Quadrotor State Estimation and Obstacle Detection

Robot Autonomy Project

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I. Dynamics
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III. Planning
IV. Control Architecture
V. State Estimation (EKF)
VI. Sensors
VII. SLAM (RTAB Map)
VIII. Obstacle Detection
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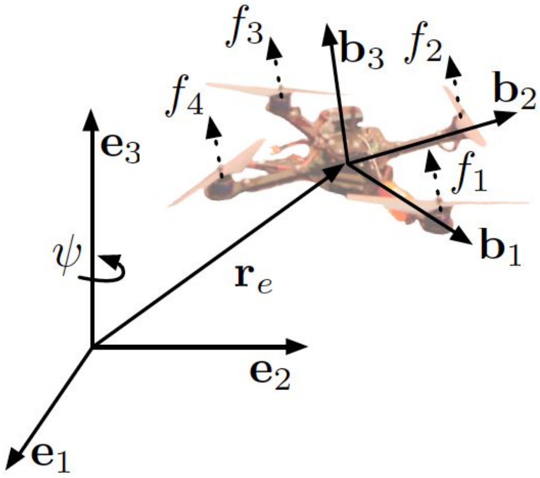
Quadrotor Dynamics



Control inputs:

$$[f\ \mathrm{M}]^T, f \in \mathbb{R}, \mathrm{M} \in \mathbb{R}^3$$

State:

$$[x\ v\ R\ \Omega]^T$$

Dynamics:

$$\dot{x} = v$$
$$m\dot{v} = mge_3 - fRe_3$$
$$\dot{R} = R\widehat{\Omega}$$
$$J\dot{\Omega} + \Omega \times J\Omega = \mathrm{M}$$

Differential Flatness

Dynamics:

$$\dot{x} = v$$
$$m\dot{v} = mge_3 - fRe_3$$
$$\dot{R} = R\widehat{\Omega}$$
$$J\dot{\Omega} + \Omega \times J\Omega = \mathrm{M}$$

Pick outputs: $y = y(x, u, \dot{u}, \ldots, u^{(p)})$

Such that:

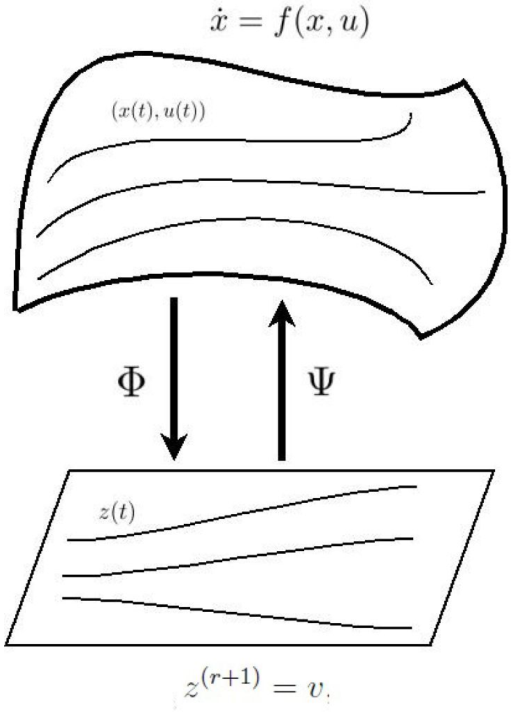
$$\begin{aligned} x &= x(y, \dot{y}, \ldots, y^{(q)}) \\ u &= u(y, \dot{y}, \ldots, y^{(q)}). \end{aligned}$$

Any 4 of the following 6 can serve as flat outputs:

X
Y
Z
Phi
Theta
Psi

Murray, Richard M., Muruhan Rathinam, and Willem Sluis. "Differential flatness of mechanical control systems: A catalog of prototype systems." *ASME international mechanical engineering congress and exposition*. 1995.

