Manipulator and Object Tracking for In Hand Model Acquisition

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Problem Statement

- Robots can never be trained for all possible objects – let them learn new ones
- Target Scenario:

1) Robot picks up unknown object using heuristic or feature-based techniques (e.g. [Saxena ‘08])

2) Robot examines object from multiple perspectives, much as a human might

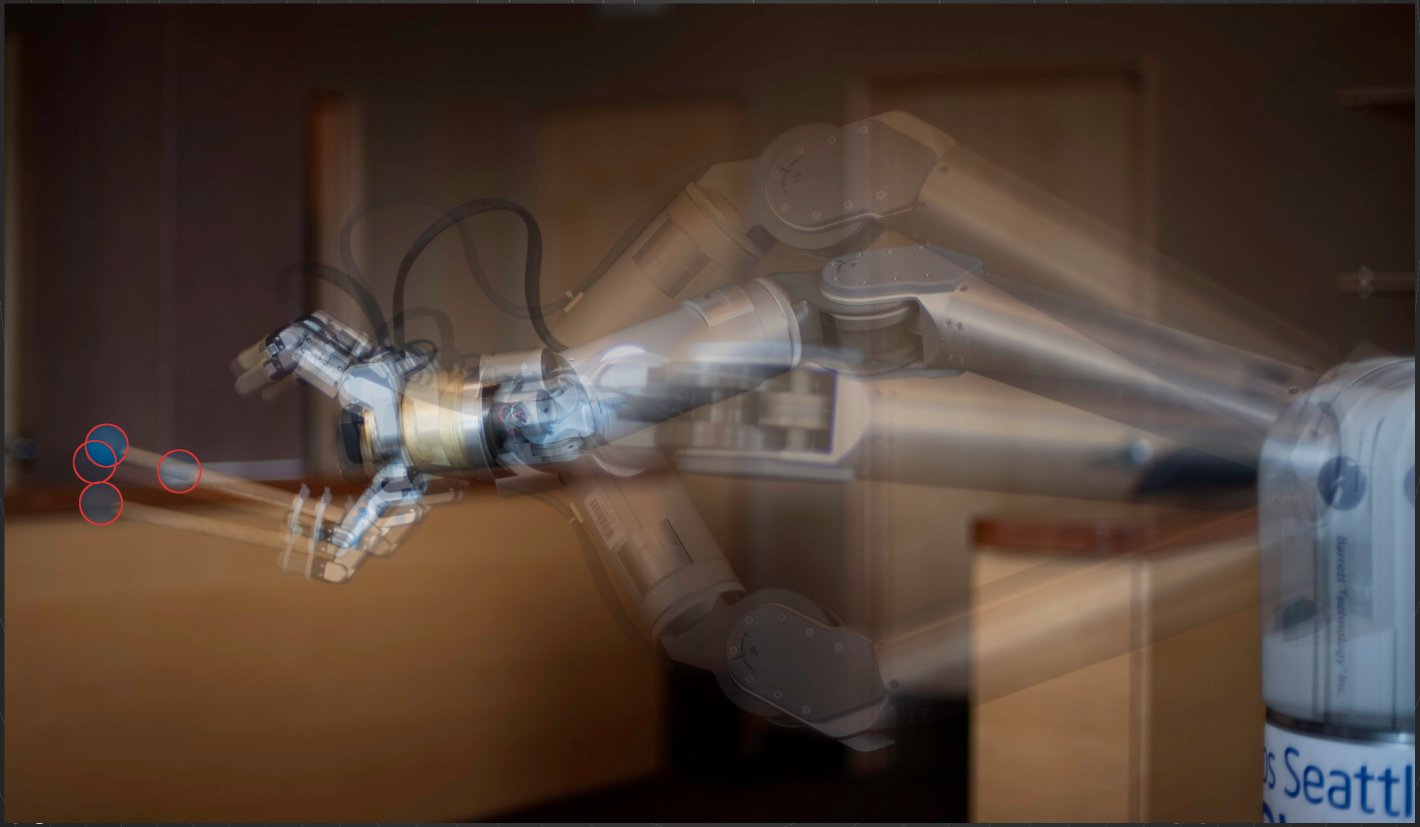
3) Robot can use learned model for later tasks (e.g. detection, pose estimation, future grasping)

