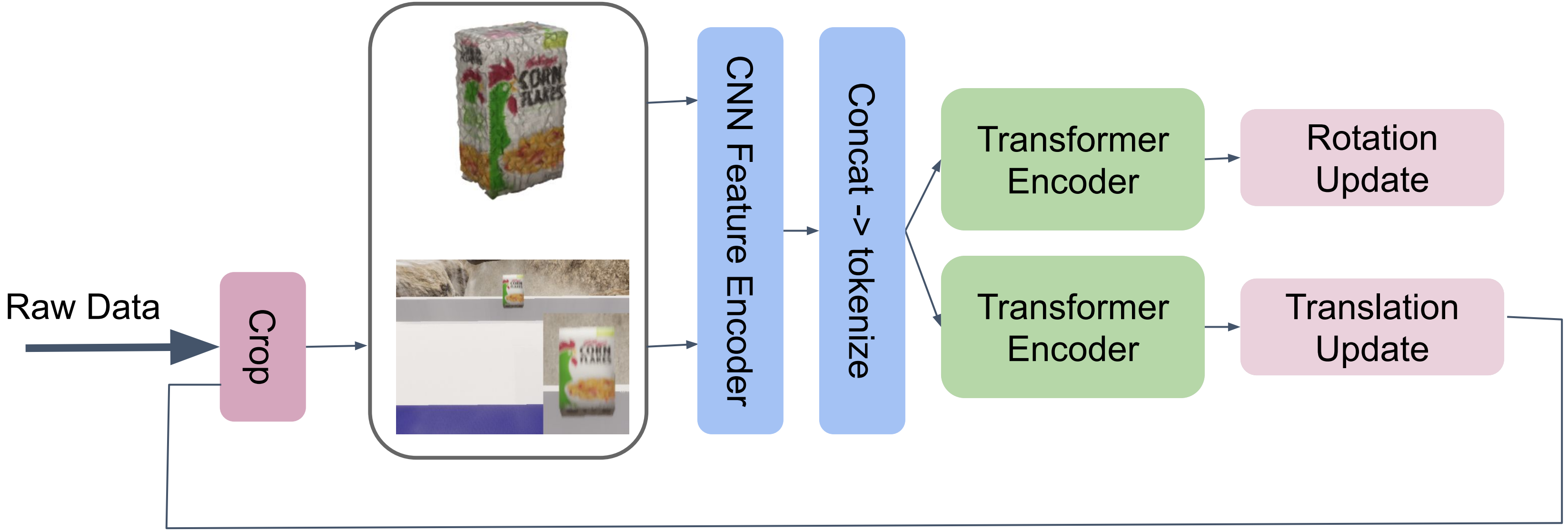
Perception Stack

Video Object Segmentation

- Cutie: Putting the Object Back Into Video Object Segmentation
- Why segmentation?
  - 2D data is easier than 3D data
  - Current 2D models outperform 3D
  - Provides a good coarse input
- Why Cutie?
  - Memory model
  - Long horizon segmentation
  - Recovers from occlusions

