# Localization and Mapping with Imaging Sonar

**Michael Kaess**

kaess@cmu.edu

The Robotics Institute

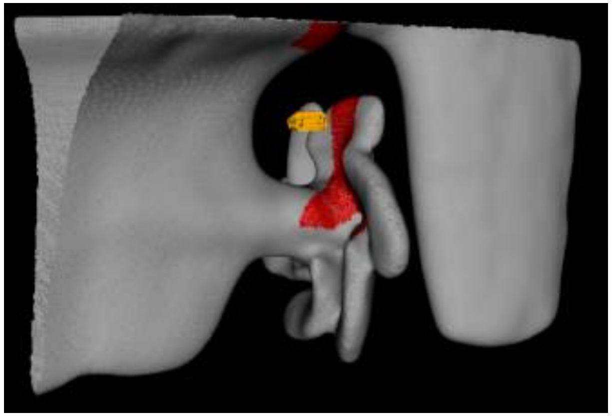
Carnegie Mellon University

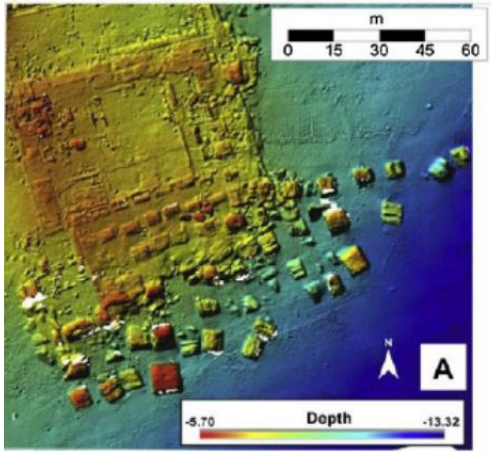
# Overview

- Motivation
- Feature-based Reconstruction
  - Original
  - Non-parametric
  - Degeneracies
- Dense Reconstruction

# Motivation

- Navigation for Autonomous Underwater Vehicles (AUVs)
  - Correct drift
- Inspection of natural and manmade structures
  - Ships in harbor, bridge pilings
  - Archeological sites
  - Reefs

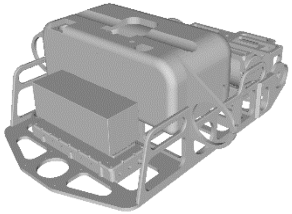





*Advanced Perception, Navigation and Planning for Autonomous In-Water Ship Hull Inspection.* F. Hover, R. Eustice, A. Kim, B. Englot, H. Johannsson, M. Kaess, and J. Leonard, IJRR 2012
*State of the art and applications in archaeological underwater 3D recording and mapping*. F. Menna, P. Agrafiotis, and . Georgopoulos, J. Cultural Heritage 2018

# Sensors for Underwater Navigation/Inspection

- What sensors should we attach to our robot?



- Camera image (0.5m distance to object)

# Underwater Imaging

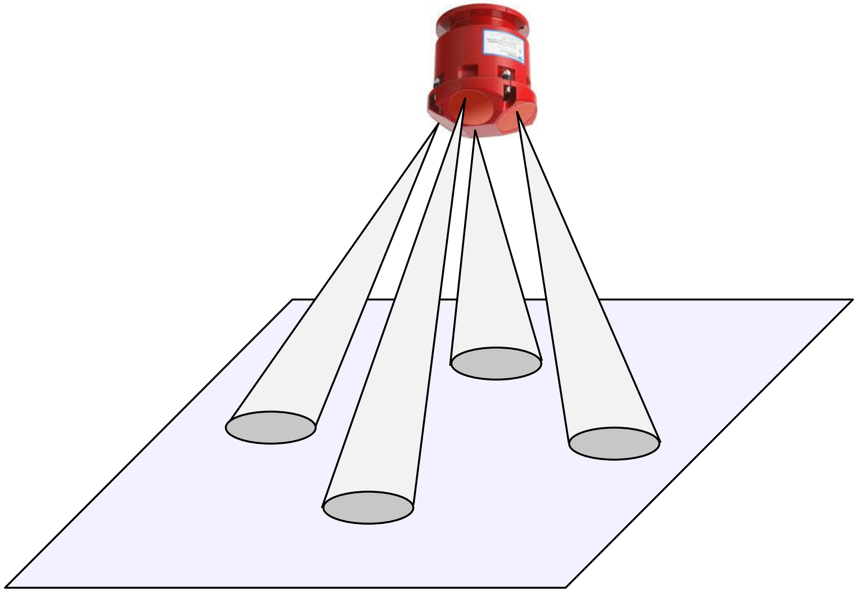
- What about other wavelengths?