In-Hand Modeling

- Visual feature matching [Pan '09]
- ICP-based surface matching [Weise '09]
- No explicit tracking of hand
  - Hand subtraction not straightforward
  - Cannot register textureless or symmetric objects

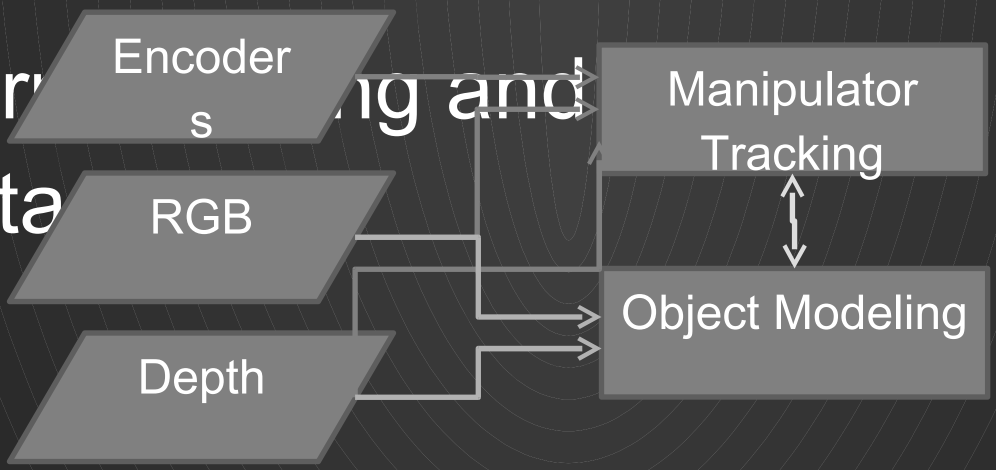
Encoders for Object Modeling

- Commonly used but requires high accuracy e.g. [Sato '97], [Kraft '08]



