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# Multi-view object pose distribution tracking for pre-grasp planning on mobile robots

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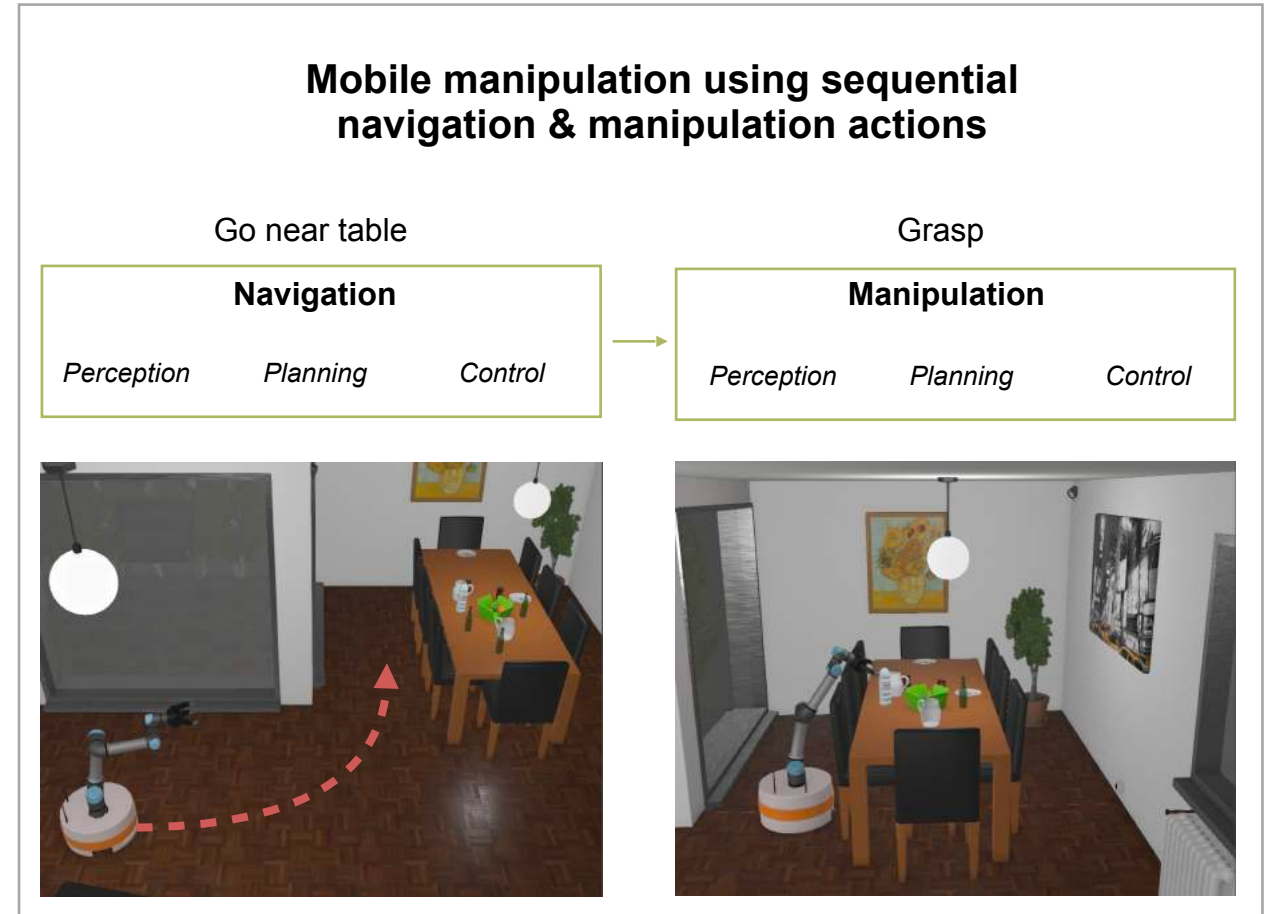