- Radio waves don't propagate far underwater: no GPS…

# Underwater Navigation: Acoustic!

- Seafloor tracking with a DVL (Doppler velocity log, an acoustic odometry sensor)

teledynemarine.com

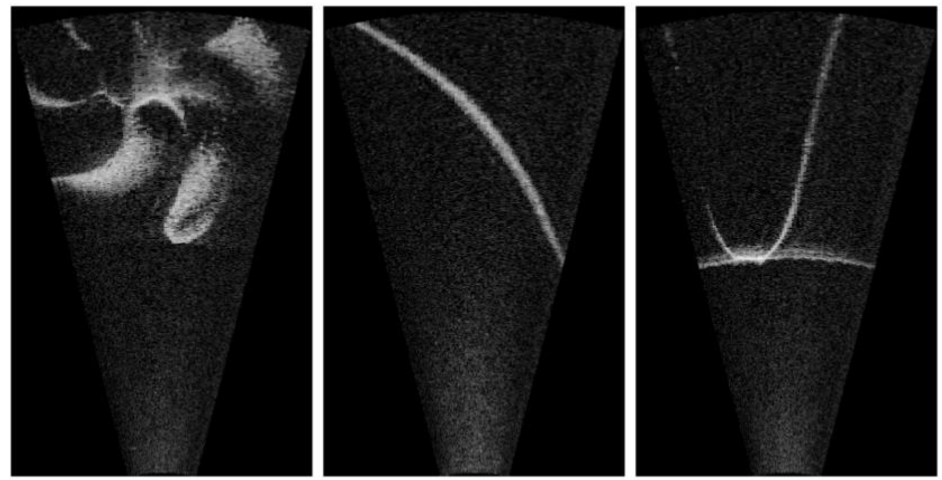


- Usually combined with an IMU as navigation solution
- State estimate will drift over time

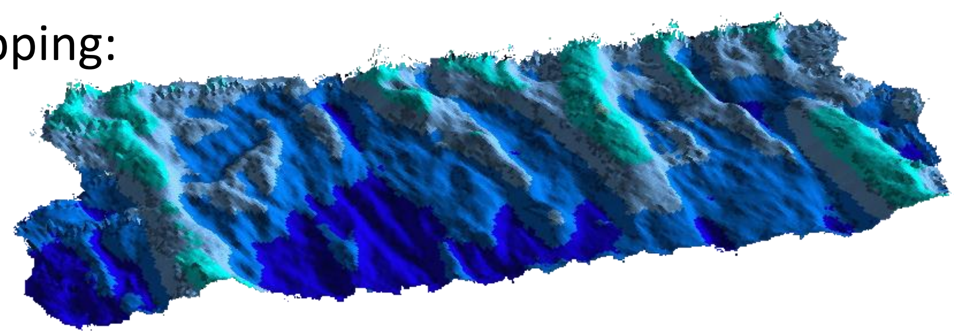
# Underwater Imaging: Acoustic!

Profiling sonar

soundmetrics.com



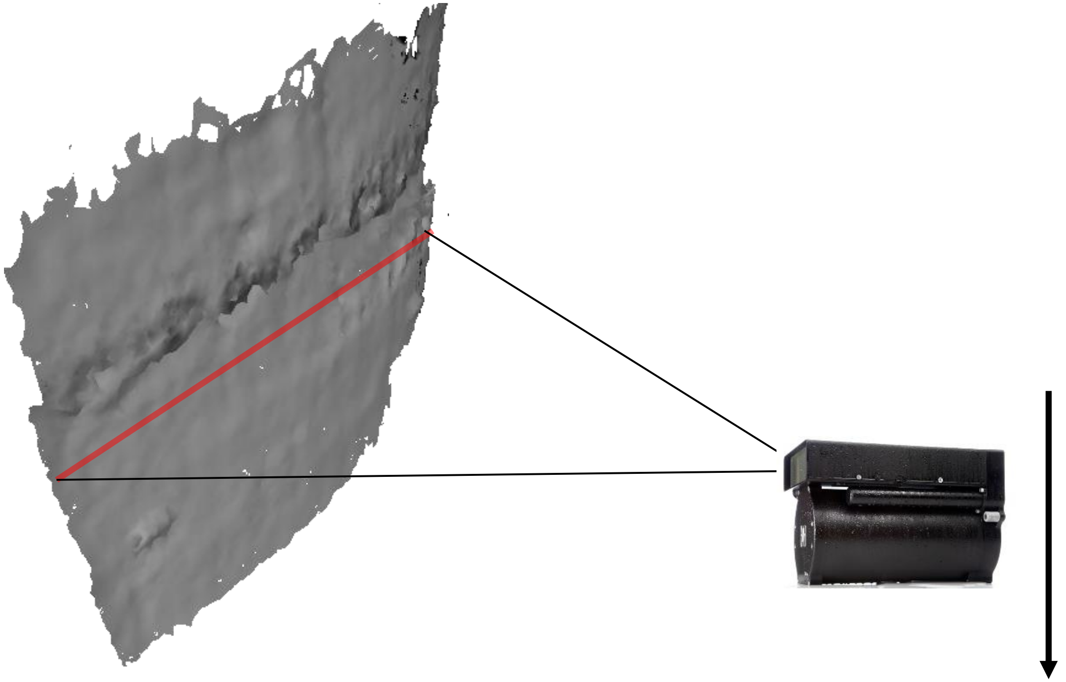
- Uses phased array of transducer for image forming
- Often used for bathymetric mapping:



Seafloor survey by WHOI (Woods Hole Oceanographic Institute)

# Submaps

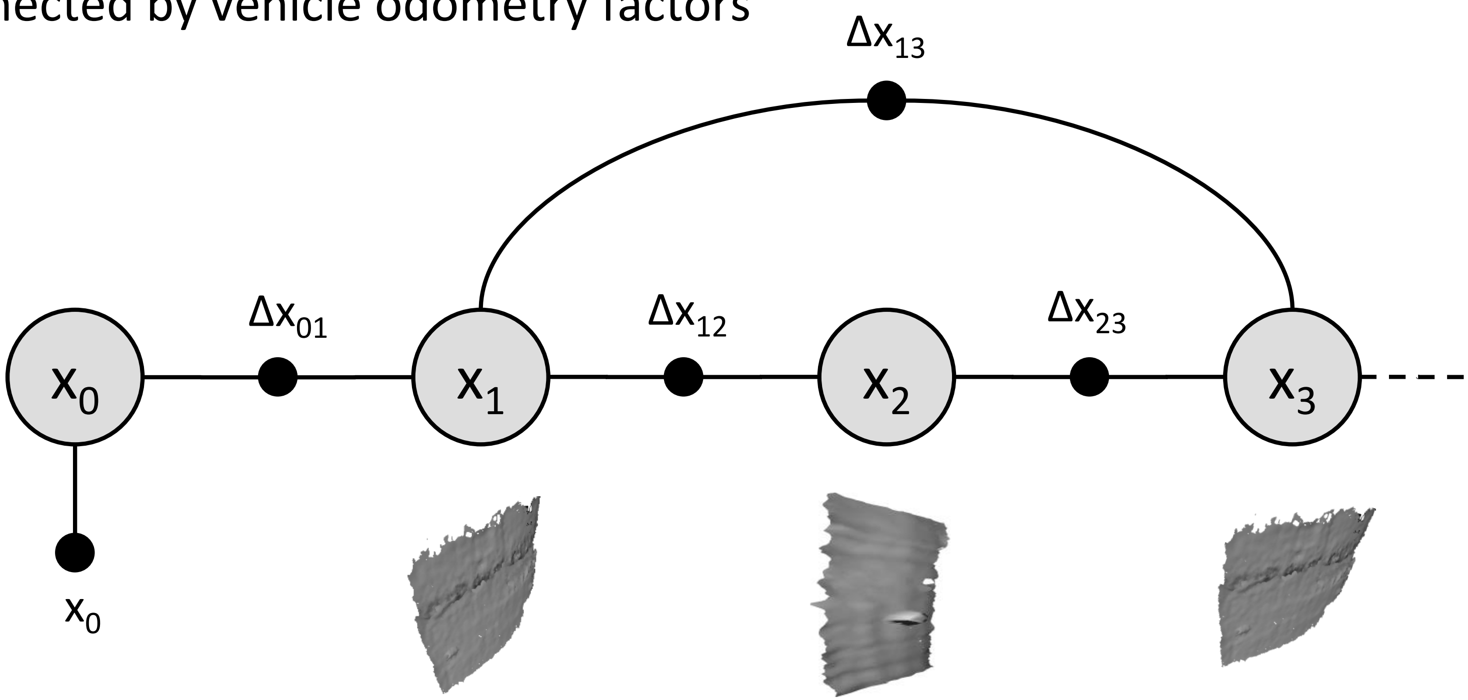
- Idea: Accumulate several scans using vehicle odometry



- Low drift over 30 seconds
- Submap can be considered as a single measurement of the surface