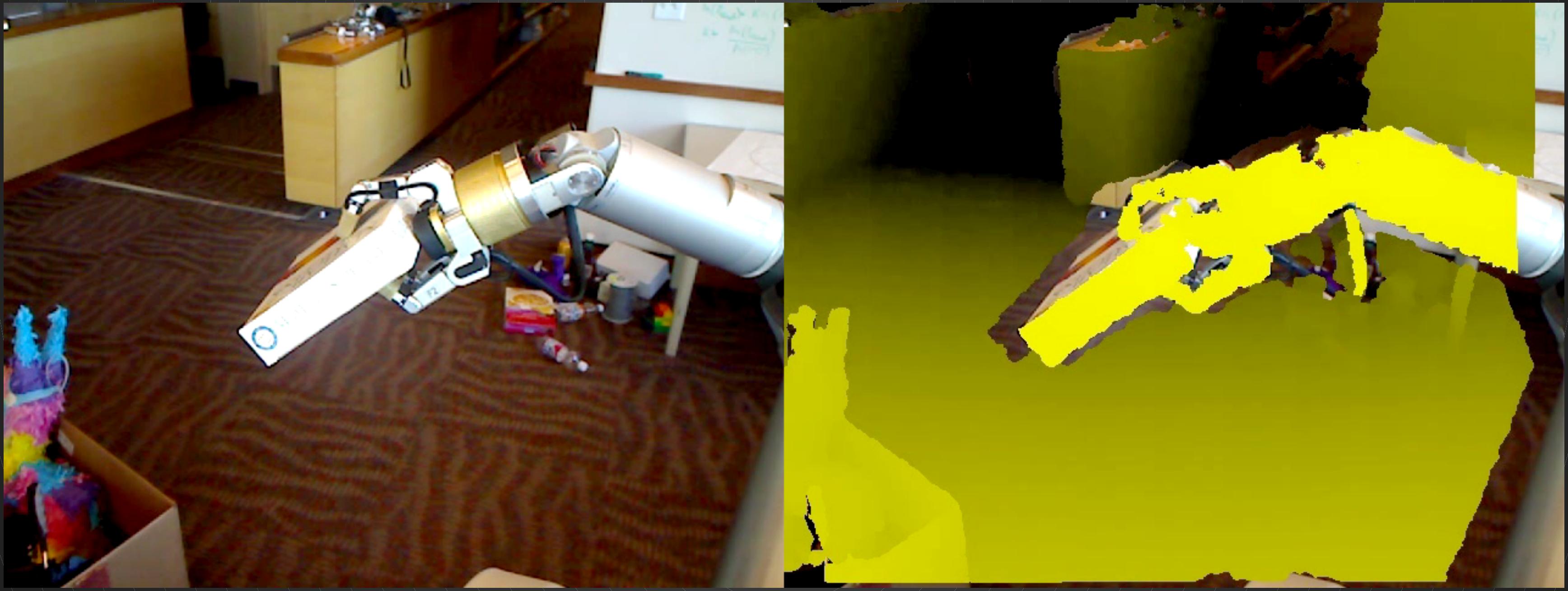
Proposed Framework

- Use encoders only to the extent to which they are reliable
- Use vision and shape to improve alignment
- Perfor ng and simulta



Depth Sensor

- 640x480 RGB + Depth at 30 Hz
- Developed for gaming applications



Articulated ICP for Robot Arm and Hand Tracking

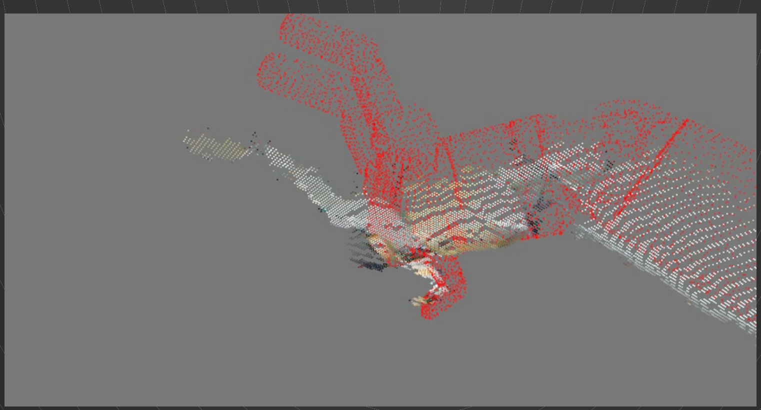
Joint Hand and Object Tracking

Object Modeling

Articulated ICP

- Goal: Find joint angles (and global transform) best aligning observed and expected clouds
- Iterates between correspondence selection and parameter estimation

$$E_{pt-to-plane}(T) = \sum_{i=1}^{M} \omega_i [(T(x_s^i) - x_d^i) \cdot n_d^i]^2$$



Integration Into Kalman Filter

- State: Joint angles + global transformation

- Encoders for motion update

$$\bar{\mu}_k = m_{k-1} + \mathbf{B}(\tilde{q}_k - \tilde{q}_{k-1})$$

- Kalman covariance fed back into ICP to give preference to adjusting less certain DoFs

