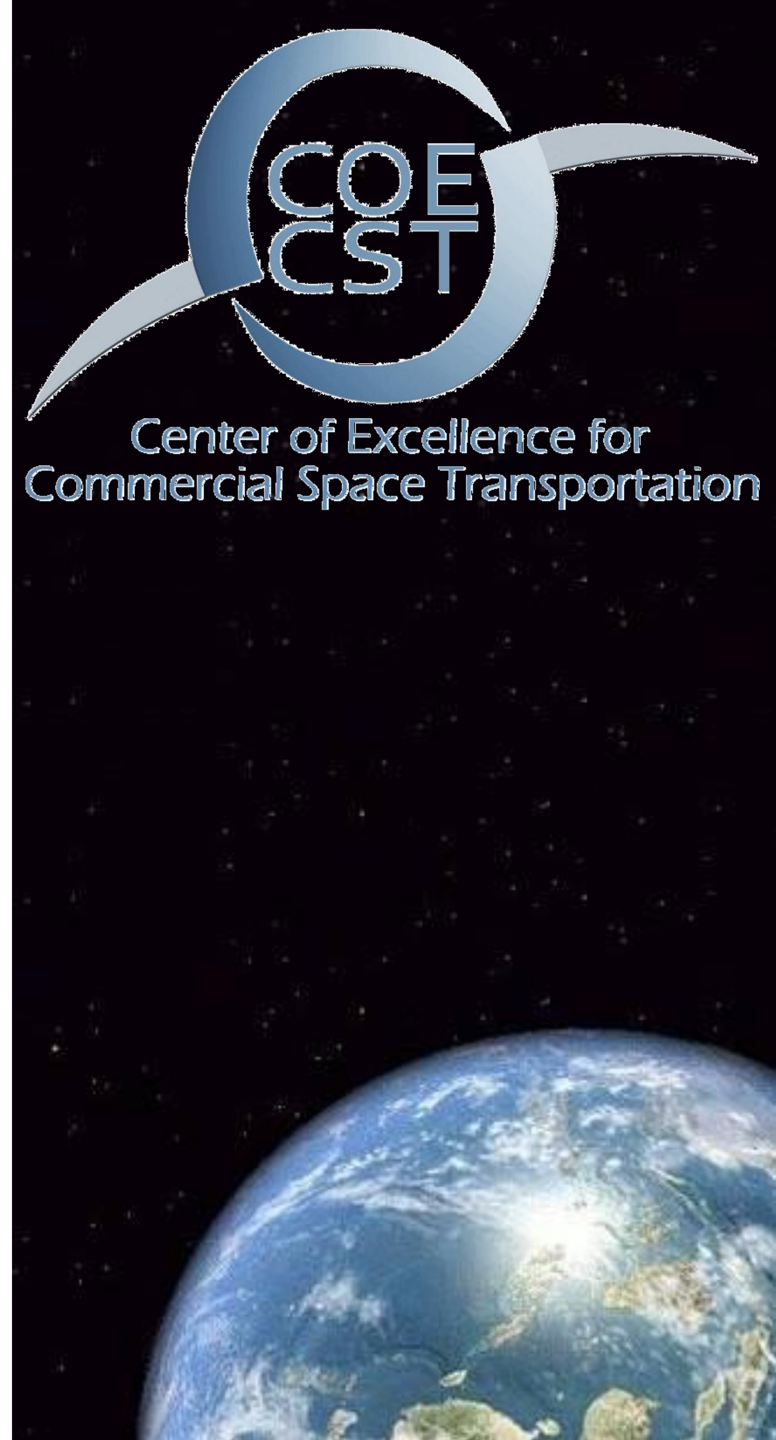
COE CST Third Annual Technical Meeting:

Task Area 244:

AUTONOMOUS RENDEZVOUS AND DOCKING
(Using nano-satellites for inspection and proximity operations)