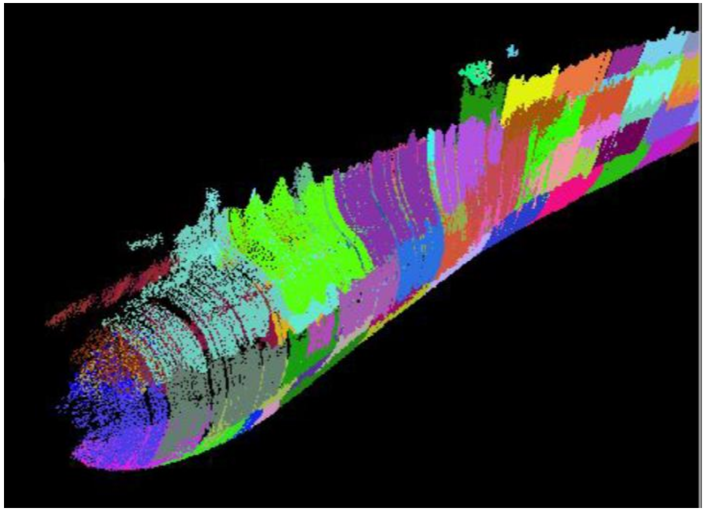
# Factor Graph over Submaps

- Estimate pose of each submap
- Connected by vehicle odometry factors

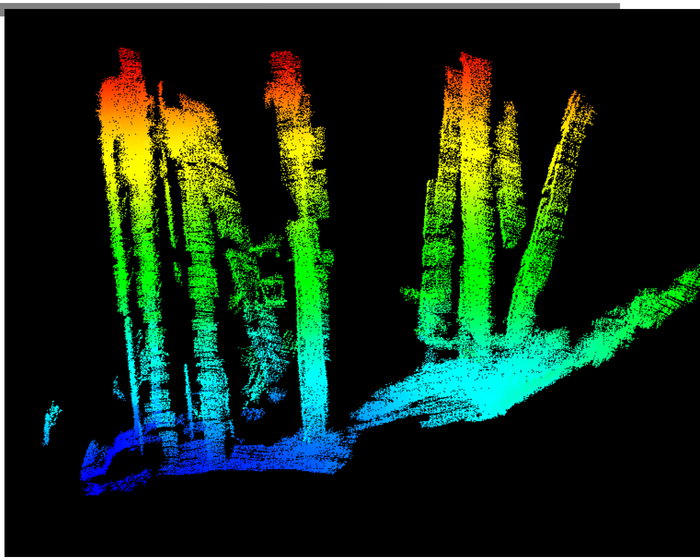



- Loop closure factor from registering submaps of the same area
- Also called a "pose graph"