# Motivation

Enabling robust and efficient manipulation on mobile robots

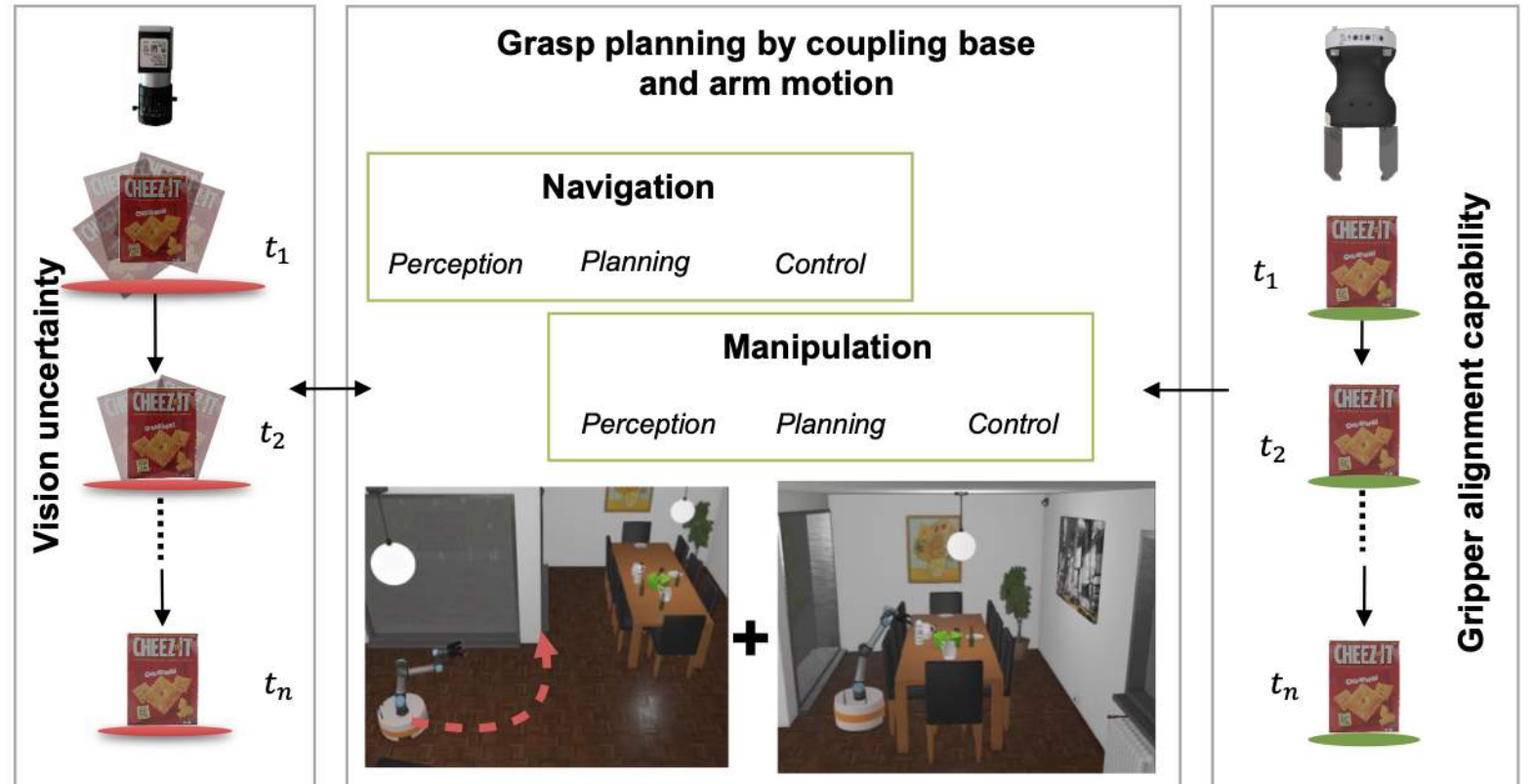
# Mobile Manipulation - sequential approach

- Goto near the object table
- Observe the object and estimate its 6D pose
- Plan grasp
- Execute grasp