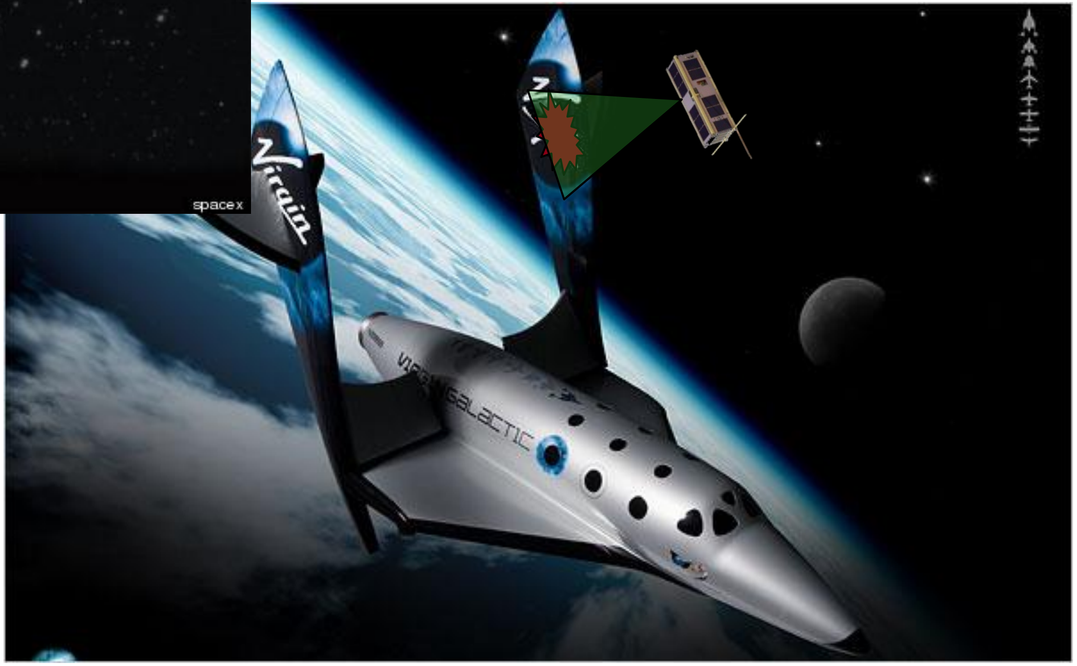
PI: Steve Rock
Stanford University

October 30, 2013



Motivation

Nanosatellite Observer for "Eye in the Sky" Inspection



Target Potentially Undergoing Complex, Tumbling Motion

Statement of Purpose

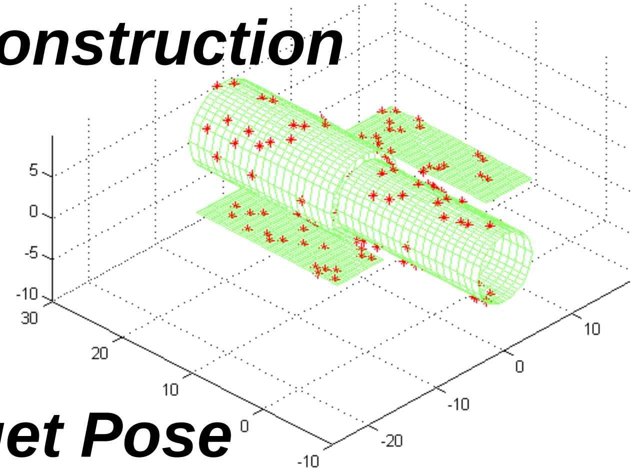
- Goal: To develop new technology for spacecraft proximity operations that is safety enabling

- Target Reconstruction and Pose Estimation

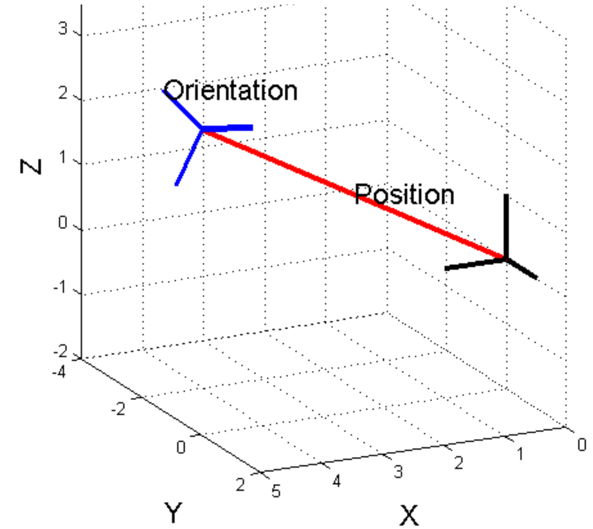
- Unstructured rendezvous situations
  - Tumbling target motion
  - No a priori information
  - Uncommunicative target

- Enable this capability on a nano-satellite observer
  - **Small satellites impose sensing, size, and power constraints**

Target Reconstruction



Target Pose



Outline

- Prior Work as of Last Technical Meeting
  - Monocular Vision and Sparse-Pattern Range Data
    - Estimation Methodology
    - Simulation Results
- Work Since Technical Meeting
  - Shift in Direction
    - *Flash LIDA*R and Visual Imagery scheduling for minimal power consumption
  - Hardware Testbed
    - 6-DOF relative motion simulation
  - Estimation Codebase

