Robust Visual Localization

- 2D Laser Localization:
  - Wheel Odometry required
  - Flat-world assumptions

- Aim: Flexible, mobile, 3D with recovery mechanisms
- Motivating Applications:

State Estimation
-Traditional
-Stochastic

Kinect Localization:
-Visual Odometry
-Depth Simulation

Results:
-Multi-robot demos
-Future work

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Bayesian Filters

Grid Based Methods

- Cannot scale to high dimensionality

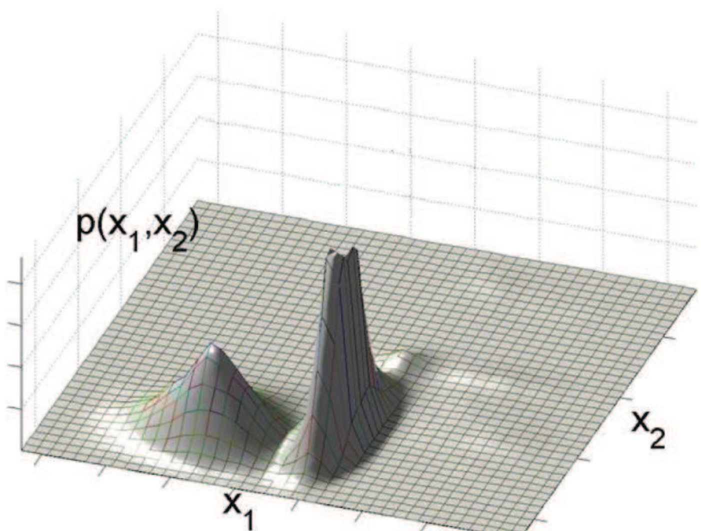
Kalman Filter

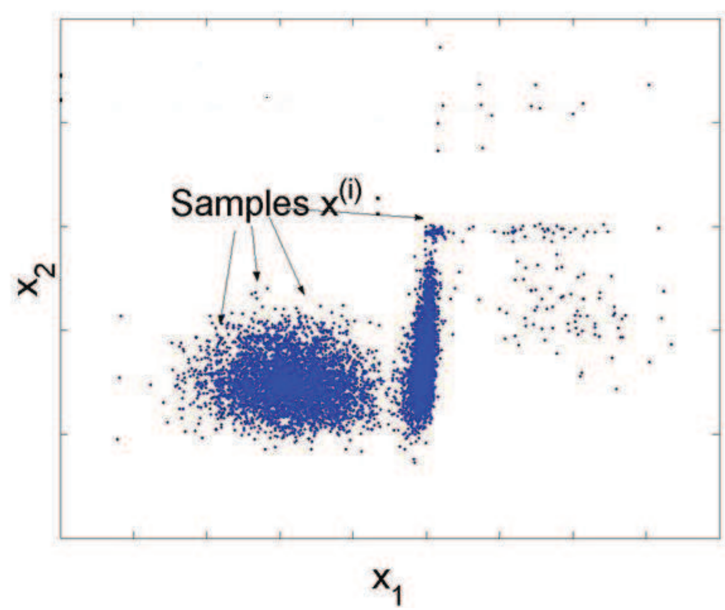
- Optimal **linear** systems in **Gaussian** noise
- Extended Kalman Filter
  - Non-linear using local linearization (may be incorrect)
  - Data must still be Gaussian

Monte Carlo Integration

Bayesian numerical integration technique:

- State approximated as a cloud of discrete samples
- Samples weighted according to their likelihoods
- Parameters of the distribution can be estimated from a large set of samples