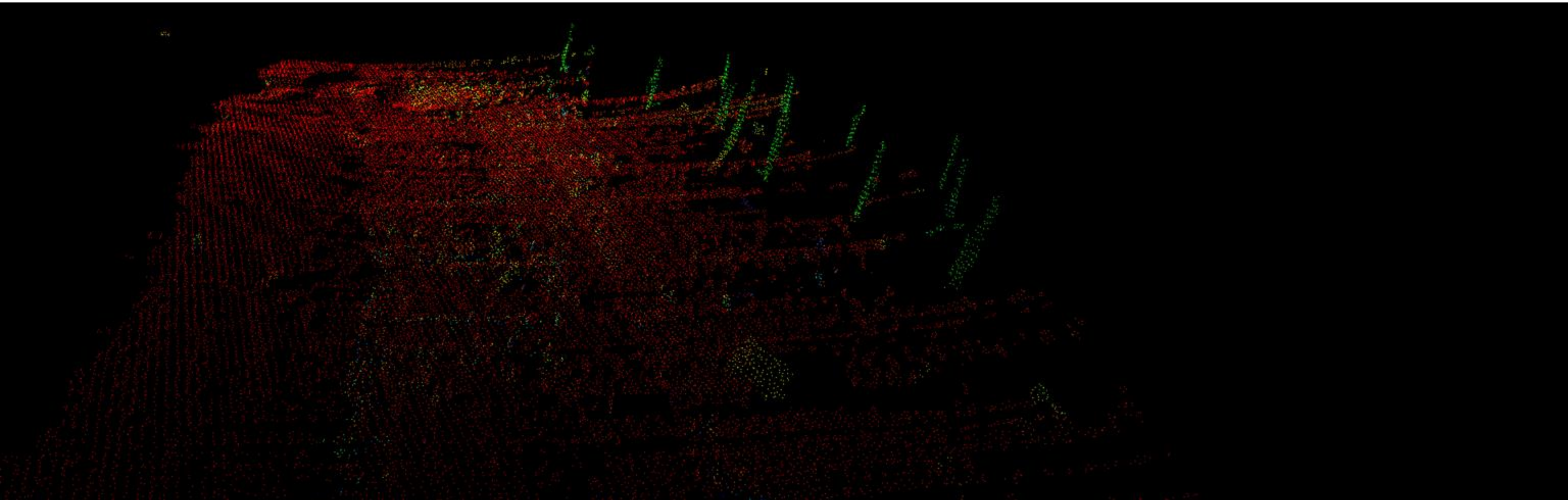
# Mapping Less Structured Environments



Ship hull



Seafloor and pilings under a pier



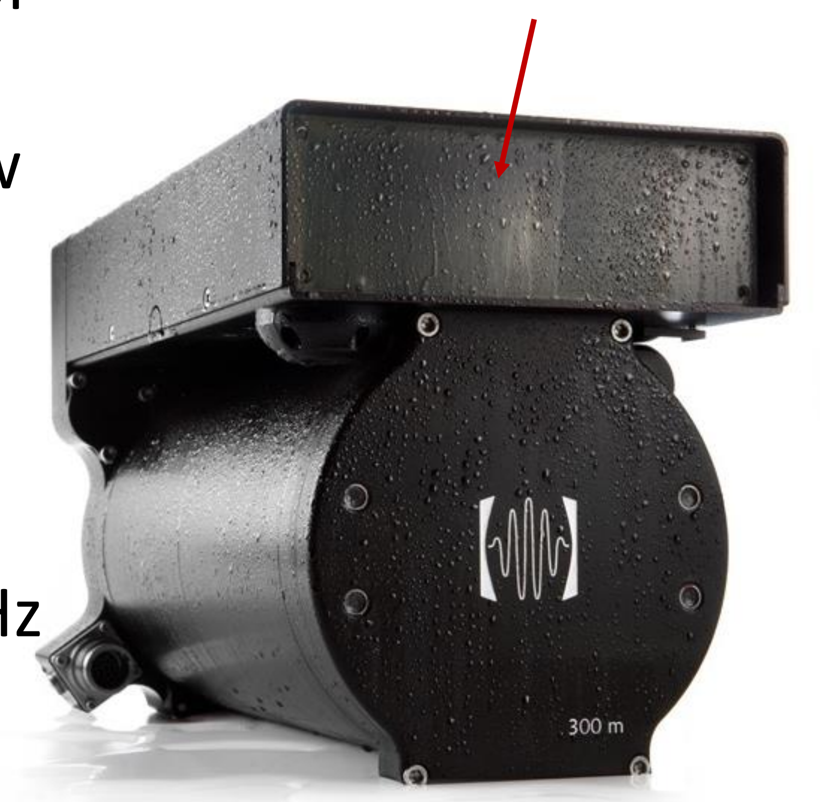
# Feature-based (Sparse) Reconstruction

# Imaging Sonar aka Forward-Looking Sonar

- Covers a larger volume of water in one ping
- Relevant because of slow sound speed in water (about 1500 m/s)

- Active, acoustic sensor
- Frequency: around 2 MHz
- Range: up to 10s of meters

Acoustic lens



# Prior Work

- Planar assumption
  - Johannsson, Kaess, Englot, Hover, and Leonard, IROS 2010
  - Normal distance transform
- Locally planar assumption
  - Aykin and Negahdaripour, JFR 2013
  - Gaussian distribution transform
- Pairwise
  - Brahim, Gueriot, Daniel, and Solaiman, Oceans 2011
  - Evolutionary algorithm to recover 3D geometry