Team Members

- PIs: Steve Rock

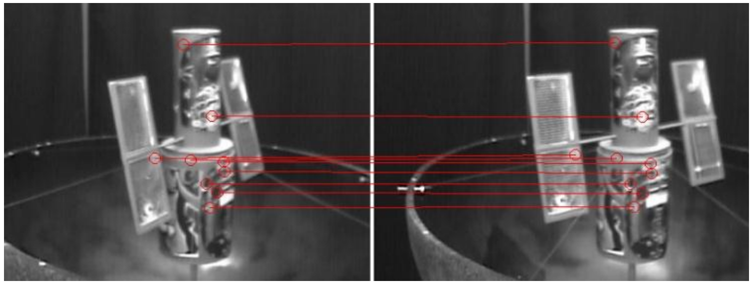
- Students:
  - Jose Padial, PhD Candidate
  - Andrew Smith, PhD Candidate

- Department of Aeronautics & Astronautics, Stanford University

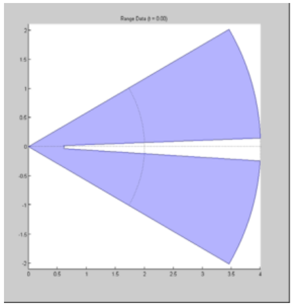
Prior Investigation as of Last TM

- **Fusion of vision and sparse pattern range data**
  - Power and size drove sensor choice
    - Camera can be tiny and very low power (passive sensor)
    - There exist small line-scanning range finders with *relatively* low power consumption

- **Monocular vision**
  - Robust feature tracking (SIFT) provides frame-to-frame correspondence

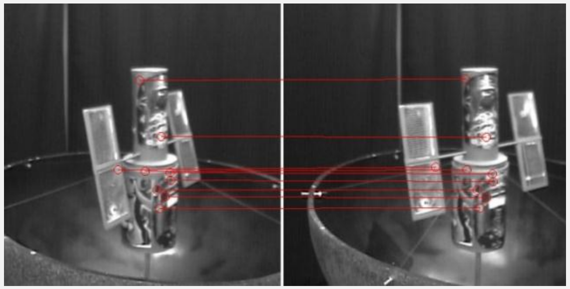


- **Sparse-pattern Range Data**
  - e.g. Line-scanning Laser
  - Provides 3D mapping of target geometry



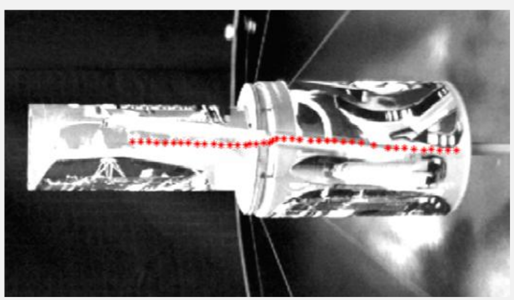
Algorithm Overview

Frame-to-Frame Vision Correspondence



Incorporate Range Returns

- Project range returns onto images
- Determine vision-range correspondence



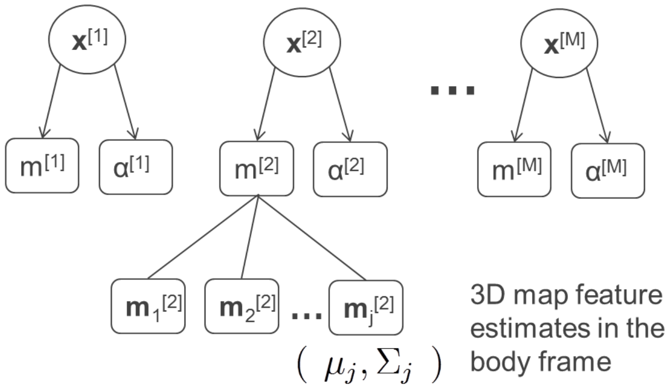
Pose Estimates

Target Map

Rao-Blackwellised Particle Filter Framework

- Visual feature tracking drives particle weighting
- Vision-range correspondence for scale factor estimation

Algorithm Details



Details of the algorithm in:

Padial et al, "Tumbling Target Reconstruction and Pose Estimation through Fusion of Monocular Vision and Sparse-Pattern Range Data", *IEEE MFI Conference 2012.*