Differential Flatness



Any 4 of the following 6 can serve as flat outputs:

X
Y
Z
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Theta
Psi

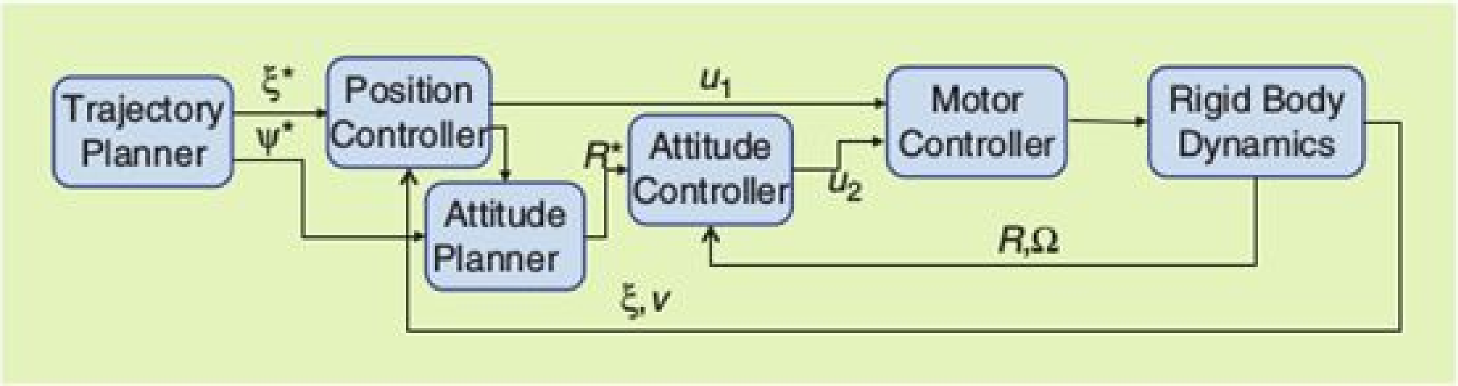
Trajectory Planning:

$$\min \int_{t_0}^{t_m} \mu_r \left\| \frac{d^{k_r} \mathbf{r_T}}{dt^{k_r}} \right\|^2 + \mu_\psi \frac{d^{k_\psi} \psi_\mathbf{T}}{dt^{k_\psi}}^2 dt$$