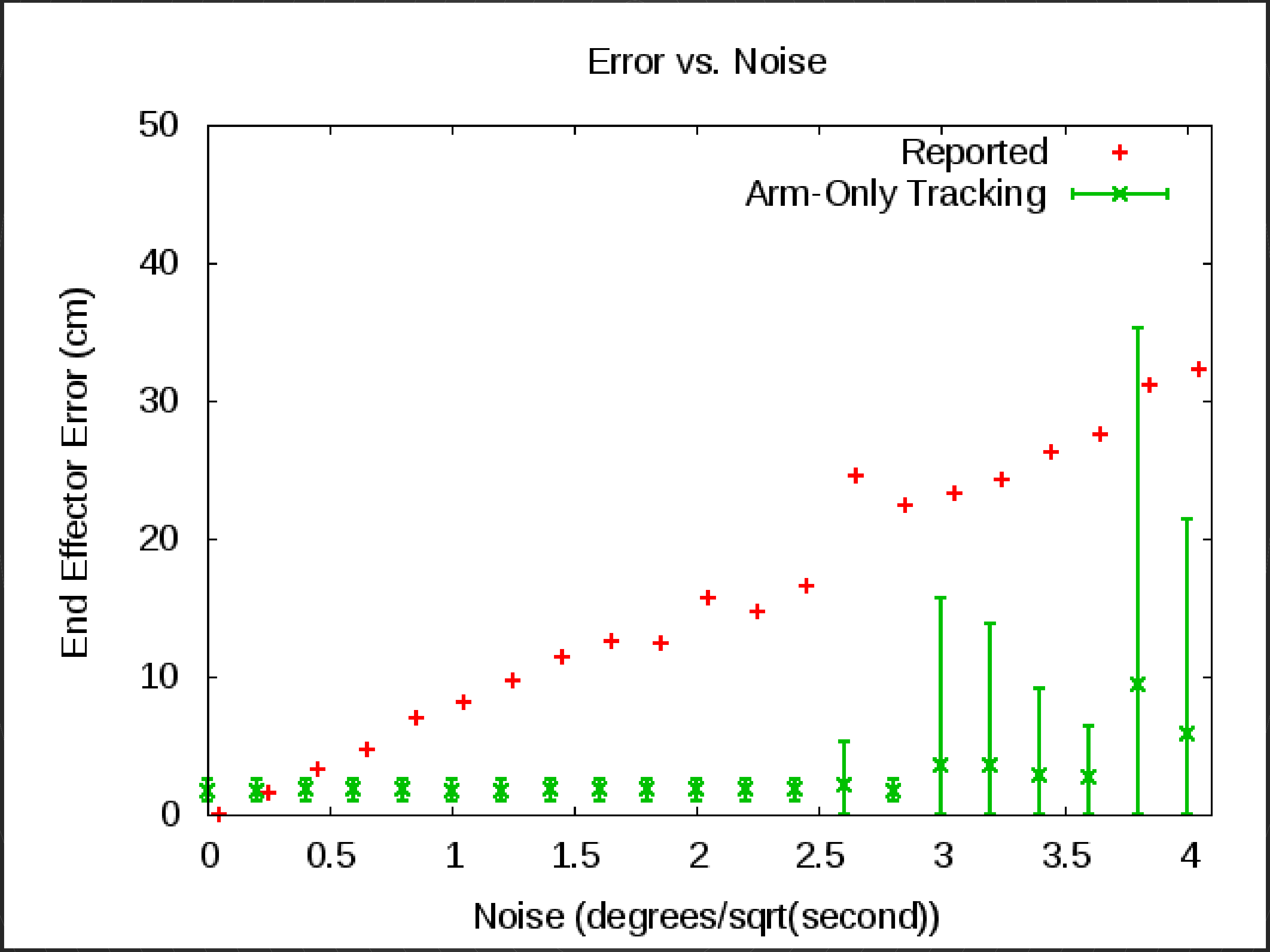
$$E_{prior}(T) = (T - \bar{\mu}_k)\bar{\Sigma}_k^{-1}(T - \bar{\mu}_k)$$

$$T^* = \arg\min_T [E_{pt-to-plane}(T) + E_{prior}(T)]$$

$$\mu_k$$

Tracking with Added Noise

Tracking Results



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Object Modeling

Joint Tracking

- Motivation
  - Need accurate pose of object within hand
  - Object may occlude hand, making tracking more difficult