2D Vision Feature Measurements

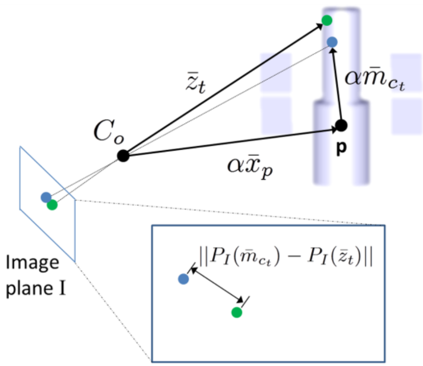
$$y_i^t = [u_i, v_i]_t^T$$

Expected Vision Measurements

$$\hat{y}_j^{t\,[i]} = K(R_t^{[i]} \mu_j^{[i]} + \bar{x}_{p,t}^{[i]})$$

Particle Weighting

$$w^{[i]} = \prod_{j=1}^{N} \frac{1}{|2\pi\Sigma_j^{[i]}|^{0.5}} e^{-\frac{1}{2}||y_j^t - \hat{y}_j^{t\,[i]}||^2_{\Sigma_j^{[i]}}}$$



Vision-range Correspondence

$$\hat{c}_t = \arg\min_{c_t} \quad ||P_I(\bar{m}_{c_t}) - P_I(\bar{z}_t)||$$
$$\text{subject to } ||P_I(\bar{m}_{c_t}) - P_I(\bar{z}_t)|| \leq \beta$$

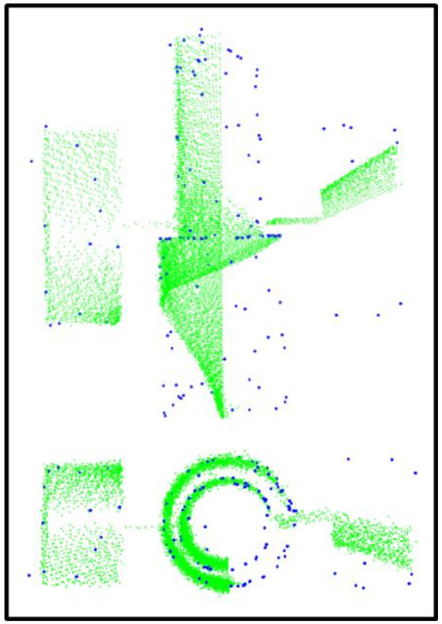
Scale Estimation System is *Linear*

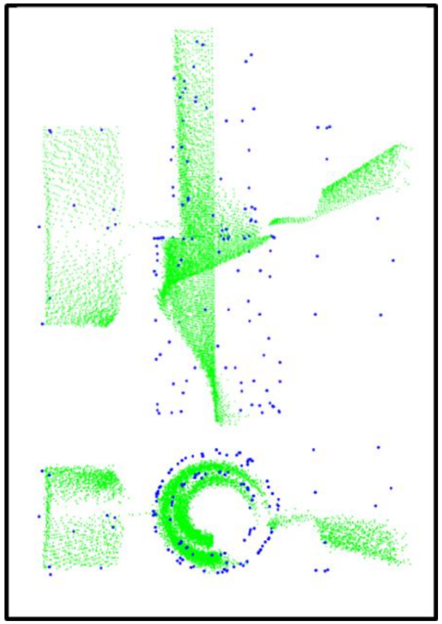
$$\bar{z}_t = (\ R(\bar{\theta}_t)^{B/C} \bar{x}_{p,t} + \bar{m}_{\hat{c}_t})\alpha_t + \bar{\delta}_z$$
$$\bar{\delta}_z \sim \mathcal{N}(0, \Gamma_{z_t})$$

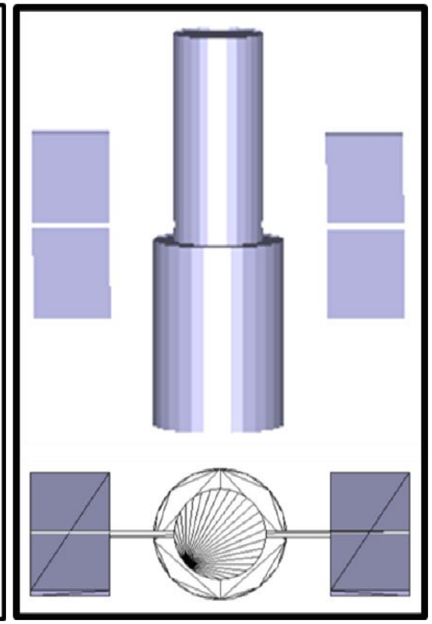
Gaussian Measurement Distribution is *Linear* in Scale