Perception Stack

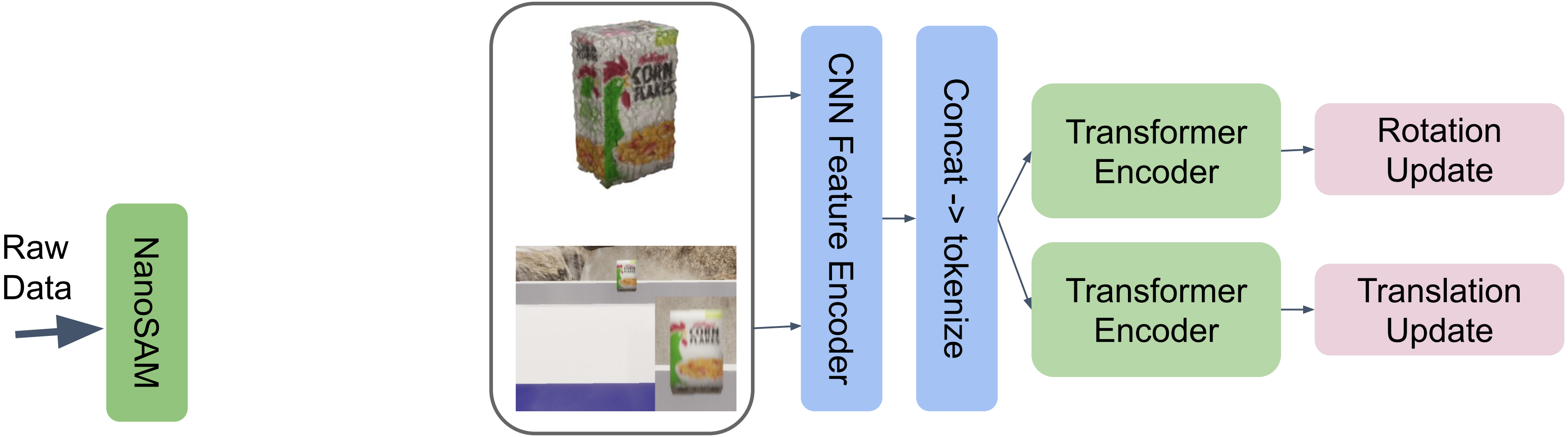
FoundationPose



FoundationPose Architecture

Perception Stack

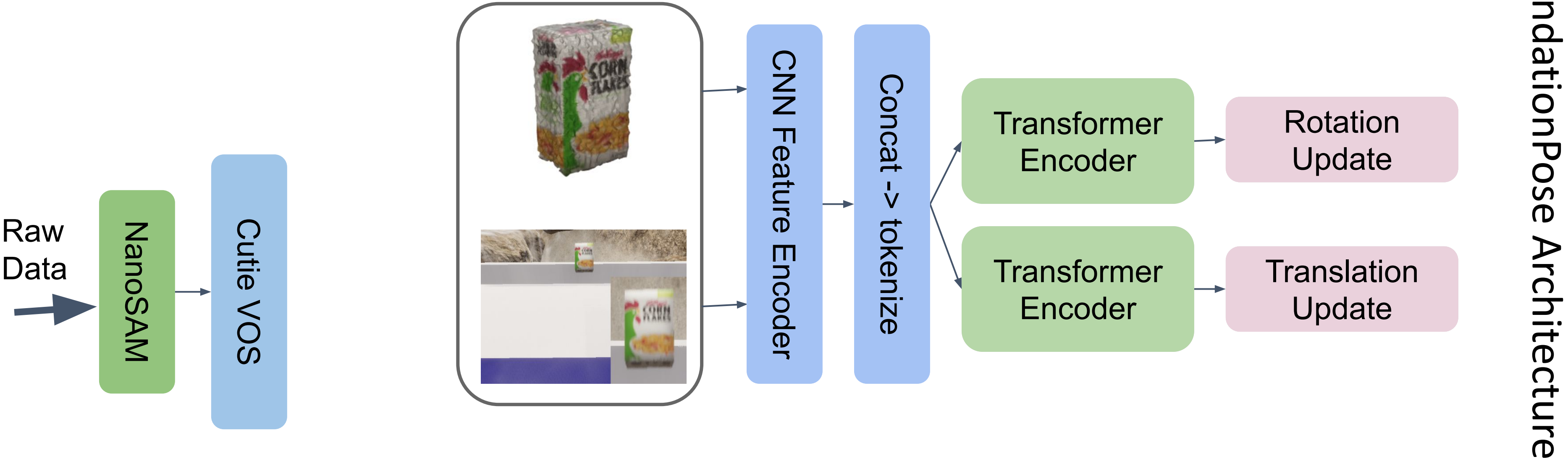
FoundationPose Improvement



FoundationPose Architecture