# Problem formulation

- Estimating object pose distribution (uncertainty) to ensure success of grasping task
- Estimating full object pose distribution while robot is still navigating towards the object to enable pre-grasp planning





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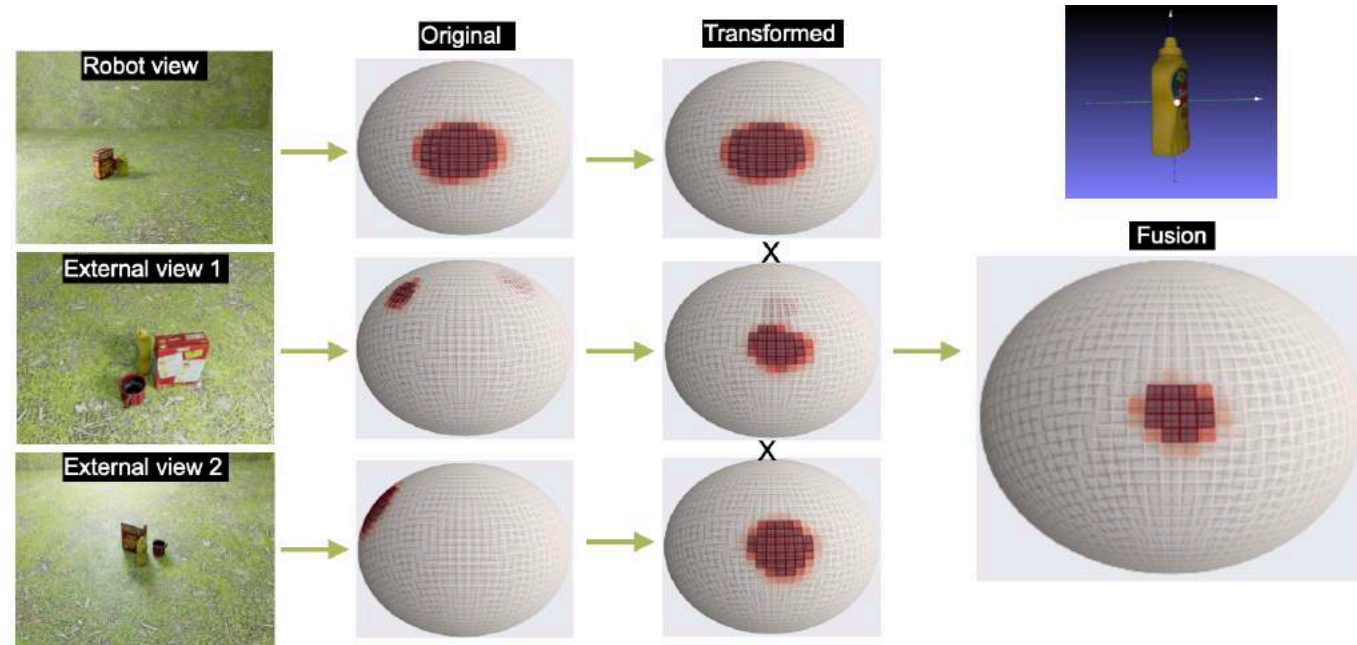