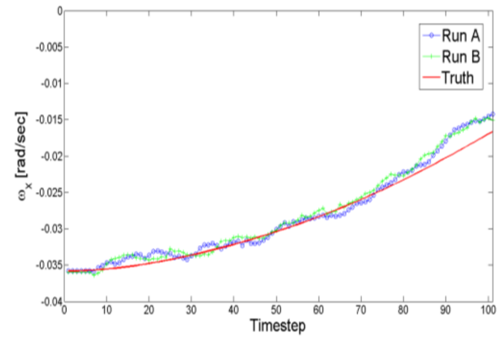
$$p(z_t|\alpha_t, x^t, z^{t-1}, c^t) \sim \mathcal{N}(z_t;\ (R(\bar{\theta}_t)^{B/C}\bar{x}_{p,t} + \bar{m}_{\hat{c}_t})\alpha_t,\ \Gamma_{z_t} + \alpha_t^2 \Sigma_{\hat{c}_t})$$

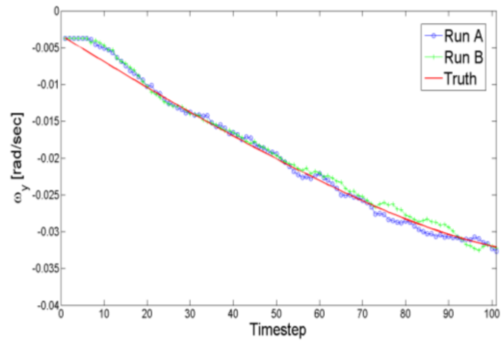
Simulation Results

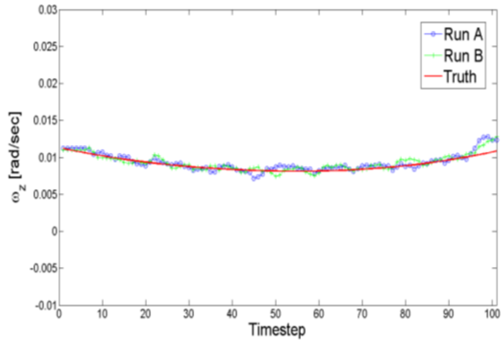












Run A: 0.42% scale error, 3.42% angular velocity error

Run B: 4.36% scale error, 3.68% angular velocity error

Target Model

Estimate Error	Mean	Std. Deviation	Max
Scale	2.14%	0.86%	4.36%
Angular Velocity	3.62%	0.71%	5.77%

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  - Current Direction
    - *3D Flash LIDAR* and Visual Imagery scheduling for minimal power consumption
  - Hardware Testbed
    - 6-DOF relative motion simulation
  - Estimation Codebase

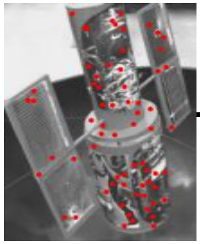
Current Investigation Direction

- **3D Flash LIDAR**
  - Flash LIDAR systems are coming down in size and power consumption
  - Dense 3D data is far more rich than that obtained by line-scanning laser range finders
    - Capable of use in frame-to-frame correspondence
    - Allows for computationally less intense estimation as compared to monocular vision + line-scan range data
- **Nanosatellite observer craft our goal**
  - Power consumption of the Flash LIDAR still too high
  - *Potential solution*: Intelligent scheduling of “flashes” in order to minimize power consumption while maintaining estimation performance

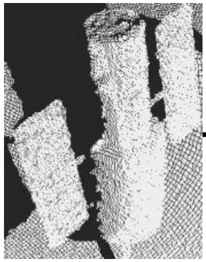
Current Investigation Direction

Sensor Scheduling for Minimal Power Consumption

- Fusion of 3D Flash LIDAR and visual imagery data for pose estimation and target reconstruction
- Develop scheduling algorithms to selectively choose when to "flash" LIDAR in order to minimize power consumption while maintaining sufficient pose estimation and target reconstruction performance



Visual Imagery



3D Range Data

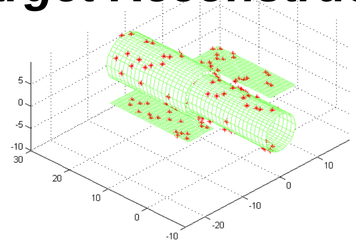
Data Fusion and Estimation Method

- Feature (SIFT) correspondence
- Pose estimation with 3D point alignment

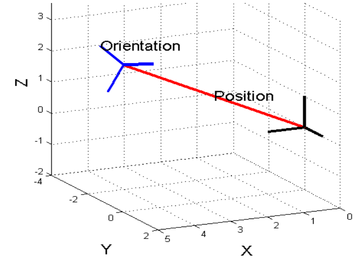
Scheduling for Minimal Power Consumption

- When should the LIDAR flash?