# Monocular vs Sonar

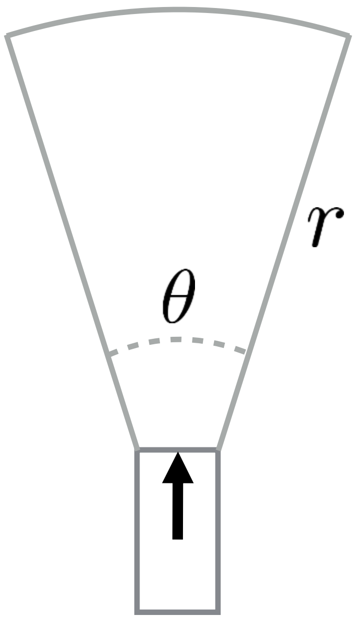

**vs**


**2D image measurement of 3D world**

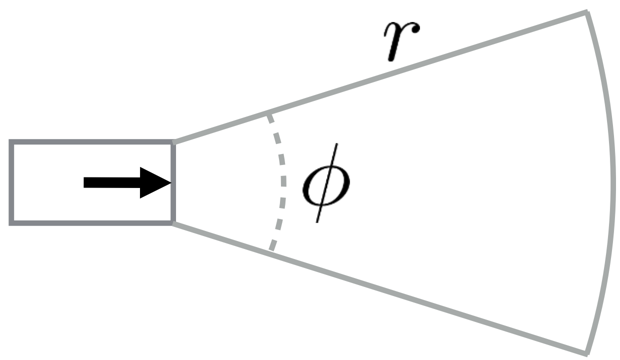
# Sonar Frustum

Spherical coordinates: $(\theta, r, \phi)$

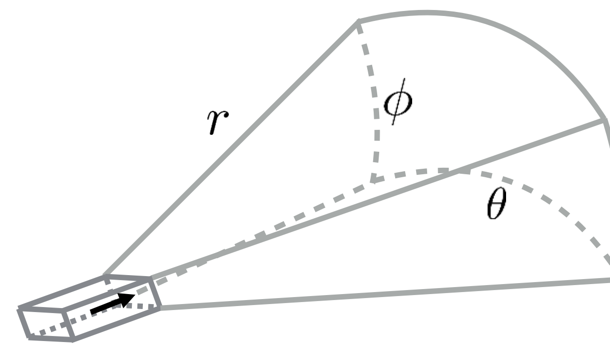
bearing range elevation




Top view



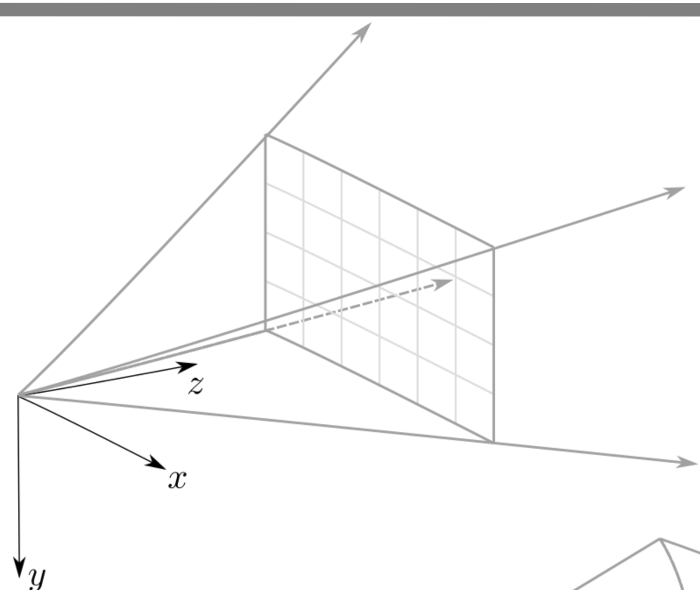

Side view



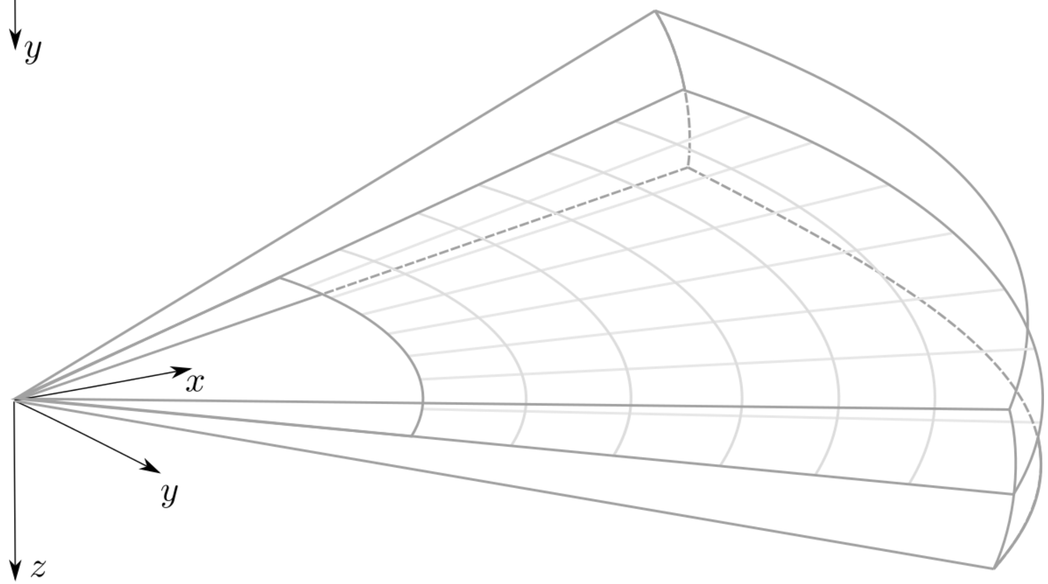

Isotropic view

# Sensor Frustum – Comparison

Monocular

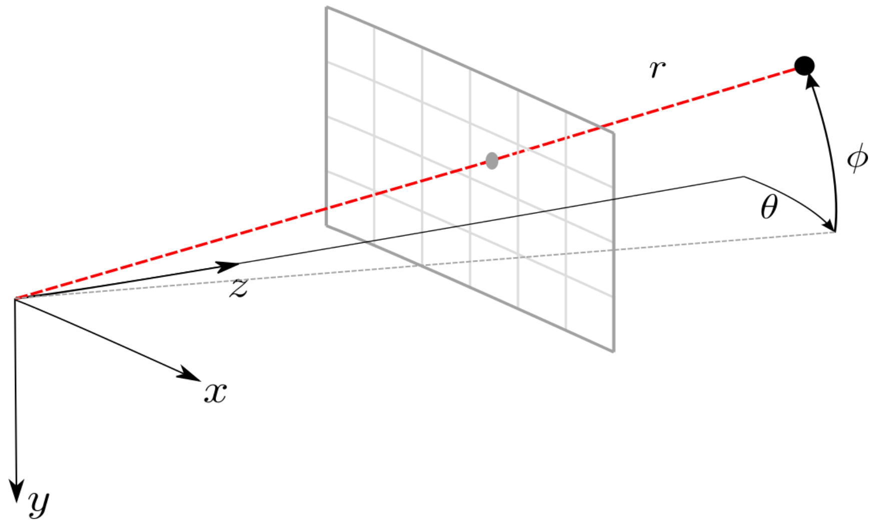



Sonar

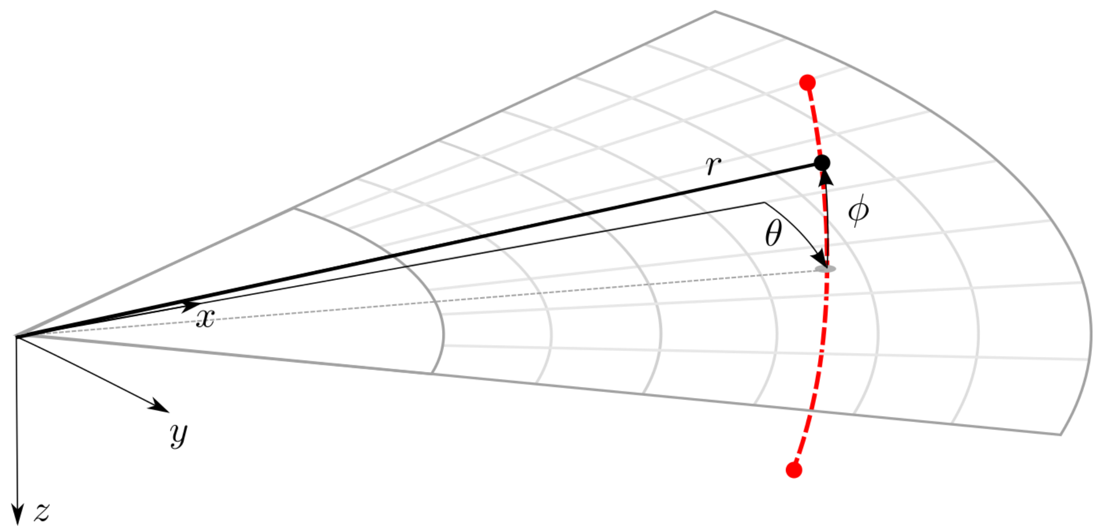