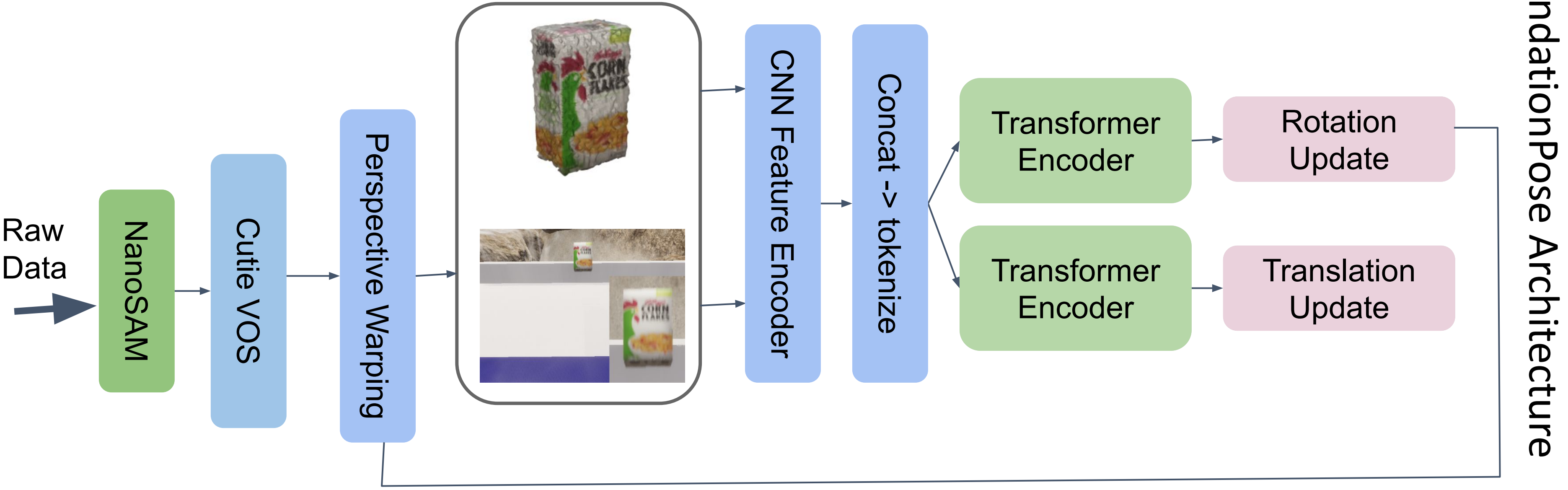
Perception Stack

FoundationPose Improvement



Perception Stack

FoundationPose Improvement



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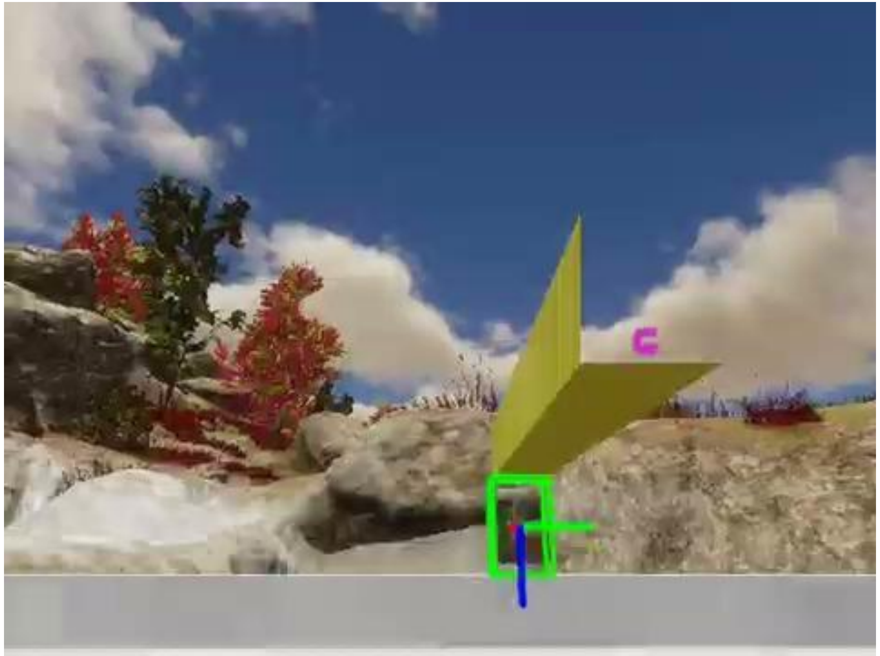
Perception Stack