Particle Filter – Overview 1

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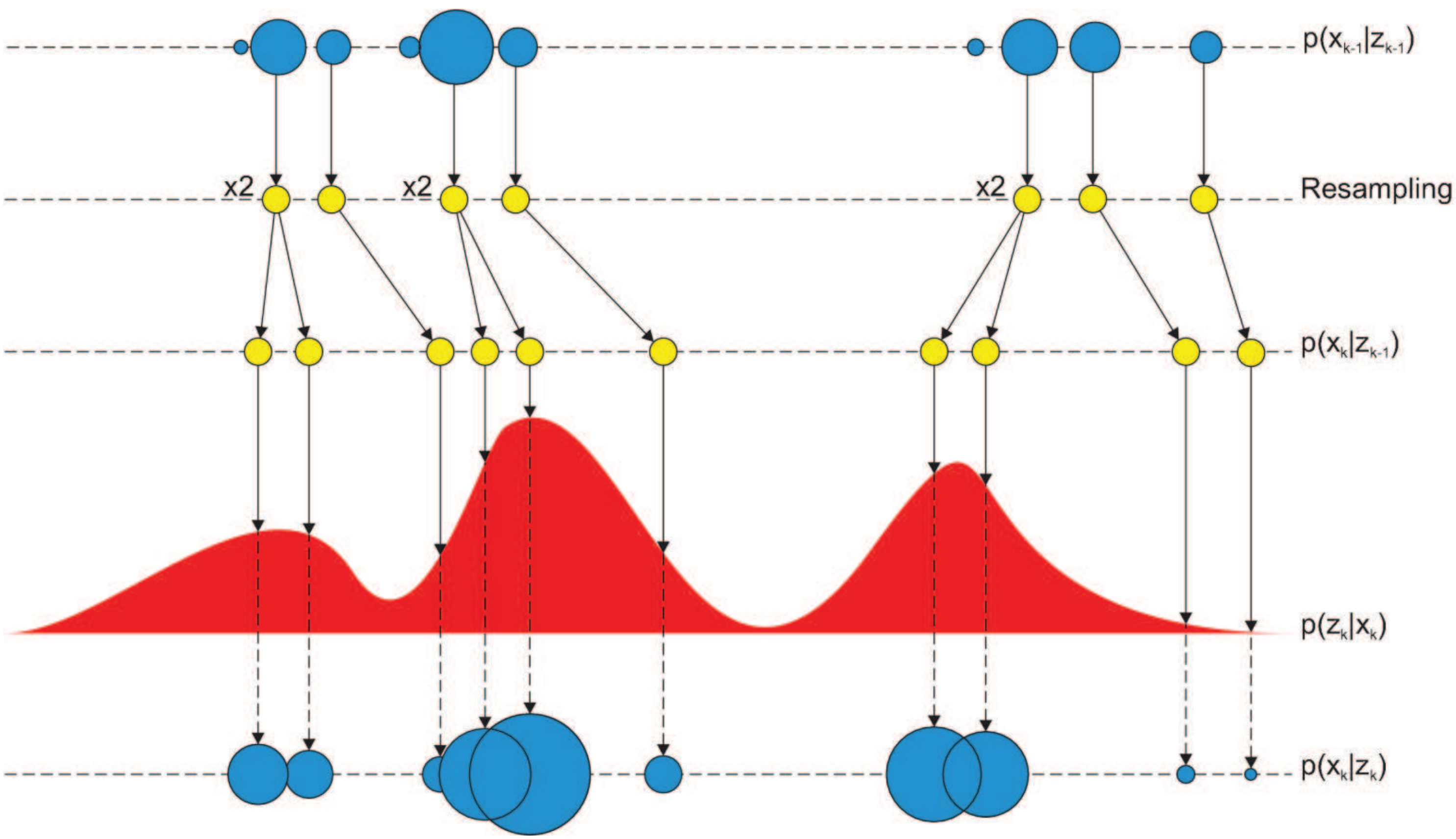

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Particle Filter – Overview 2

M. Isard Microsoft Research

Implementation Issues:

