6DOF Global Pose Estimation using 3D Sensors

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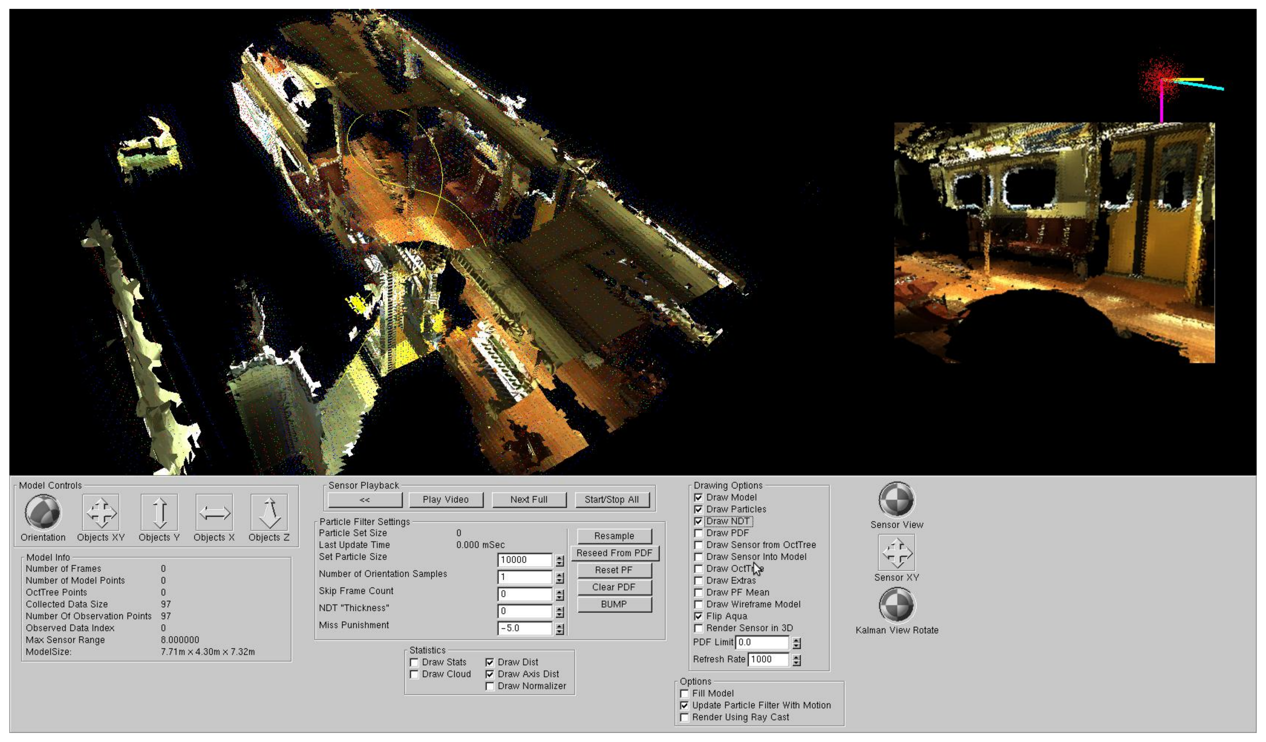
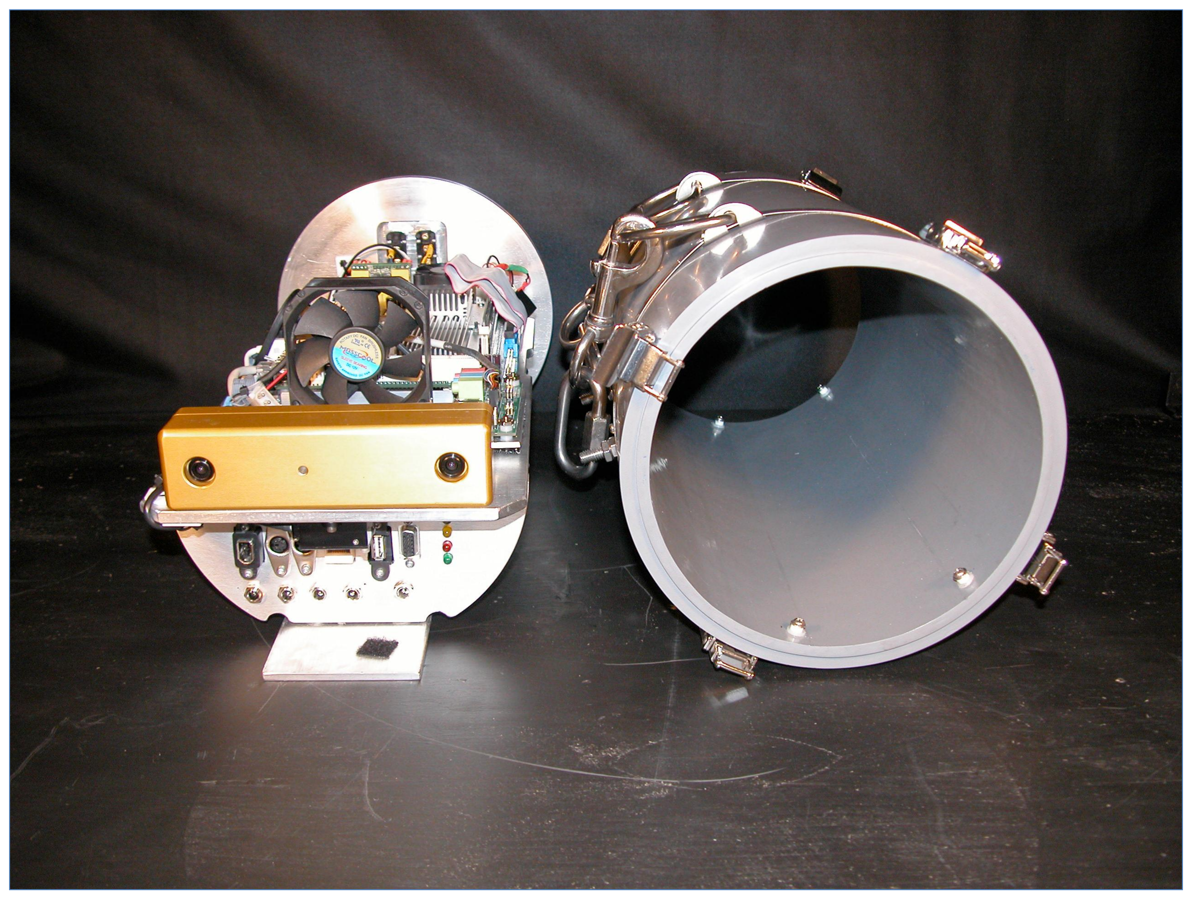
Introduction