# Proposed approach

Multi-view object pose distribution tracking

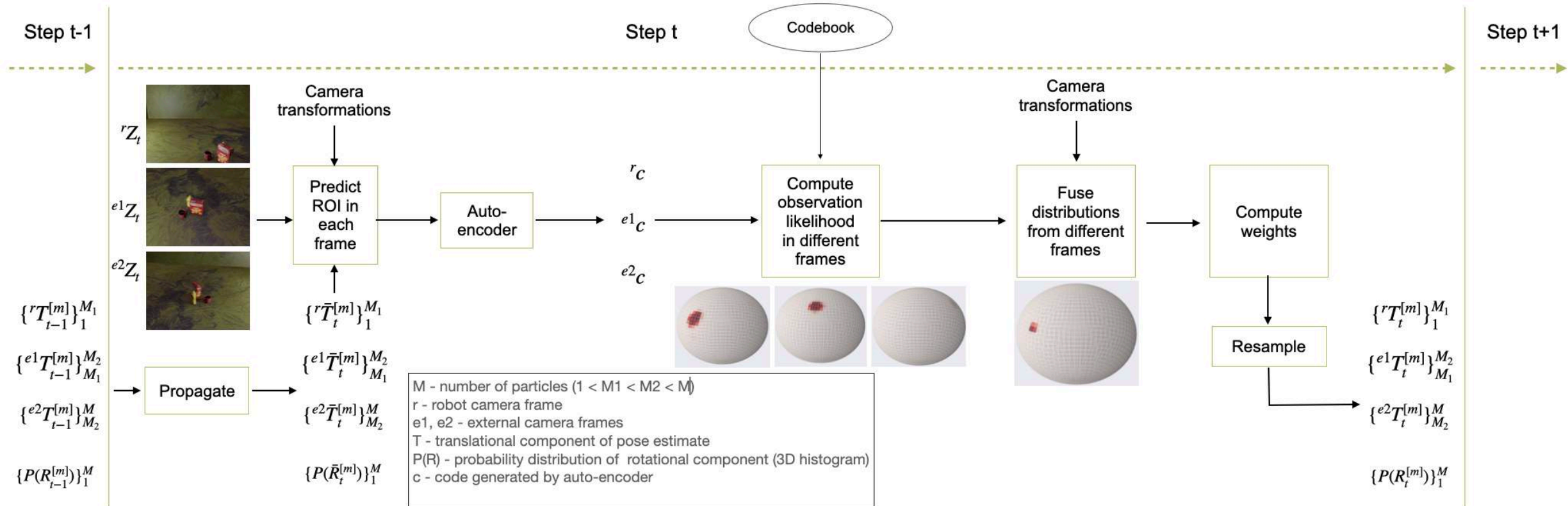
# Proposed approach

- Rao-Blackwellized particle filter with de-noising auto-encoder for verifying observations [1]
- Extended to fuse information from external cameras
- Both translation and orientation distributions are modeled as a multi-modal distributions



[1] Deng, Xinke, et al. "Poserbpf: A rao-blackwellized particle filter for 6-d object pose tracking." *IEEE Transactions on Robotics* 37.5 (2021): 1328-1342.