FoundationPose + VOS results

- High Disturbance
- Low visibility of object



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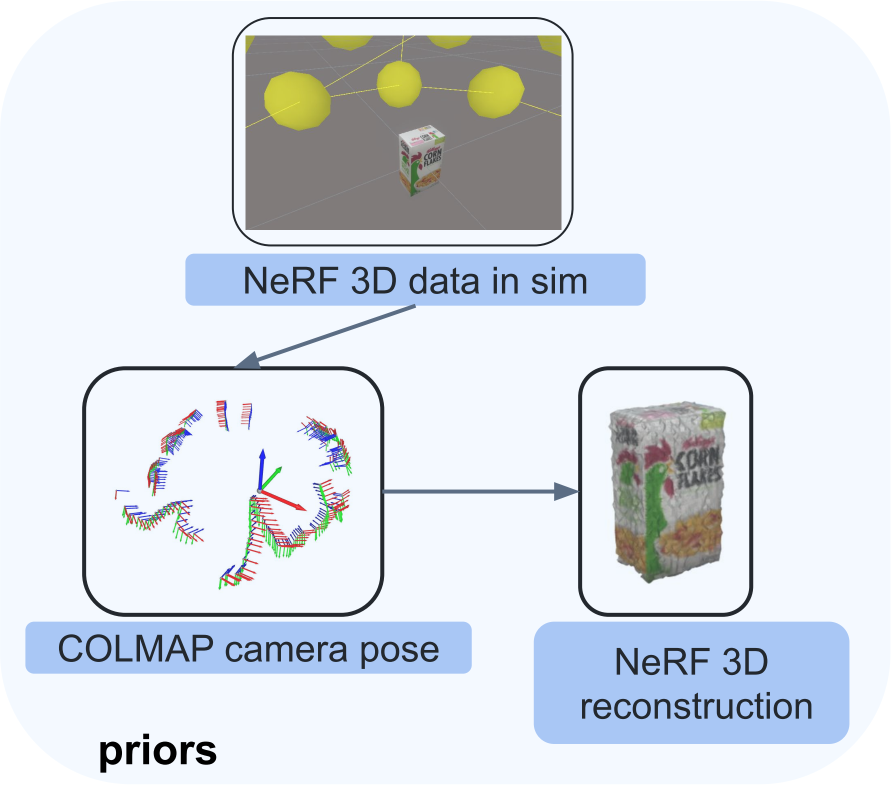
Perception Stack