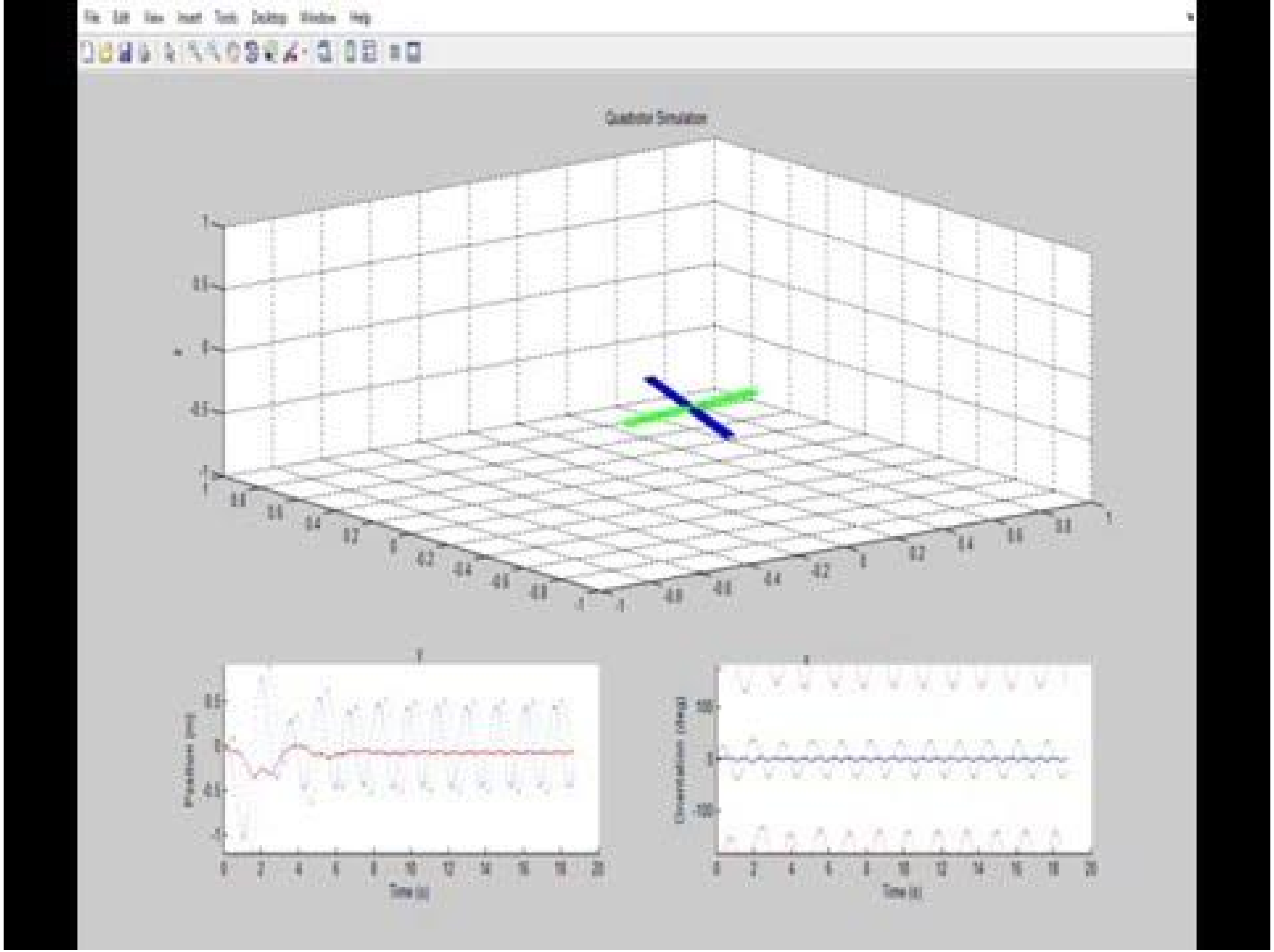
kr = 4, kψ = 2

Mellinger, Daniel, Nathan Michael, and Vijay Kumar. "Trajectory generation and control for precise aggressive maneuvers with quadrotors." *The International Journal of Robotics Research* (2012): 0278364911434236.

CONTROL ARCHITECTURE



Mahony, Robert, Vijay Kumar, and Peter Corke. "Multirotor aerial vehicles: Modeling, estimation, and control of quadrotor." IEEE Robotics & amp amp Automation Magazine 19 (2012): 20-32.

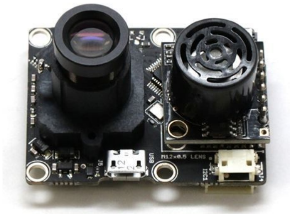

File Edit View Insert Tools Desktop Window Help
Quadrotor Simulation
Position (m)
Time (s)
Orientation (deg)
Time (s)