Target Reconstruction



Target Pose



Current Investigation Direction

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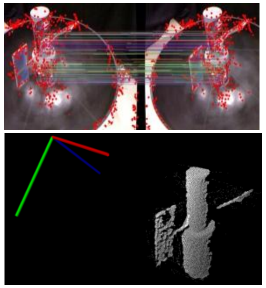
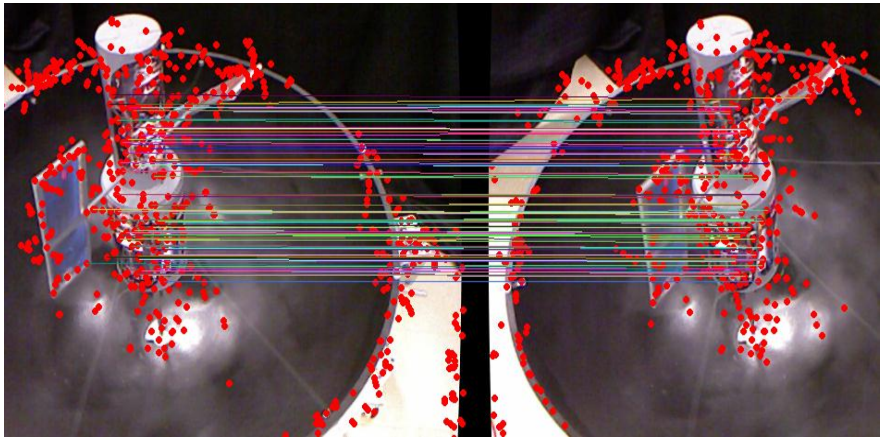
In order to investigate sensor scheduling need to develop baseline capabilities

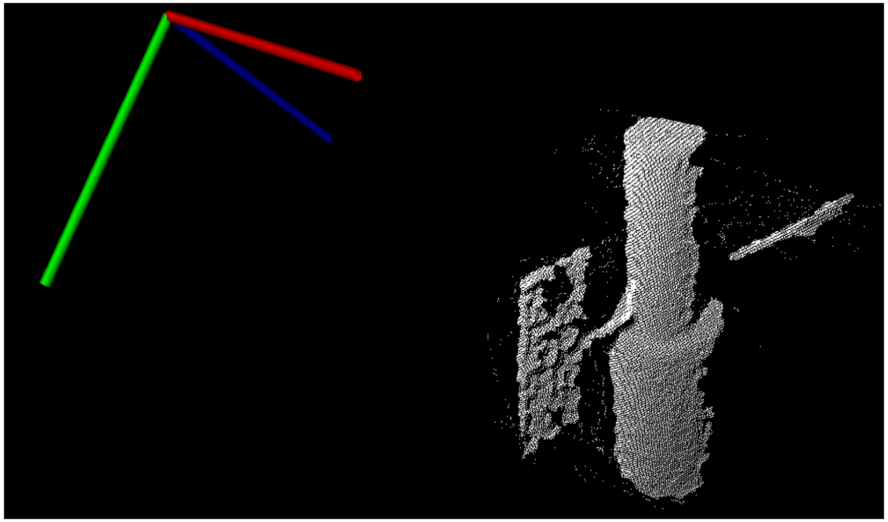


Estimation Algorithm
Pose estimation and target reconstruction with visual imagery and 3D range data

Hardware Testbed
6-DOF relative motion between target and observer

Estimation Methodology

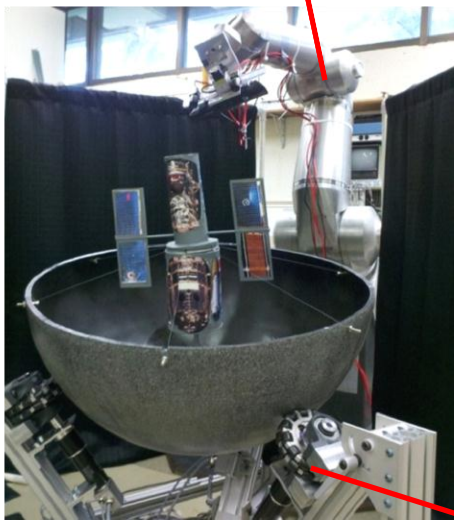




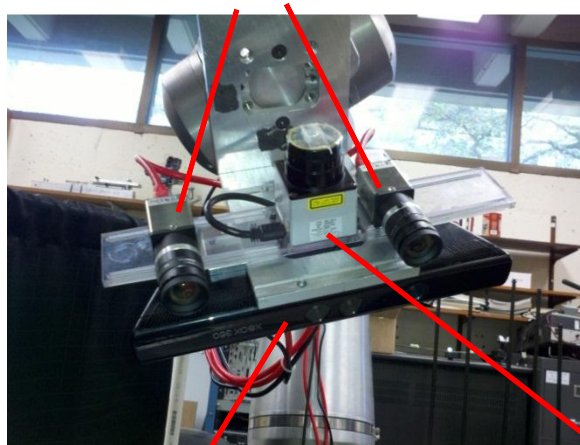
- **Vision feature correspondence (SIFT)**
  - Provides the alignment of points between 2 successive frames
- **Range data provides depth for corresponding points (full 3D points)**
  - Well-known Horn's method used to estimate rotation and translation of target between frames (relative to observer frame)
- **Estimation is *well-behaved* compared to monocular vision case**