FoundationPose pipeline



NeRF 3D data in sim

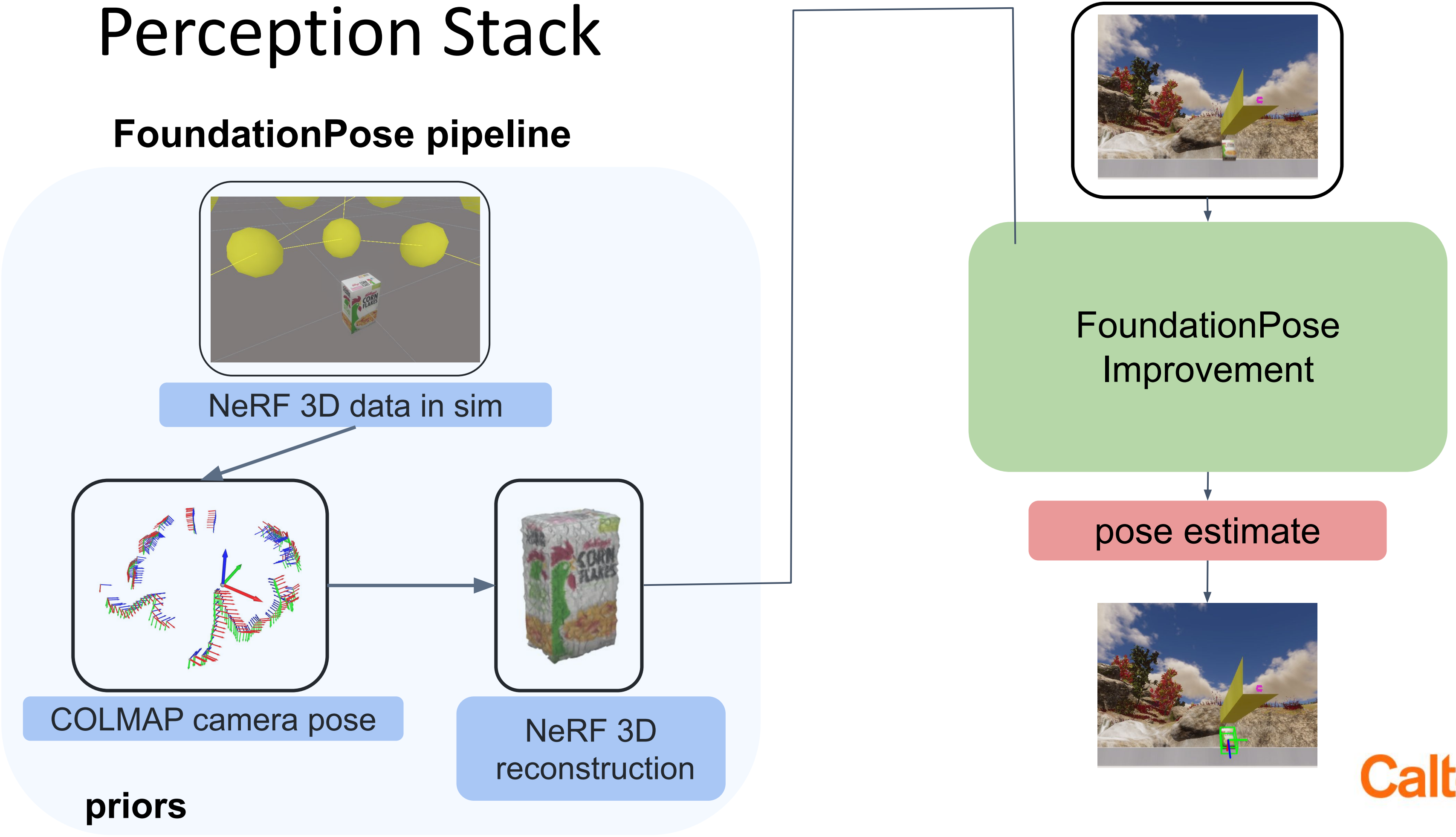
COLMAP camera pose

NeRF 3D reconstruction

priors

Perception Stack

FoundationPose pipeline



NeRF 3D data in sim

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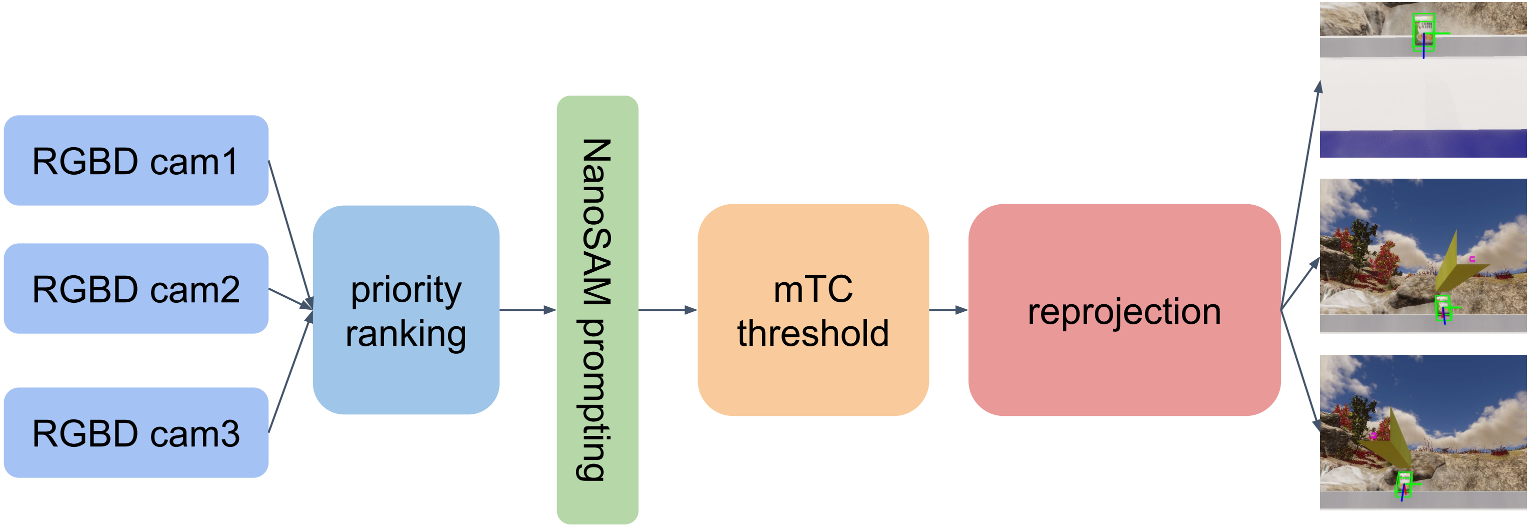
FoundationPose Improvement

pose estimate

Perception Stack

Multi-Cam integration & deployment

- Under complete occlusion in one camera:
    - Switch between cameras with priority ranking
    - mTC to know when object recovered from occlusion



RGBD cam1

RGBD cam2

RGBD cam3

priority ranking

NanoSAM prompting

mTC threshold

reprojection

Perception Stack

Multi-Cam integration & deployment

- Under complete occlusion in one camera:
  - Switch between cameras with priority ranking
  - mTC to know when object recovered from occlusion
- Implement ROS2 interface for:
  - Multicam data
  - Pose tracking
  - Simulation to perception

Perception Stack