- Degeneracy
- High dimensionality
- Importance Sampling

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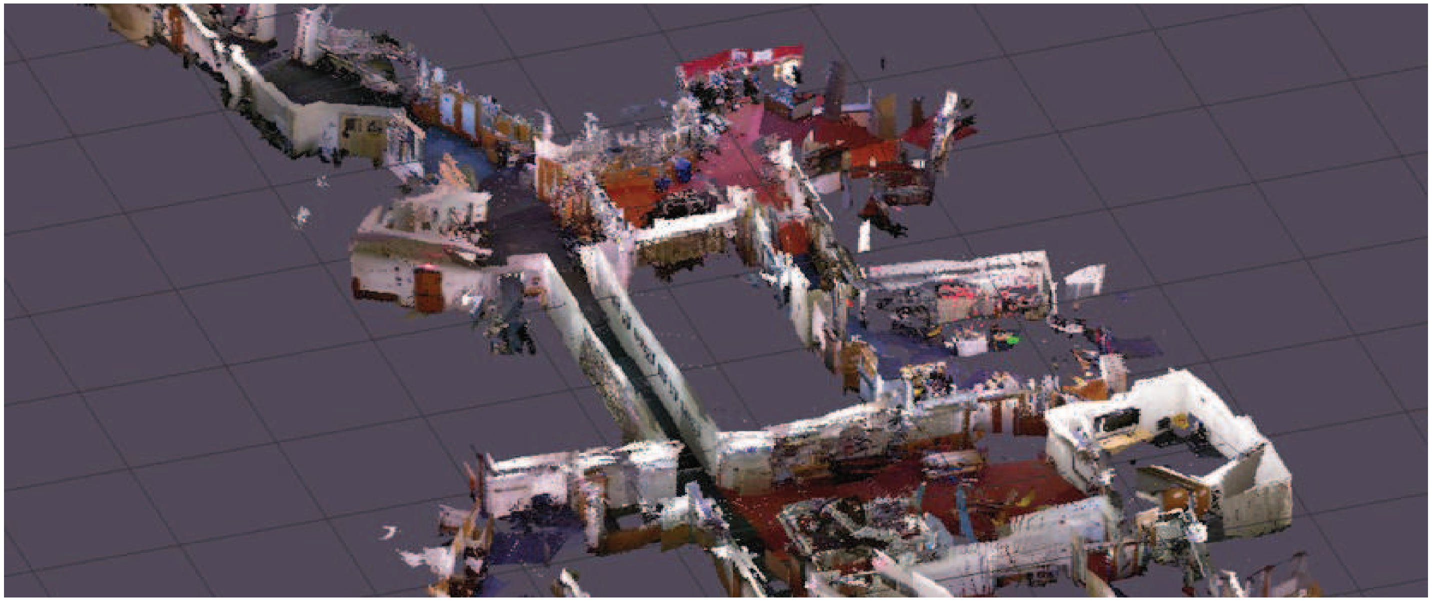
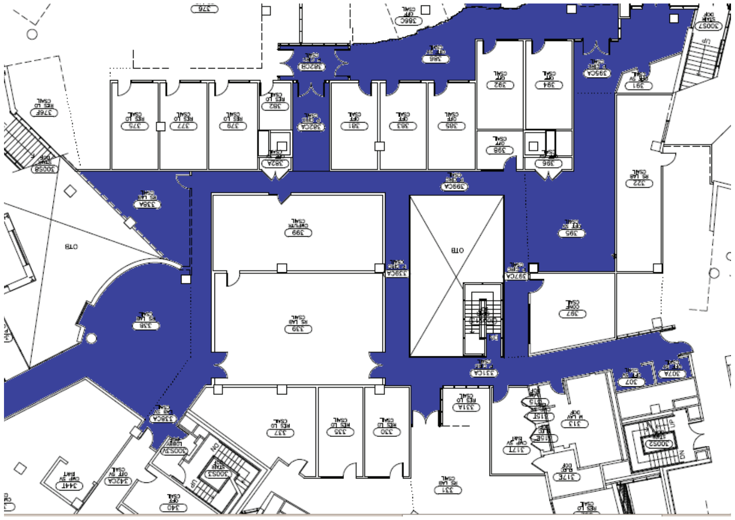
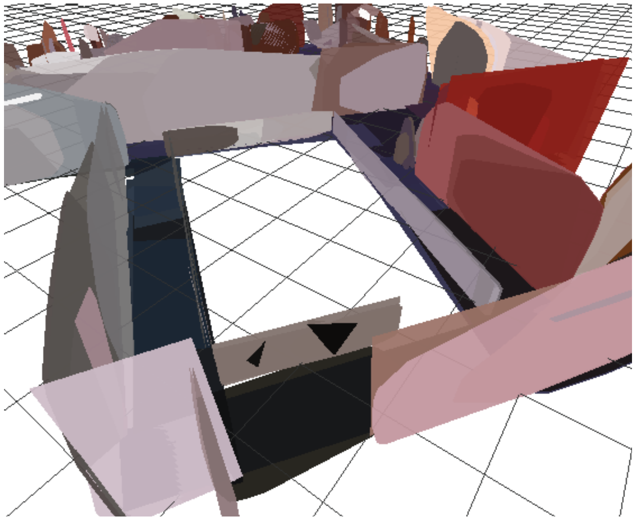
Input: Low-Fi Planar Map







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Particle Propagation – Visual Odometry