• How can a robot operating in a 3D environment determine where it is (without prior knowledge of its location), given a model of its environment and onboard sensors capable of obtaining 3D measurements of that environment?
• This problem is known as 'Global Pose Estimation' and current approaches to the problem typically assume a point robot operating on a plane where only three pose parameters need to be estimated (cf. [1,2])
• The 3D version requires the development of techniques that can deal with the increased computational complexity of this problem.

The AQUA submersible robot [3].



(Left) A subway car model from the CS2M project. Robot and path (in yellow) visualize ground truth of the robot`s path. The visible points represent a discretized PDF indicating the probability of observing an object at that position.
(Right) Sensor data: range and colour data, (Top Right) EKF state.



The AQUA sensor: an example of an (underwater) 3D point cloud sensor [4].

Background

• Pose estimation is inherently probabilistic, requiring a probability distribution which reflects the likelihood of the robot being at a particular pose.
• A popular approach to approximate the probability distribution is Monte Carlo Localization[4] which makes use of a particle filter to implement a Bayes filter.

Approach

• The particle filter must deal with problems related to the sampling of a higher dimensional problem space, due to the additional parameters required in 6DOF localization,
• The primary sensor inputs are a 3D point cloud generating sensor and an IMU.

Reduced Computation

• We prevent particles from evolving to highly unlikely poses through the use of inertial orientation reference data.
• A common approach to estimating the probability of the received data for each particle is by ray casting the model to obtain the expected sensor reading. Due to the increased dimensionality of the problem being considered, this is far too slow. Instead, we precompute a discretized probability measure, (the NDT [5]) for the entire model, and use it as a lookup table, resulting in constant time computation of the probability measure.
• Due to the enormous number of points needed to adequately represent an environment, we approximate the 3D point cloud as a triangle mesh, vastly reducing the number of scene elements in the map.