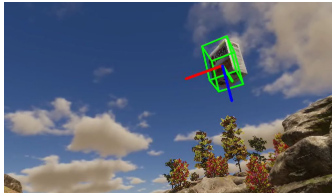
Multi-Cam integration & deployment

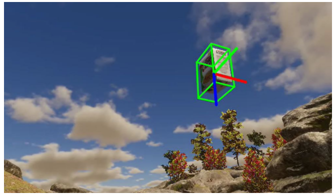
- Under complete occlusion in one camera:
  - Switch between cameras with priority ranking
  - mTC to know when object recovered from occlusion
- Implement ROS2 interface for:
  - Multicam data
  - Pose tracking
  - Simulation to perception
- TensorRT Optimization on VOS
  - 20% improvement
    - 3 modules

Perception Stack

Safety-Critical use

Which pose estimate do we trust more?
How we do know?





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Perception Stack

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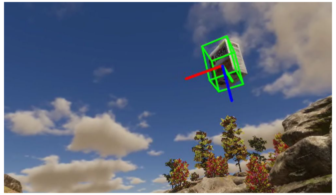

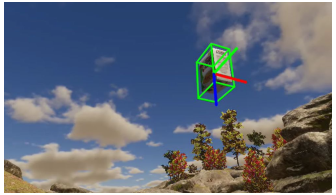

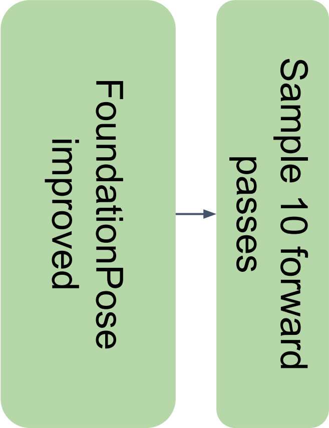

FoundationPose improved

Sample 10 forward passes

Perception Stack

Safety-Critical use

Which pose estimate do we trust more?
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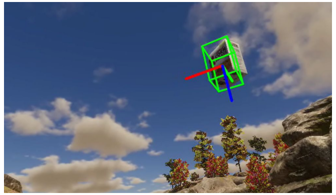