- Add pose of object within hand to Kalman state
- Add object matching into ICP

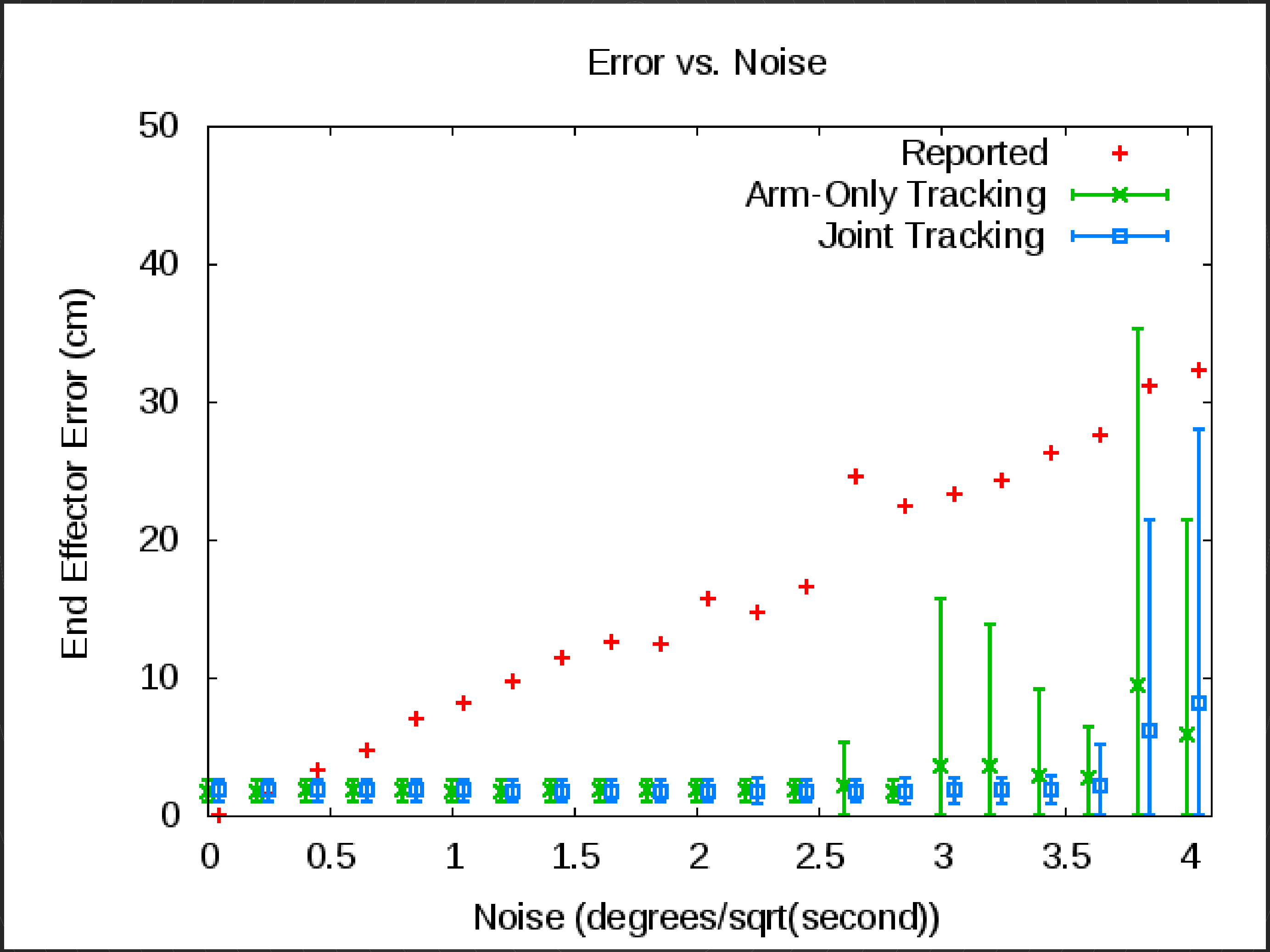
SIFT matching

- Use object texture for additional constraints
- Keep estimates of 3D locations of SIFT keypoints within object model
- Add geometrically consistent frame-to-model matches as point-to-point correspondences

$$E_{sift}(T) = \underset{(\kappa_\sigma, \kappa_\tau) \quad \Sigma}{} \; | T(\kappa_\sigma) - \kappa_\tau |^2$$

$$T^* = \underset{T}{\alpha\rho\gamma\,\mu\,\iota\nu}[E_{\pi\tau-\tau o-\pi\lambda\alpha\nu\varepsilon}(T) + E_{\pi\rho\iota o\rho}(T) + E_{\sigma\iota\phi\tau}(T)]$$

Joint Tracking Results



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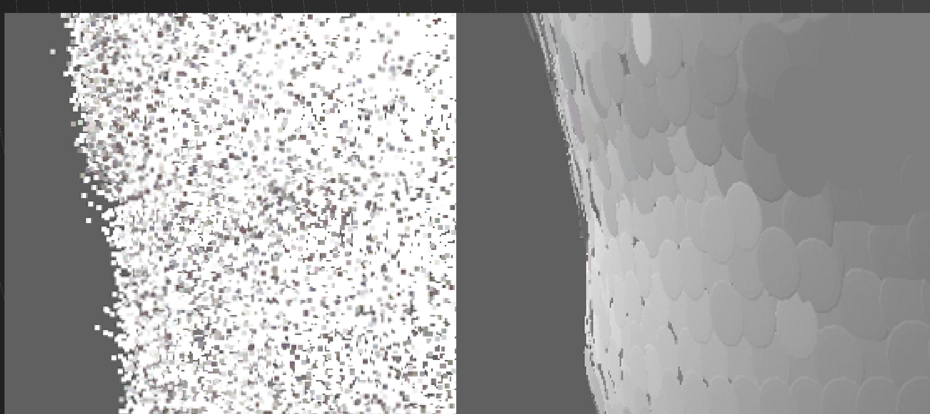
Articulated ICP for Robot Arm and Hand Tracking