# Sensor Models – Comparison

Monocular




Sonar



# Monocular vs Sonar


VS

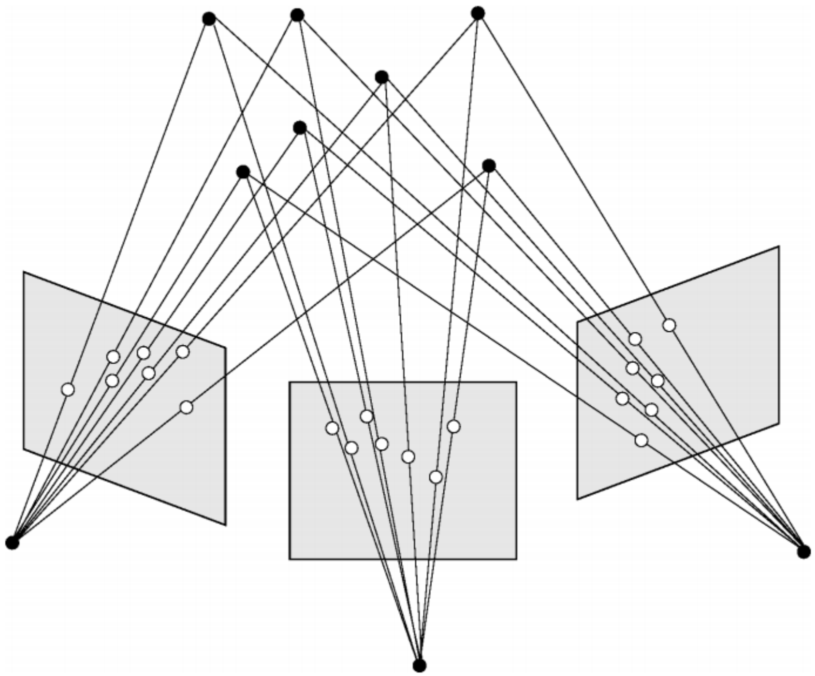
- Ambiguity in range
  - Unconstrained $r \in [0, \infty]$
- Resolution, SNR are high
- 1 pixel $\leftrightarrow$ single surface patch
- Photometric consistency

- High turbidity reduces range (1m or less)

- Ambiguity in elevation
  - Constrained $\phi \in [\phi_{min}, \phi_{max}]$
- Resolution, SNR are low
- 1 pixel $\leftrightarrow$ *multiple* surface patch
- Viewpoint variance