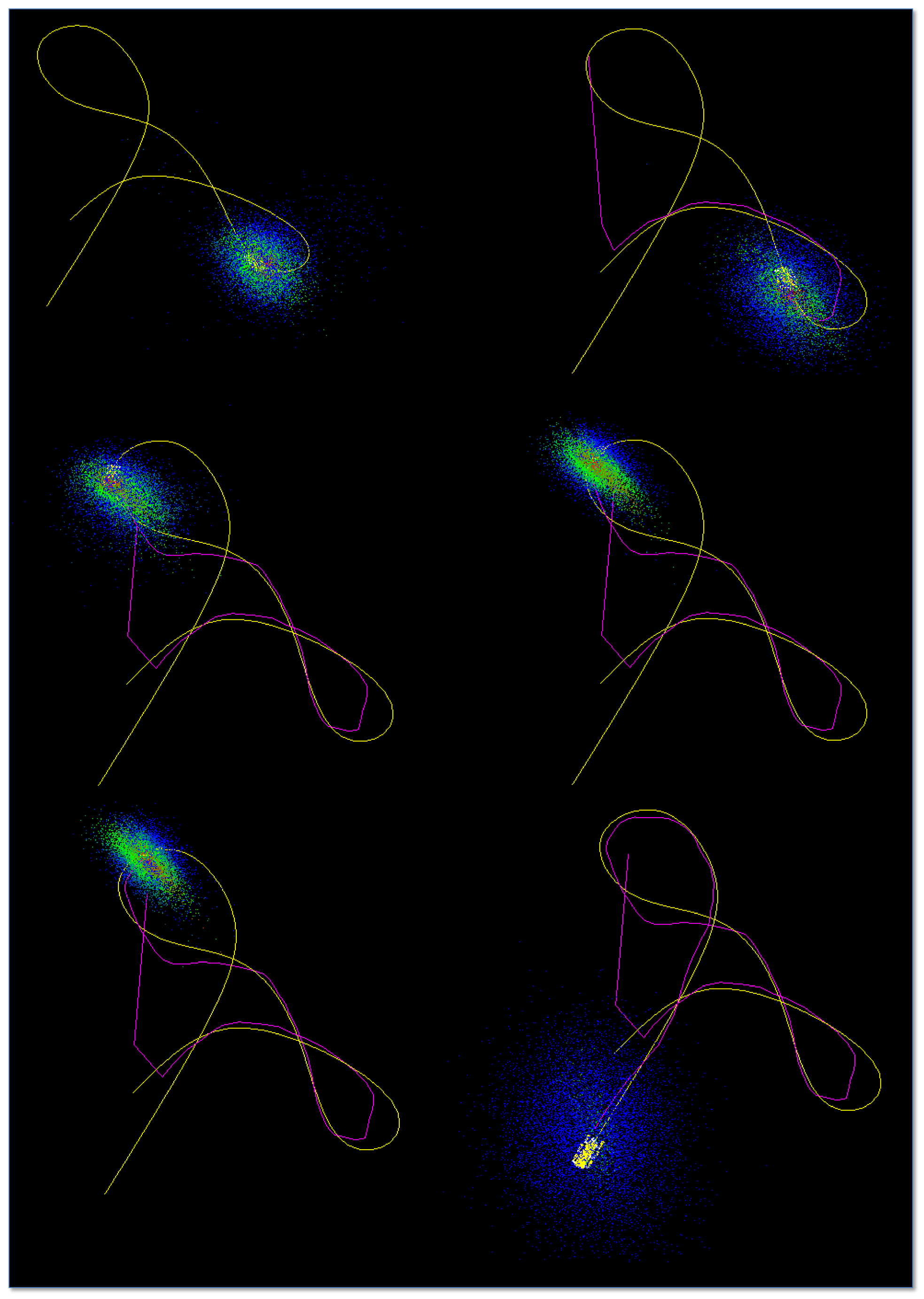
Variant of Bayes Filter

$$bel(x_t,\theta_t) = \eta * p(z_t|x_t,\theta_t) * p(i_t|x_t,\theta_t) * \int p(\theta_t|u_{t-1}, i_t, \theta_{t-1}) \int p(x_t|u_{t-1}, x_{t-1}, \theta_{t-1}) * bel(x_{t-1},\theta_{t-1}) dx_{t-1} d\theta_{t-1}$$

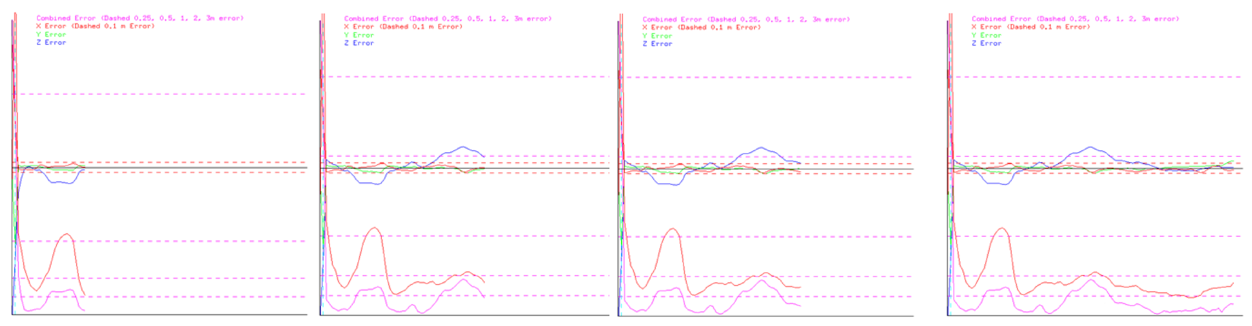
Where
bel(x, θ) the belief that the robot is at position x, θ
p(z|x, θ) the likelihood of *observing sensor reading z while* at pose x, θ
p(i |x, θ) the likelihood of observing IMU reading I while at pose x, θ
p(θ |*) an EKF for estimating the orientation based on the IMU
p(x |*) the motion model
η a normalizing constant

Ongoing Work

• Simulated testing with virtual models
• Testing with real world data from both the AQUA and C2SM projects.



Particle cloud evolution as robot moves through the model. Red indicates high probability and blue indicates low probability. The yellow line shows the ground truth, while the purple one shows the weighted particle mean, as estimated by the particle filter.



Error plots for some of the above estimates. The lower two lines indicate error distance (purple) and weighted standard deviation (red) of the particle cloud. The upper three show axis aligned error.

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References

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[5] Biber, P. The Normal Distribution Transform: A New Approach to Laser Scan Matching, 2003.

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