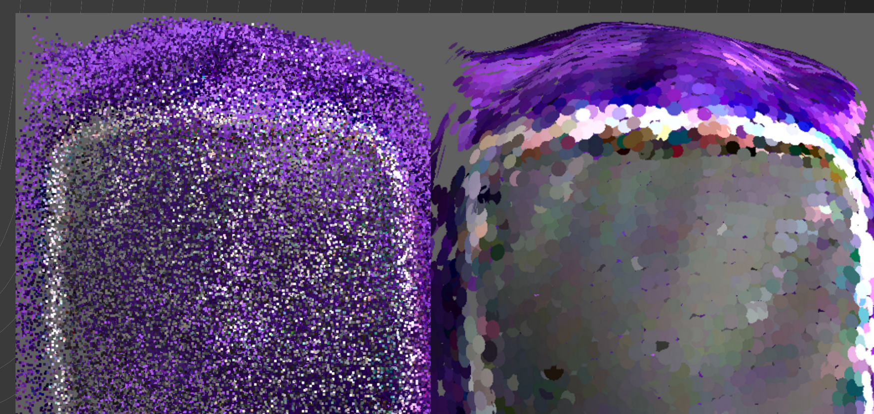
Joint Hand and Object Tracking

Object Modeling

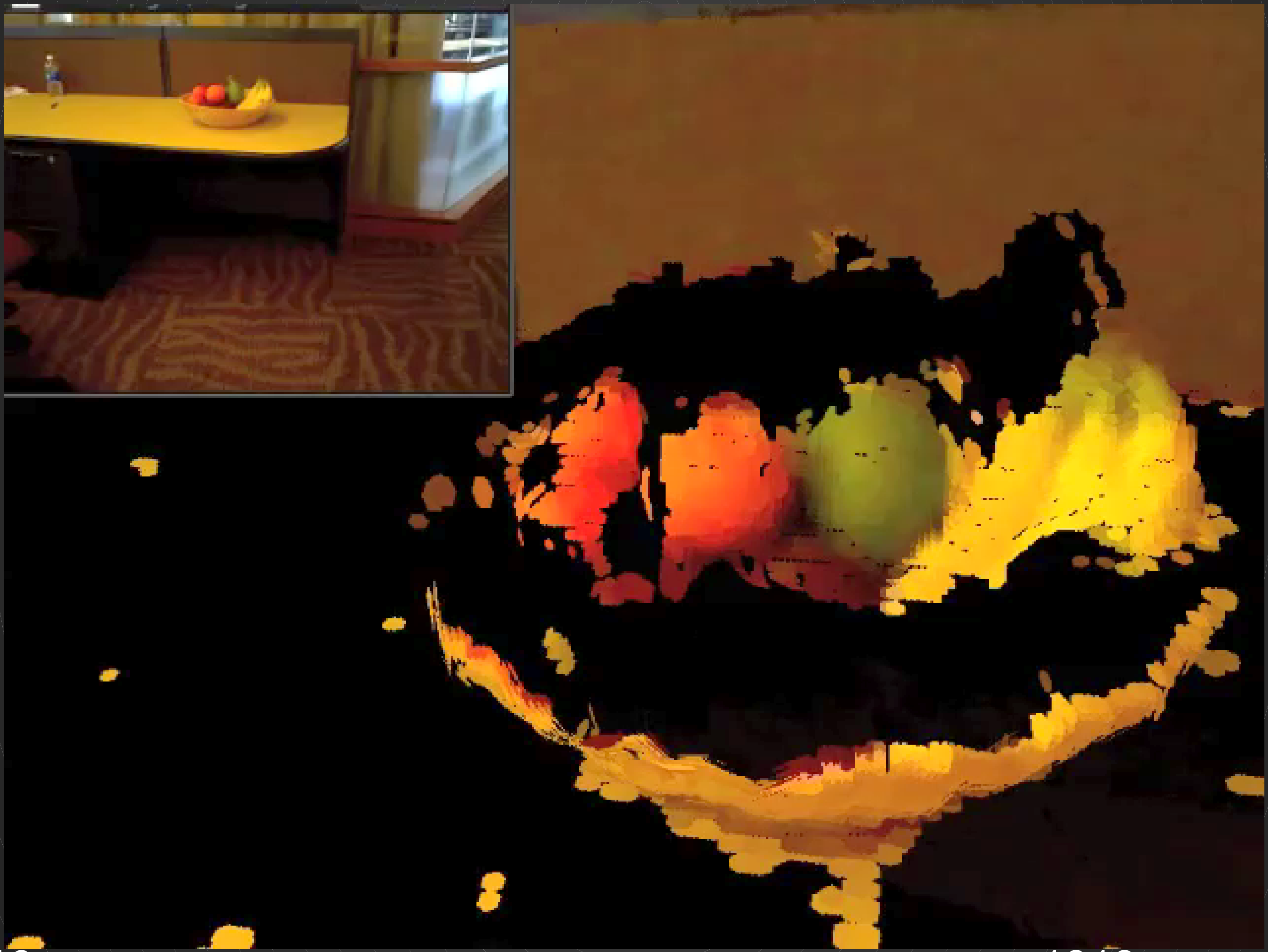
Surfel Representation

- "Surface Elements" – circular disks representing local surface patches
- Existing representation from the literature [Pfister '00], [Habbecke '07], [Weise '09]





Surfel Demonstration

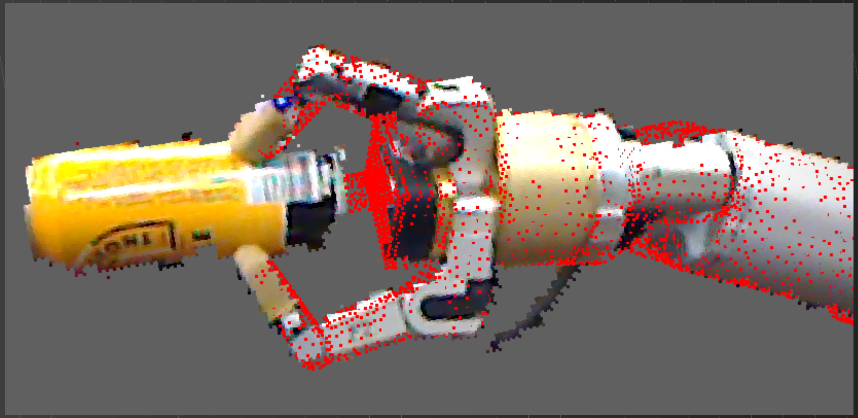


Advantages of Surfels

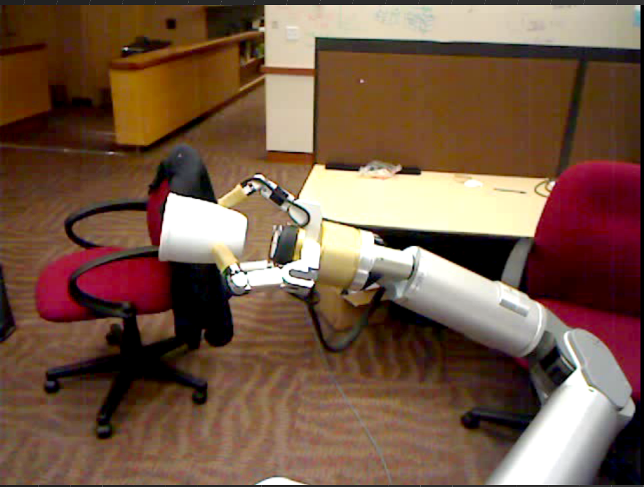
- Simple update rules
- Incremental updating
- Occlusion checking
- Efficient representation (scalable)
- Automatic resizing

Modeling

- Object detected based on tracking result
- Surfel model transformed to align with sensor data
- Surfels modified according to update rules



Tracking + Modeling



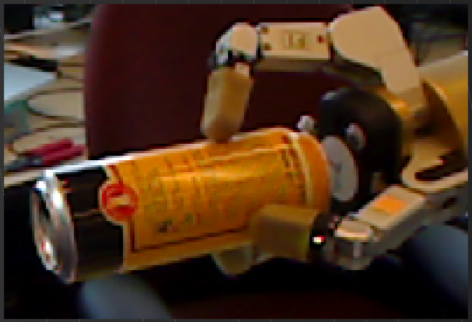
Modeling Properties

- Averaging of noise
- Can handle symmetric and textureless objects
- Limitations
  - Holes where gripper occludes object
  - Rigid objects only
  - Motion speed limited by motion blur and ICP