# Proposed architecture



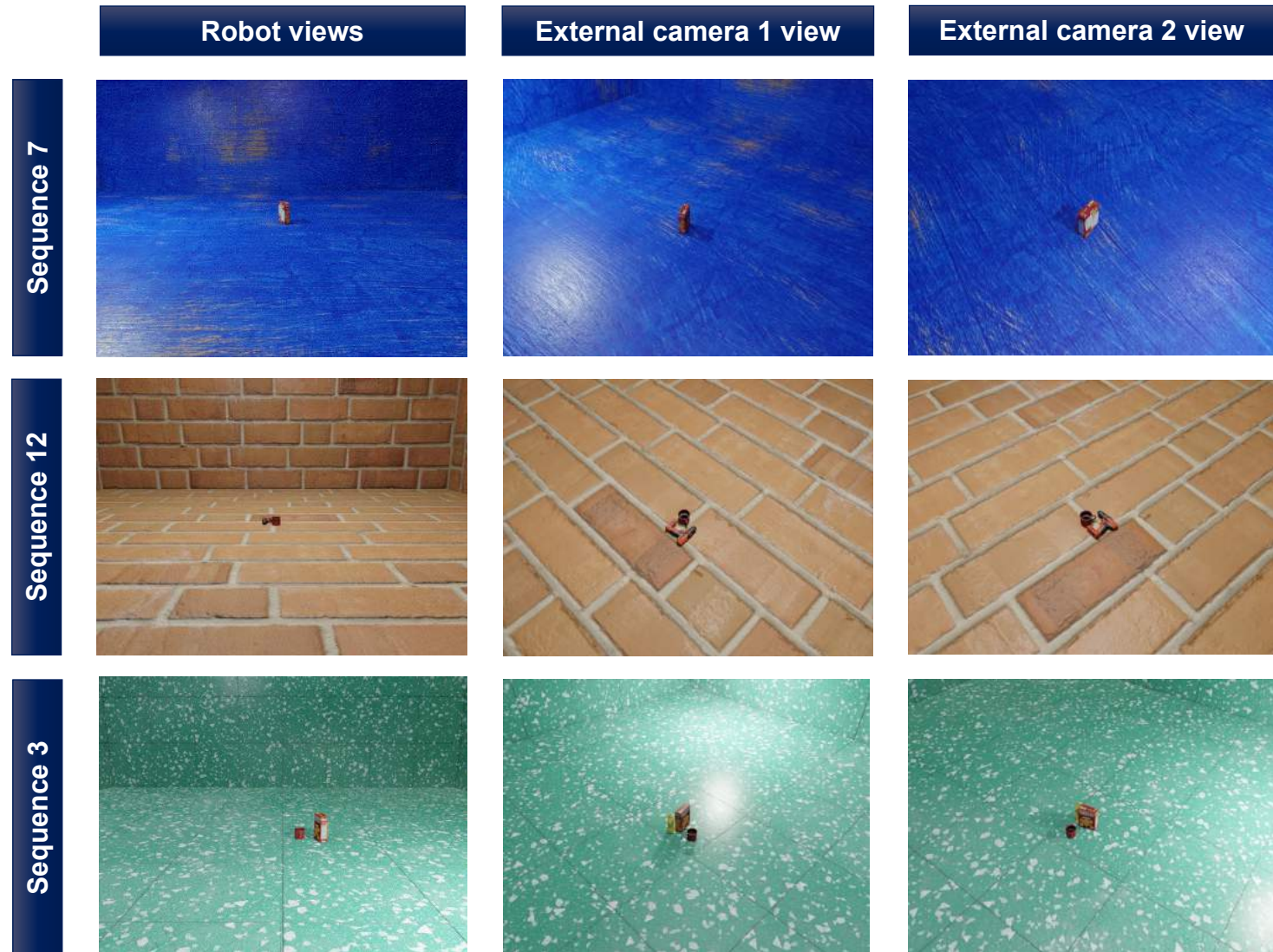
# Experimental evaluation



# Evaluation dataset

- Simulated dataset [1] containing 8 different YCB objects created using photo-realistic renderer
- Each sequence contains view from robot and external cameras with robot camera simulating robots base and arm motion

[1] L. Naik, "Multi-view rendered YCB dataset for mobile manipulation," Feb. 2022. [Online]. Available: <https://doi.org/10.5281/zenodo>.