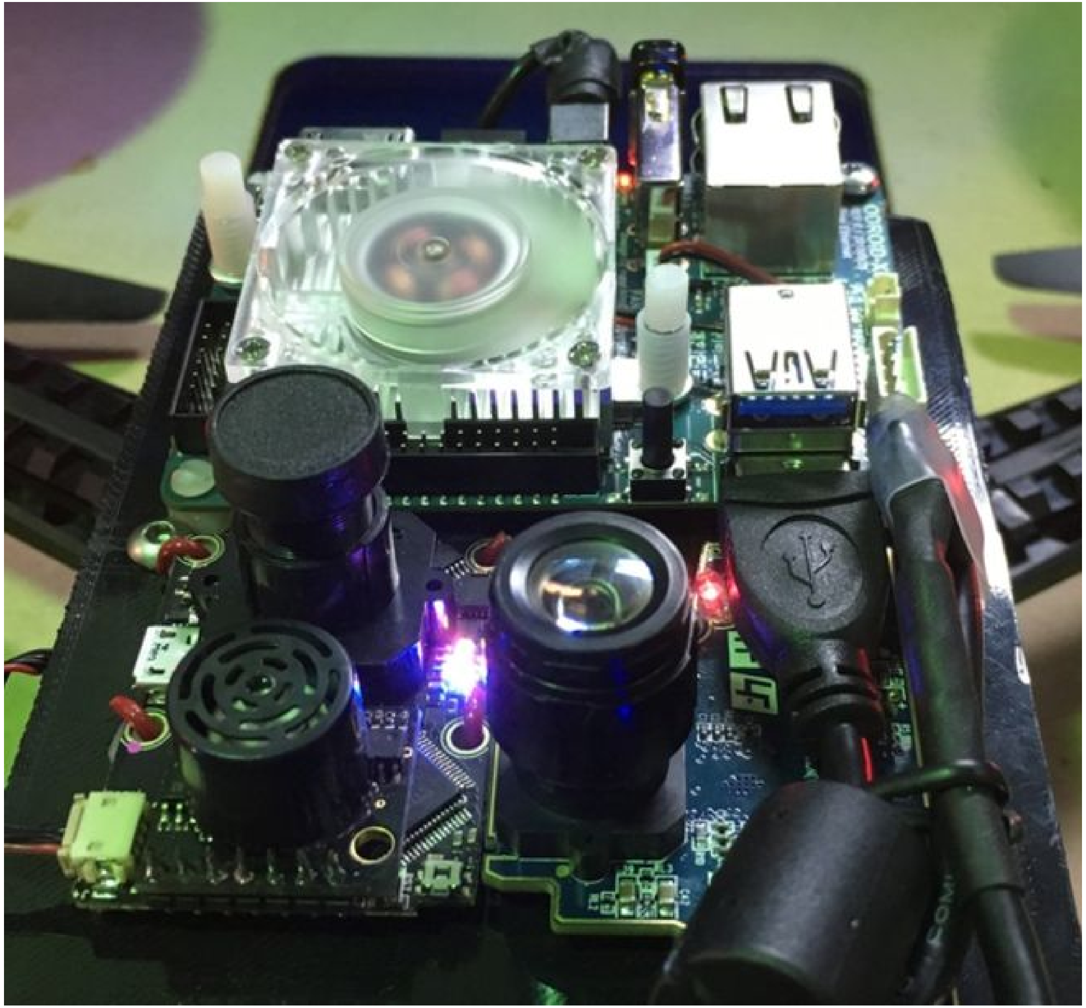
Sensors

Camera

IMU

Height Sensor





Extended Kalman Filter

Kalman Filtering: Computations

Notation:

A_t : *Motion Model*

B_t : *Control Input Model*

μ_t : *State Mean*

Σ_t : *State Variance*

Q_t : *Motion Model Noise*

C_t : *Observation Model*

R : *Observation Noise*

K_t : *Kalman Gain*

$z_t - C_t\bar{\mu}_t$: *Innovation*

$$\text{KalmanFilter}(\mu_{t-1}, \Sigma_{t-1}, u_t, z_t)$$

Prediction

$$\bar{\mu}_t = A_t \mu_{t-1} + B u_t$$

$$\bar{\Sigma}_t = A_t \Sigma_{t-1} A_t^\top + Q_t$$

Gain

$$K_t = \bar{\Sigma}_t C_t^\top (C_t \bar{\Sigma}_t C_t^\top + R\ )^{-1}$$

Update

$$\mu_t = \bar{\mu}_t + K_t(z_t - C_t \bar{\mu}_t)$$

$$\Sigma_t = (I - K_t C_t)\bar{\Sigma}_t$$

Slide courtesy Kris Kitani

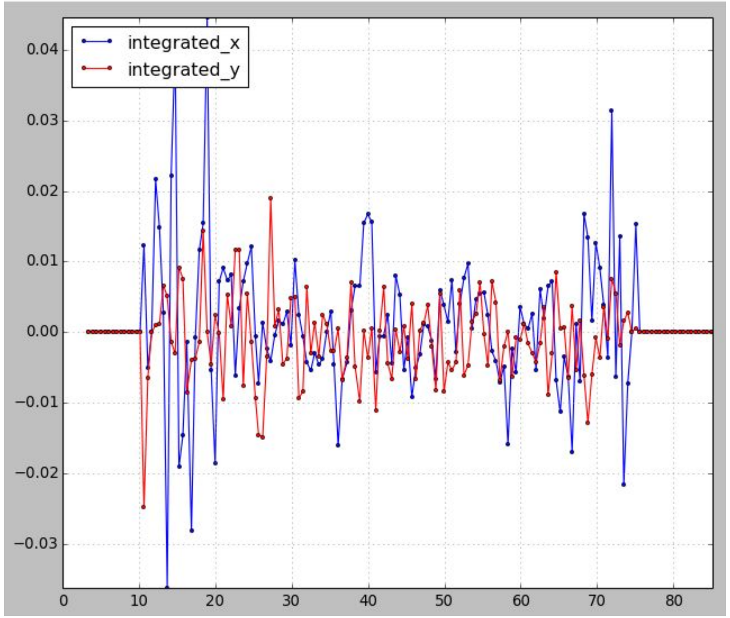
State Estimation with Optical Flow

$$v_x = \frac{T_z x - T_x \mathrm{f}}{Z} - \omega_y \mathrm{f} + \omega_z y + \frac{\omega_x xy - \omega_y x^2}{\mathrm{f}}$$