$$\mathcal{A}_k = (x_k, y_k, \phi_k, \dot{x}_k, \dot{y}_k, \dot{\phi}_k)$$

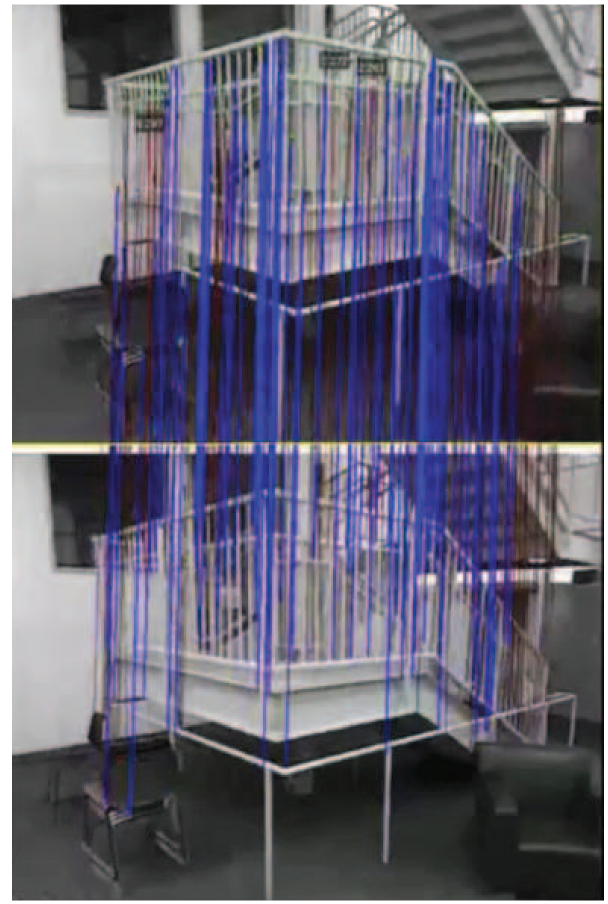
Propagate using Visual Odometry

- Fast Odom. for Vision (FoVis)[1]
- 0.08m/s mean velocity error

$$\begin{aligned} x_k &= x_{k-1} + \triangle T \dot{x}_k + e_{x,k} \quad e_{x,k} \sim \mathcal{N}(0, \sigma_x^2) \\ \dot{x}_k &= \dot{x}_{k,\text{vo}} + e_{\dot{x},k} \quad e_{\dot{x},k} \sim \mathcal{N}(0, \sigma_{\dot{x}}^2) \end{aligned}$$

VO Fails with high motion blur and featureless environments:

- Add extra noise in this situation
- Future: IMU integration



[1] A Huang, A Bachrach, P Henry, M Krainin, D Maturana, D Fox, N Roy. Visual Odometry and Mapping for Autonomous Flight Using an RGB-D Camera, ISRR 2011

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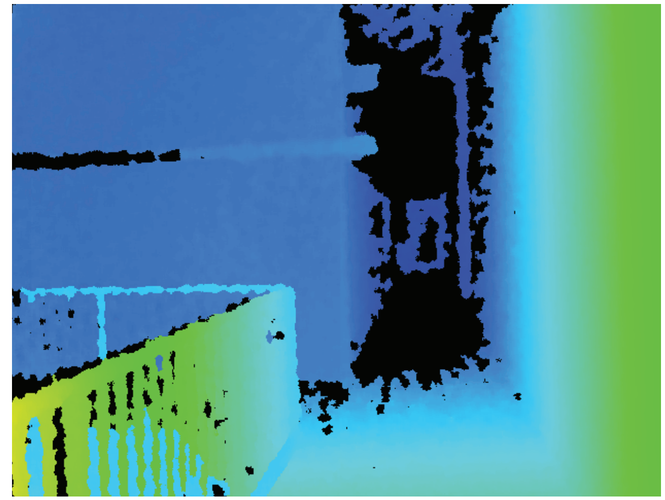
Particle Likelihood – Dense Depth

Feature Registration not reliable:

- Lighting, viewpoint, scene…

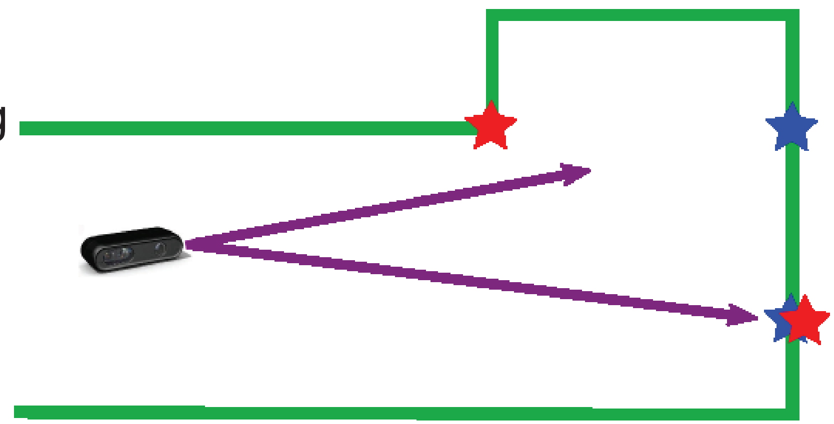


Kinect/RGB-D:

- Dense depth information
- Uncertainty quadratically increases with range *

Our solution:

- Efficient image simulation using GPU and Open GL
- Naturally captures *
- 10x quicker than a CPU 'ICP'



[1] M. Fallon, H. Johannsson, J. Leonard. Efficient Scene Simulation for Robust Monte Carlo Localization using an RGB-D Camera. ICRA 2012

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Example Depth Image Simulation