# Results - simple scenario

Robot moving closer to object - asymmetric object, no occlusions

Original robot view



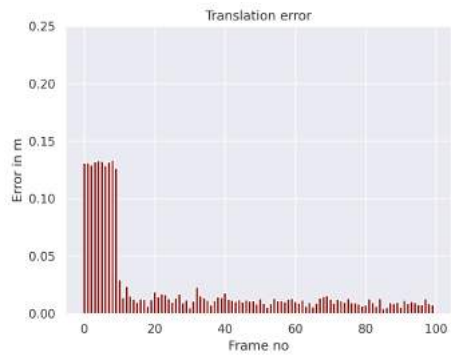
Multi-view result



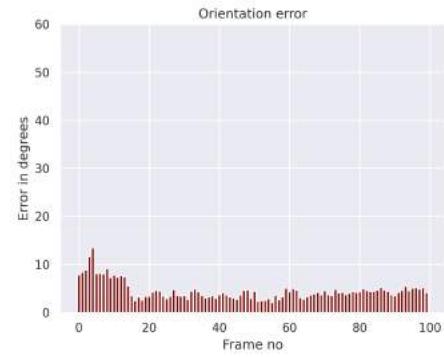
Single-view result



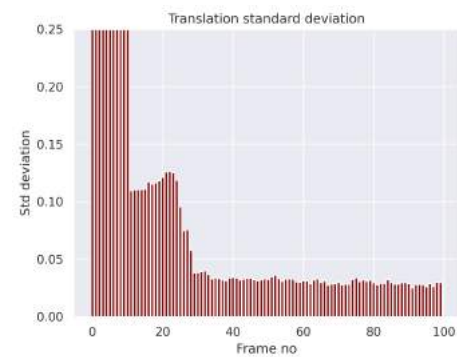
Translational error



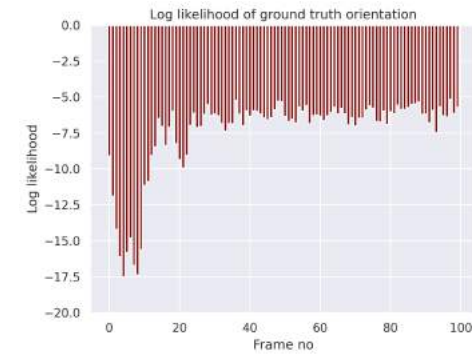
Orientation error



Translation uncertainty

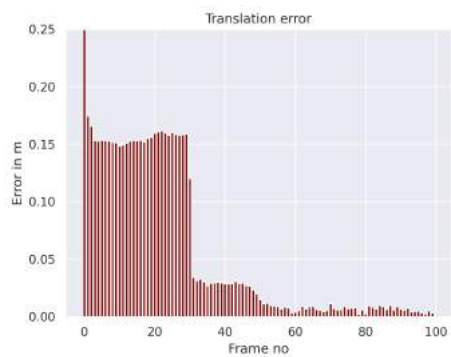


Orientation uncertainty

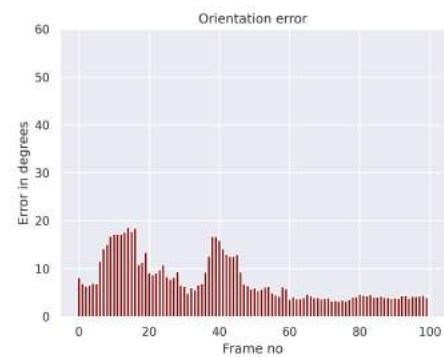


Multi-view

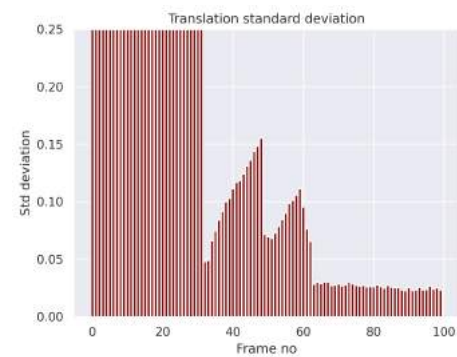
Translational error



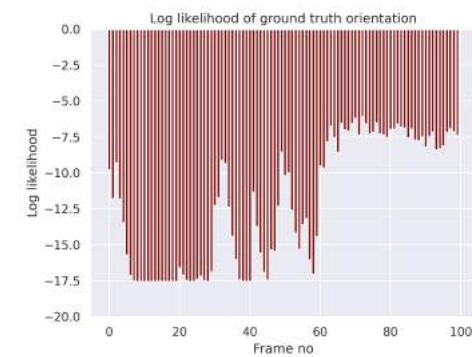
Orientation error



Translation uncertainty



Orientation uncertainty



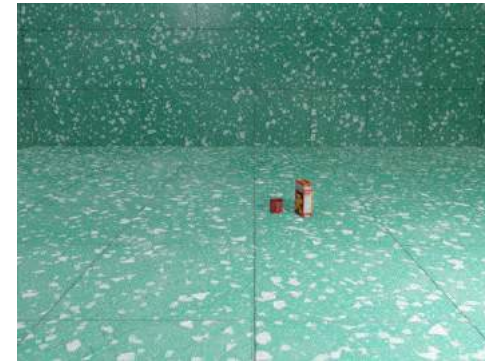
Single-view



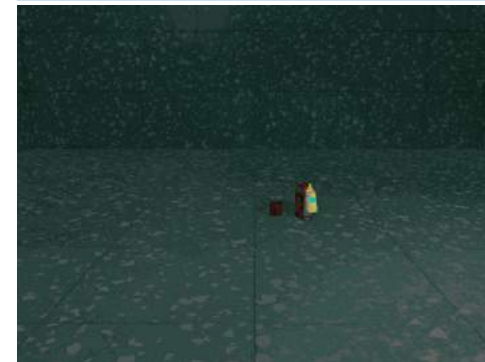
# Results - complex scenario

Robot moving closer and around the occluded object with 1 axis of symmetry

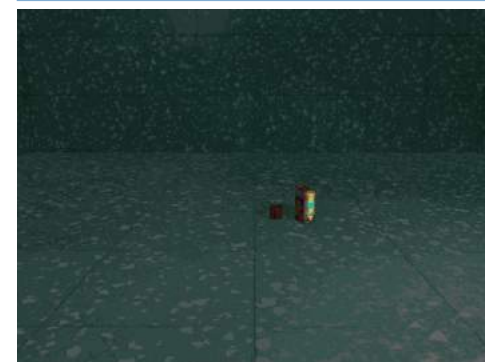
Original robot view



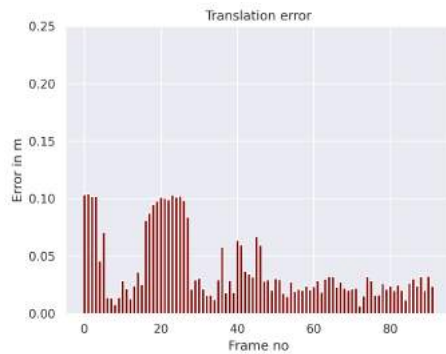
Multi-view result



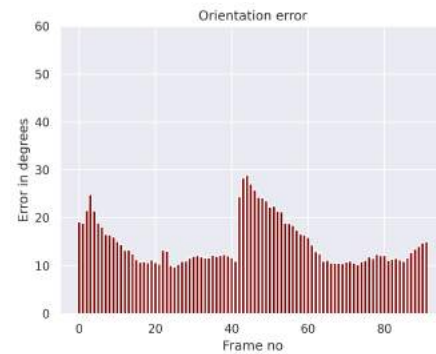
Single-view result



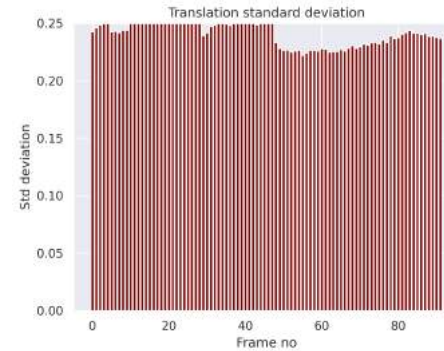
Translational error



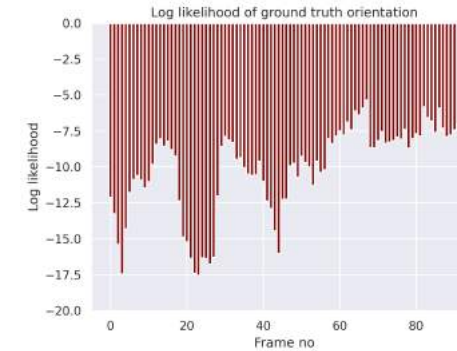
Orientation error



Translation uncertainty

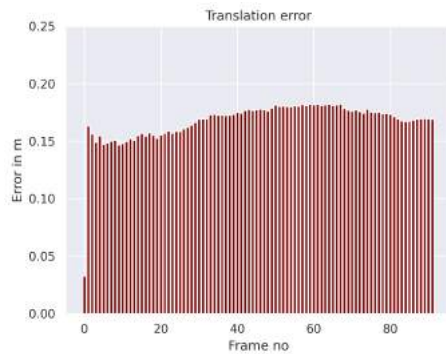


Orientation uncertainty

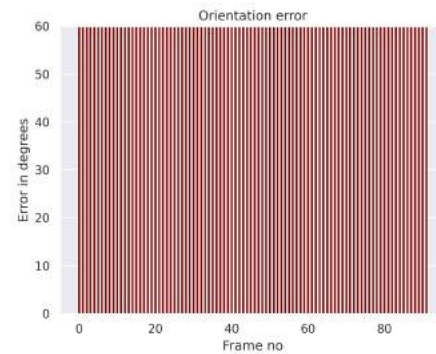


Multi-view

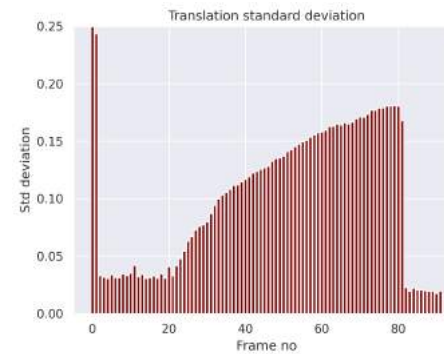
Translational error



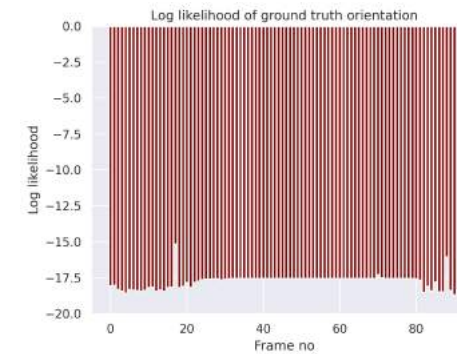