ARL Hardware Testbed

R^2 manipulator arm



Cameras



Motion Capture IR Cameras

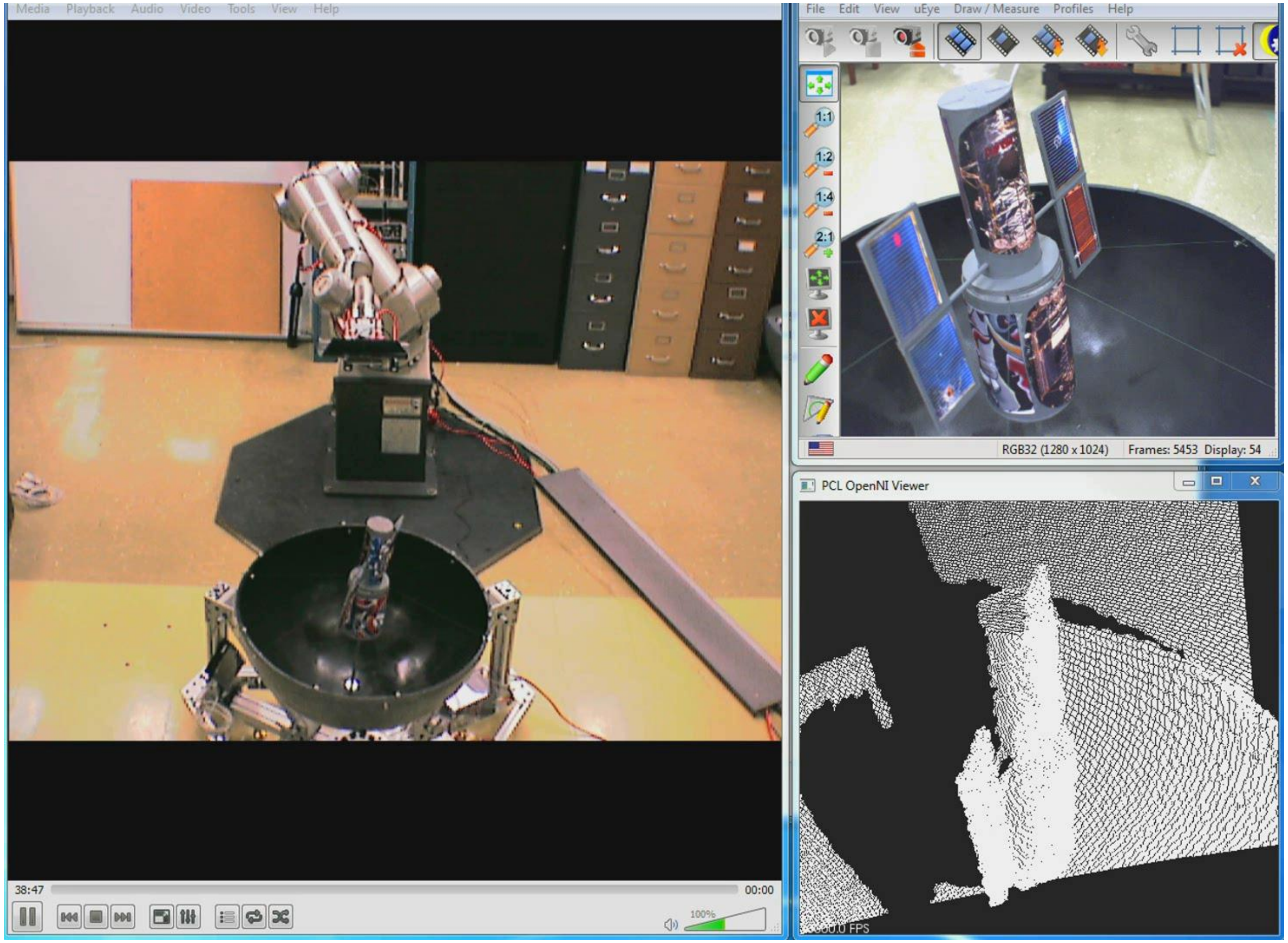
Microsoft Kinect

Line-scanning laser range finder

Tumbling base motion simulator

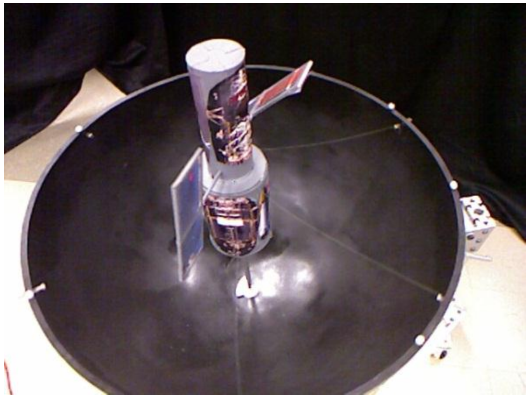
- Mounted sensors to manipulator end-effector for 6DOF relative motion
  - Microsoft Kinect as a surrogate for Flash LIDAR
- Mounted Motion Capture IR Cameras (6)