Modeling Results

Handling Multiple Grasps

- Switching Kalman filter
  - Examining object
  - Moving to or from table
  - Grasping or releasing
  - Between grasps
- Second grasp should be computed from



Summary

- Framework for simultaneously tracking robotic manipulator and modeling grasped objects
  - Incorporates information from encoders, vision, and depth
  - Joint estimation benefits tracking and modeling
  - Accurate models of symmetric and featureless objects

Future Work

- Automatic generation of motion sequences
- Self-supervised learning of objects and grasping strategies
- Development of a shared object database

Questions

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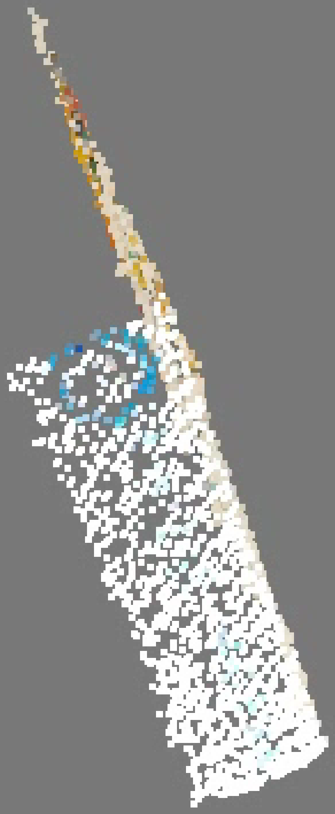
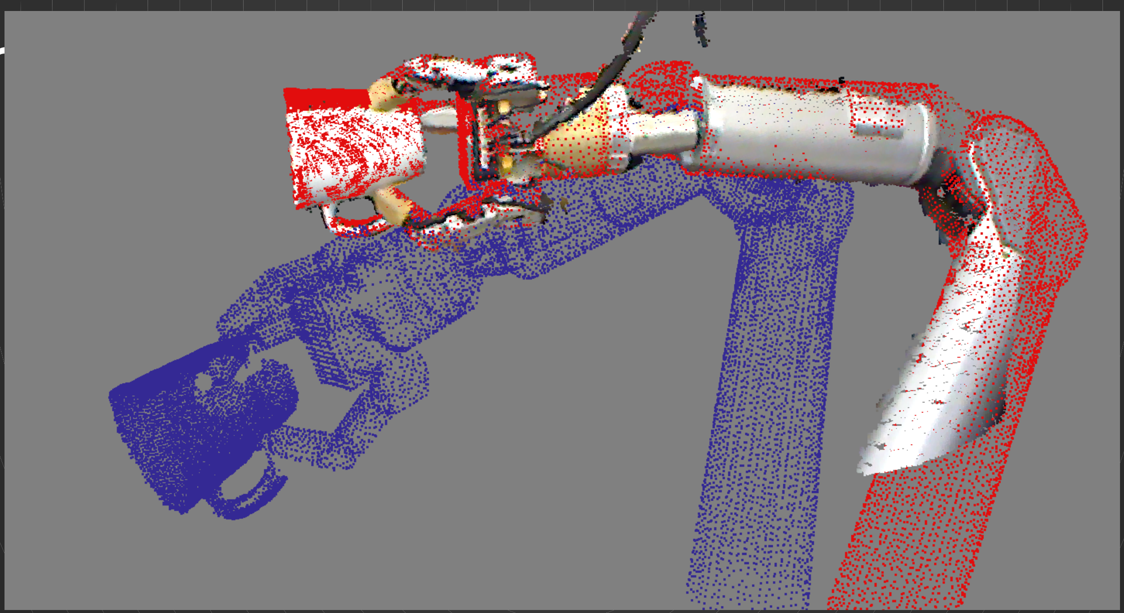


Approach Outline

Articulated Tracking

- Goal: Match a model of the arm (and manipulated object) into the sensor data
- Use shape, visual, and encoder inform



ICP Details

$$E_{pt-\varpi-\pi\lambda\alpha\nu\varepsilon}(T) = \mathop{}_{\iota=1}^{M} \omega_\iota \, \mu \, \iota\nu_{\varphi}((T(\pi_\sigma^\iota) - \pi_\tau^\varphi) \;\; \nu_\tau^\varphi)^2$$