Orientation error



Translation standard deviation



Log likelihood of ground truth orientation



Single-view

# Quantitative results

|                 | Translation error<br>(in m) |               | Orientation error<br>(in deg) |              | Translation std. dev<br>(in m) |               | Log likelihood |               |
|-----------------|-----------------------------|---------------|-------------------------------|--------------|--------------------------------|---------------|----------------|---------------|
|                 | Multi                       | Single        | Multi                         | Single       | Multi                          | Single        | Multi          | Single        |
| Cracker box     | 0.0121                      | 0.0172        | 6.33                          | 18.60        | 0.0781                         | 0.0583        | -6.91          | -11.09        |
| Mustard bottle  | 0.0251                      | 0.0621        | 10.68                         | 93.48        | 0.1191                         | 0.0601        | -7.15          | -10.97        |
| Mug             | 0.0495                      | 0.0778        | 15.69                         | 130.28       | 0.1370                         | 0.1151        | -13.70         | -17.22        |
| Sugar box       | 0.0411                      | 0.0954        | 9.50                          | 32.47        | 0.2065                         | 0.0785        | -11.25         | -13.53        |
| Banana          | 0.0800                      | 0.1937        | 15.85                         | 97.95        | 0.1640                         | 0.1495        | -14.92         | -17.63        |
| Master chef can | 0.0066                      | 0.0065        | 6.23                          | 87.06        | 0.0737                         | 0.0318        | -8.35          | -11.35        |
| Bleach cleanser | 0.0955                      | 0.2774        | 57.44                         | 152.70       | 0.2375                         | 0.2991        | -13.65         | -16.89        |
| Power drill     | 0.0561                      | 0.3125        | 17.36                         | 23.97        | 0.0837                         | 0.0444        | -11.19         | -12.74        |
| Mean            | <b>0.0457</b>               | <b>0.1303</b> | <b>17.38</b>                  | <b>75.56</b> | <b>0.1374</b>                  | <b>0.1046</b> | <b>-10.89</b>  | <b>-13.92</b> |

# Conclusions and future work

- The proposed approach can be an enabler for pre-grasp planning tasks such as
  - Selecting the order in which robot should grasp the objects
  - Optimal base position to grasp all the objects
  
- Pre-grasp planning to grasp planning
  - Using uncertainties to predict grasp failures
  - Planning actions to reduce uncertainties

# Thank you



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