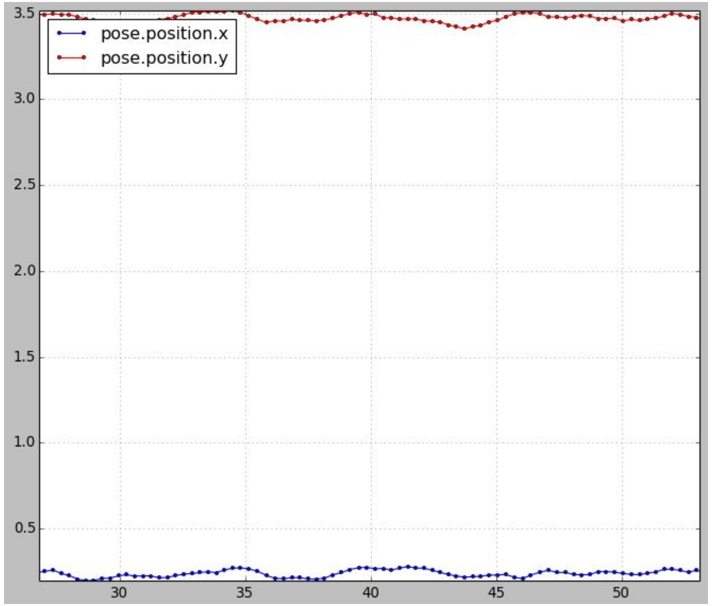
$$v_y = \frac{T_z y - T_y \mathrm{f}}{Z} + \omega_x \mathrm{f} - \omega_z x + \frac{\omega_x y^2 - \omega_y xy}{\mathrm{f}}$$

$$\frac{\mathbf{flow}}{\Delta \mathrm{time}} = \mathbf{v} = \mathrm{f}\frac{\mathrm{Z}\mathbf{V} - V_z \mathbf{P}}{\mathrm{Z}^2}$$