- Simulink-based manipulator and tumbling base control with synchronized camera/ranging data collection and IR truth data collection

ARL Hardware Testbed

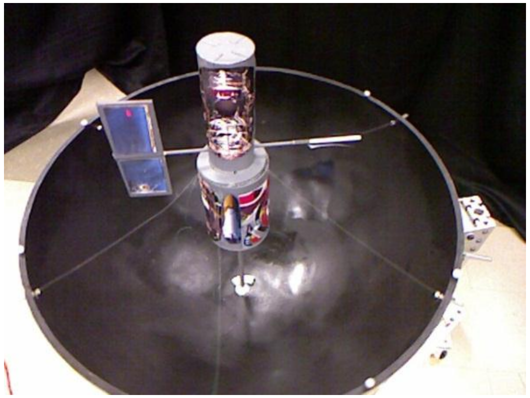


Pose Estimation / Reconstruction

Target Range of Motion

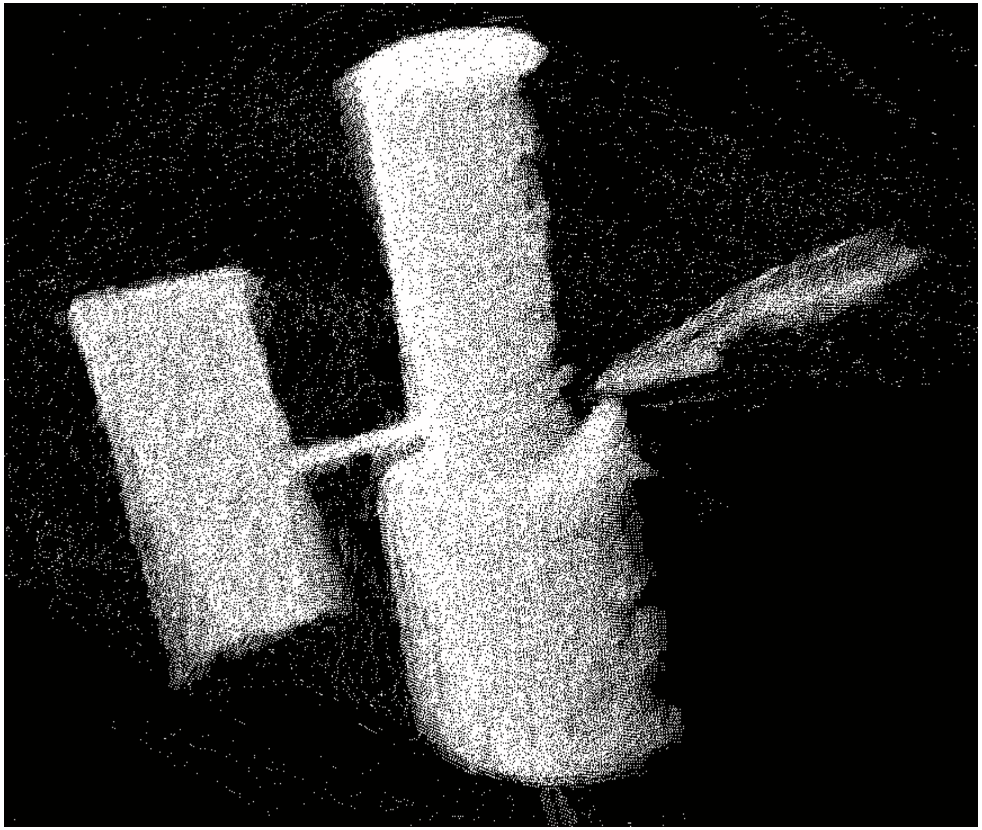


First Frame



Last Frame

Reconstruction



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