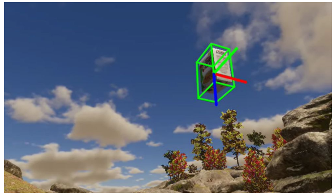

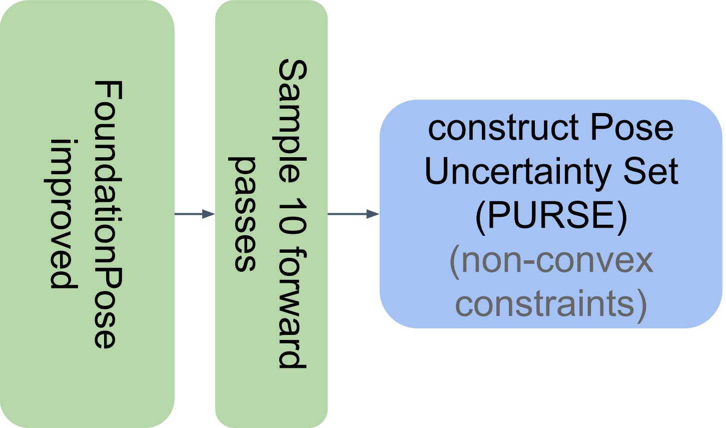

FoundationPose improved

Sample 10 forward passes

construct Pose Uncertainty Set (PURSE)
(non-convex constraints)

Perception Stack

Safety-Critical use

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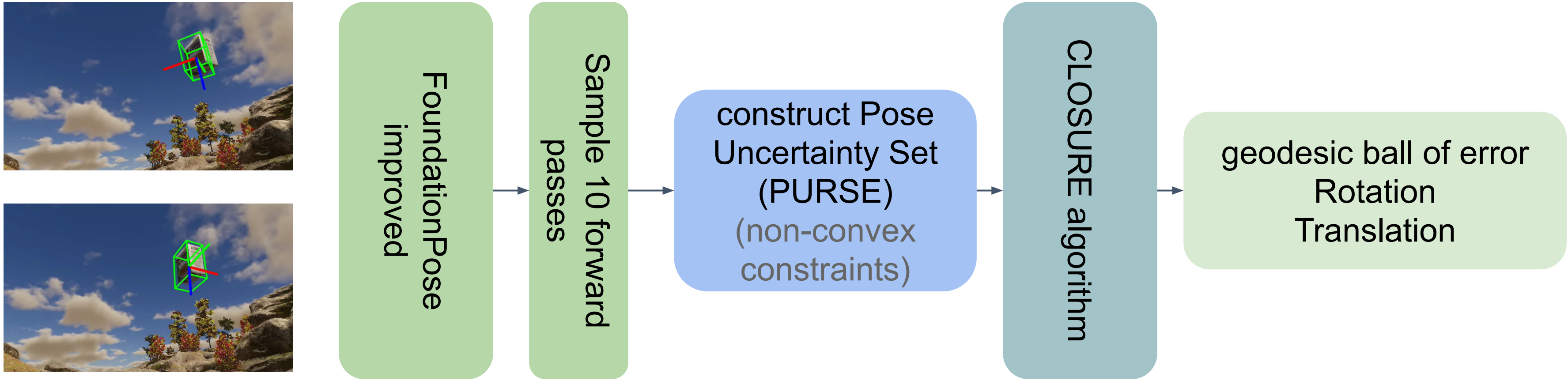


FoundationPose improved

Sample 10 forward passes

construct Pose Uncertainty Set (PURSE) (non-convex constraints)