State Estimation with Optical Flow

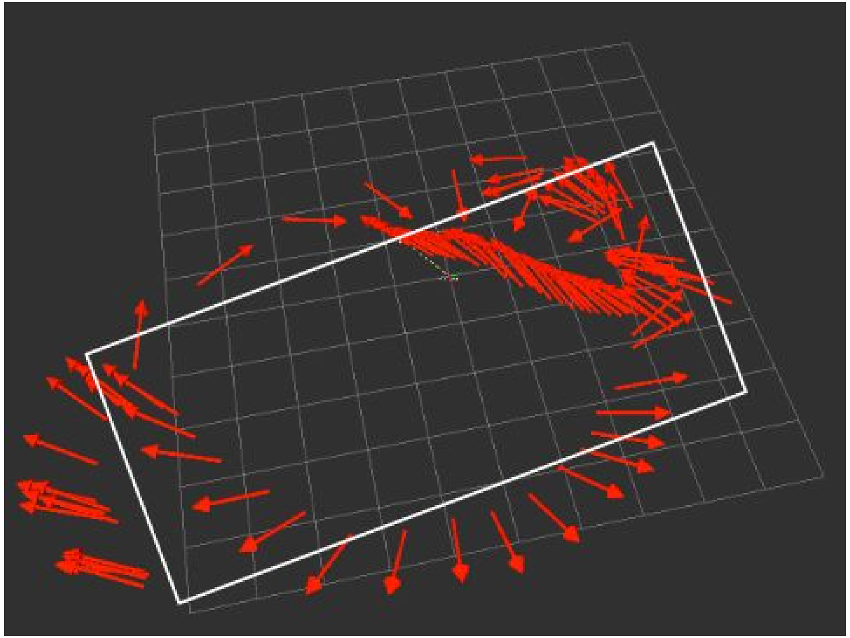


Velocity Updates from Optical Flow Camera

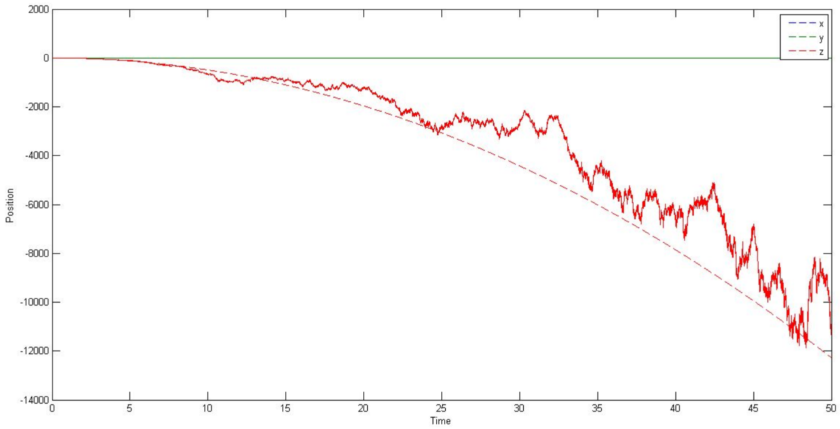


Position Updates from EKF

State Estimation with Optical Flow



Odometry Readings

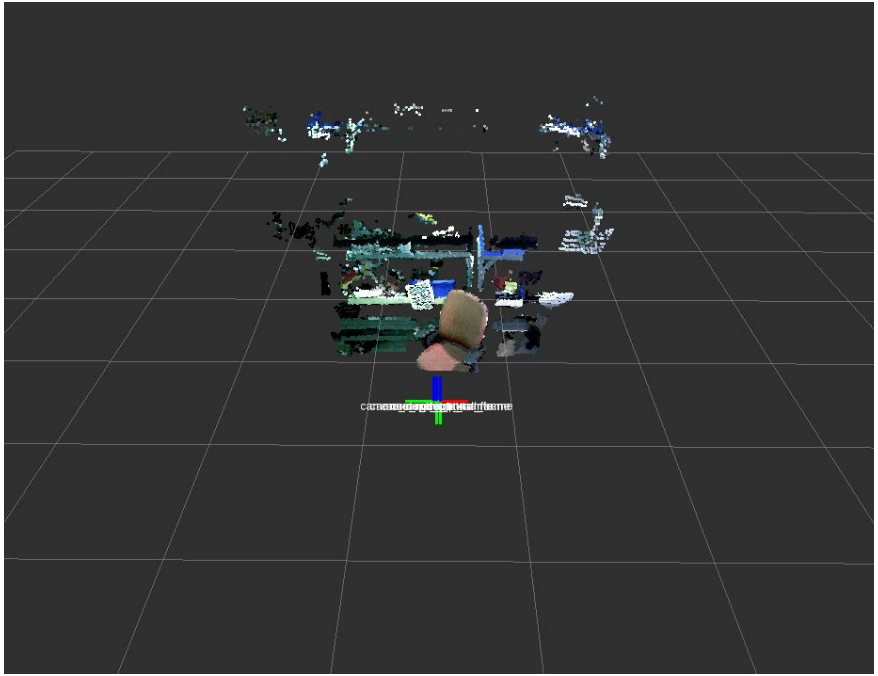


Linear Drift with Time in Simulation

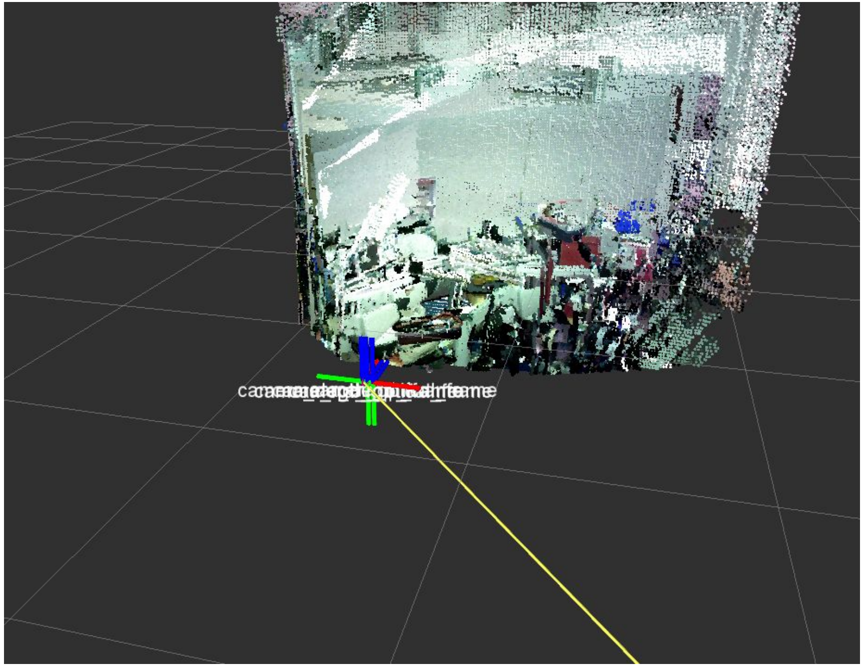
RTAB-Map

- Graph and Node based System
- Gathers RGB and Depth information
- OpenNI handles point clouds
- Uses visual words to detect loop closures

RGB-D SLAM

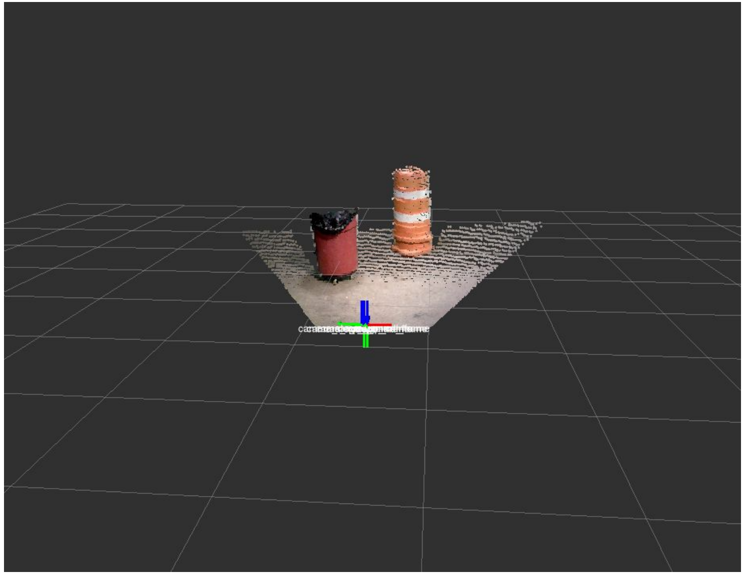


Static Map

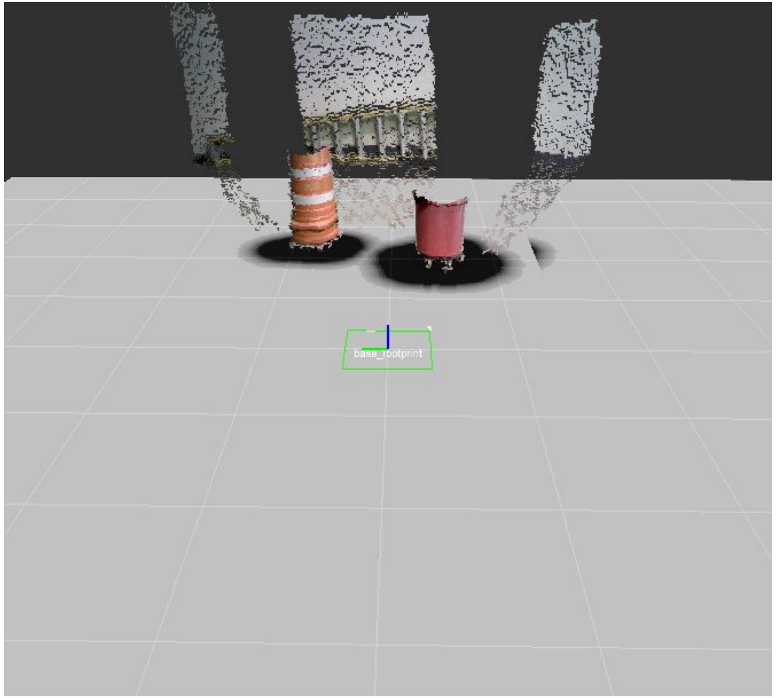


Dynamic Map Building

Obstacle Detection



RBG-D Point Cloud Data



Occupancy Grid

Visualization of Costmap and State Estimation