CLOSURE algorithm

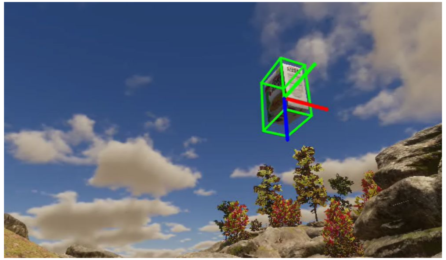
geodesic ball of error
Rotation
Translation

Perception Stack

Safety-Critical use

Results from **CLOSURE**

complete NeRF reconstruction



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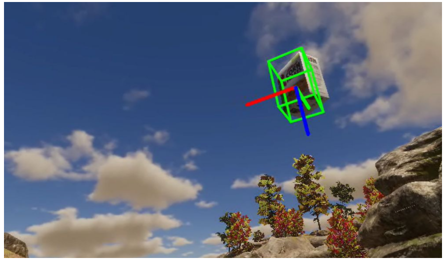

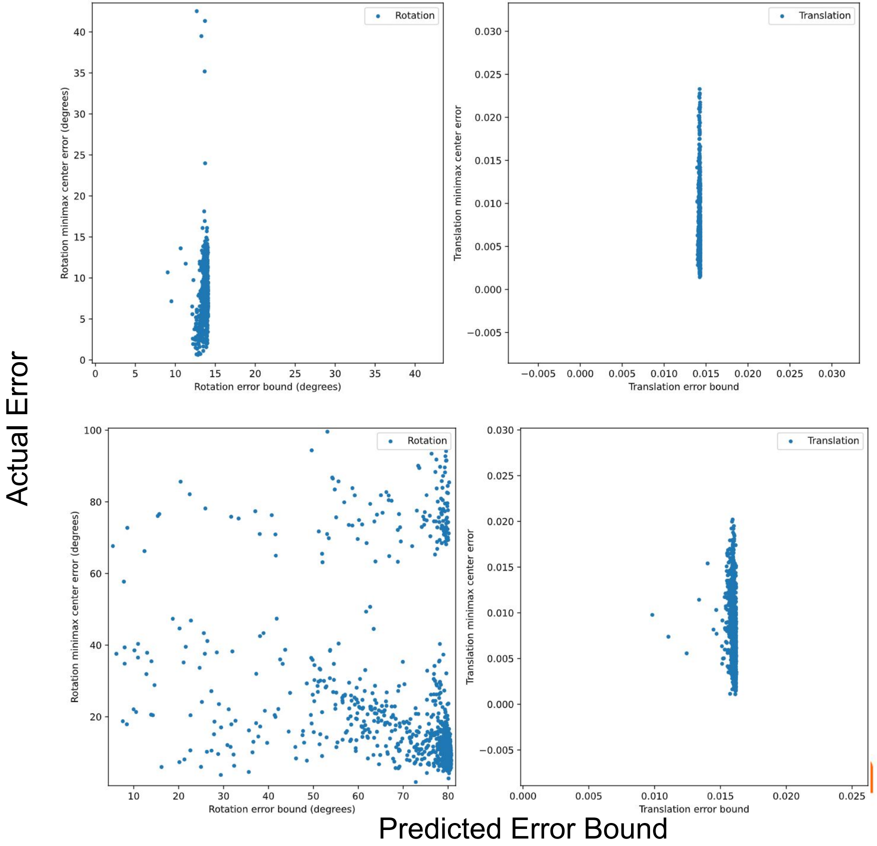

Results and Conclusion

- FoundationPose + VOS pose estimation
- Multi-Cam integration to FoundationPose
- ROS2 interface for perception
- High-fidelity simulation environment for testing
- Optimization for low compute
- Uncertainty Quantification for safety

Future Work

- More Benchmarks
- Use less priors (No 3D reconstruction of object)
- Integrate a state estimator for filtering

Acknowledgements

- Prof. Joel Burdick for giving me the opportunity to SURF with the lab, resources and guidance along the way
- Dr. Ersin Das for his guidance and support and help whenever needed
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Q&A

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