- High turbidity has no effect

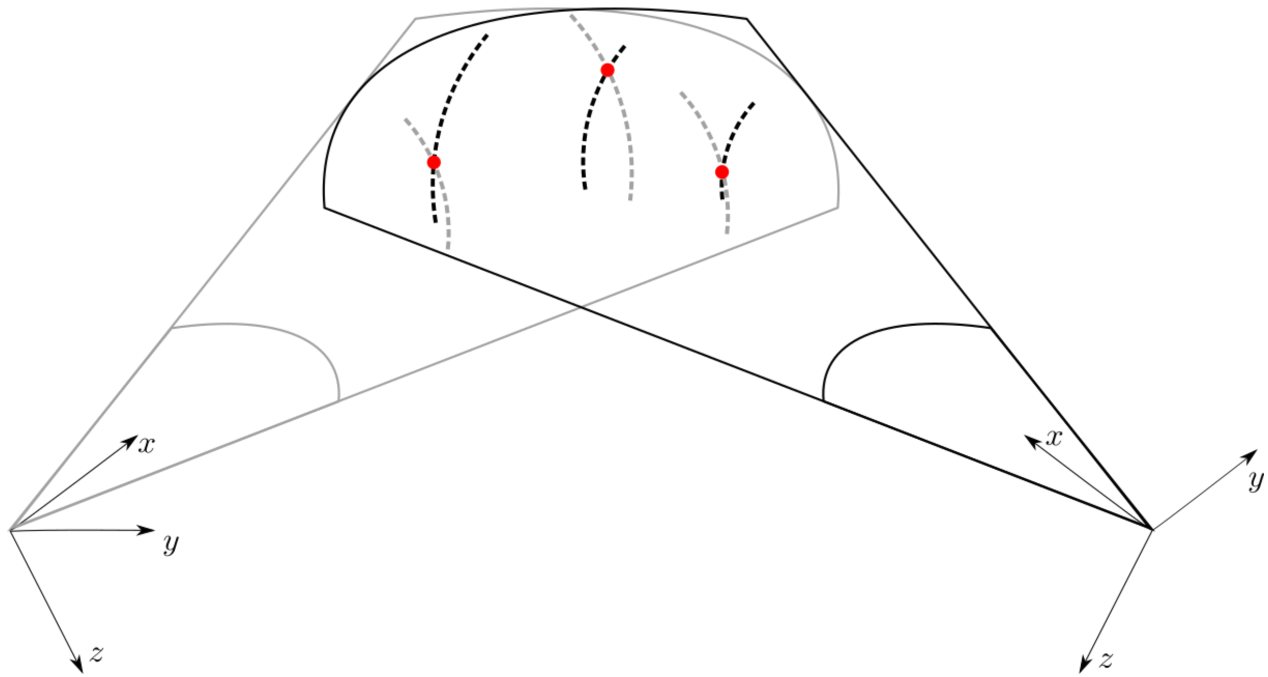
# Sparse Localization & Mapping – Monocular



**Solution: Structure from Motion (SFM)**

Optimize *reprojection error* based on pinhole camera model

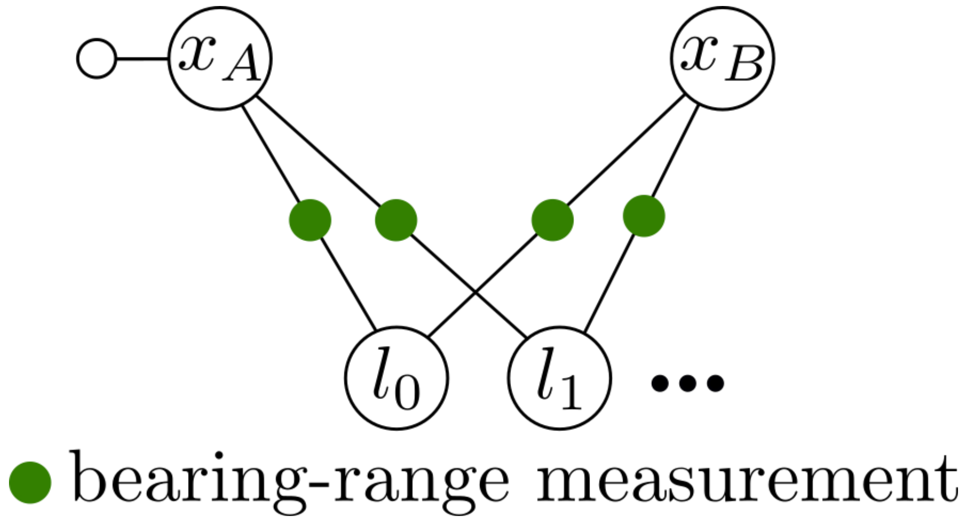
# Sparse Localization & Mapping – Sonar




**Solution: Acoustic Structure from Motion (ASFM)**

Optimize *reprojection error* based on imaging sonar sensor model

# Naïve ASFM Implementation




- Factor graph representation
- MAP estimation → Nonlinear least squares optimization
- Spherical landmark parameterization $l_i = [\theta_i, r_i, \phi_i]$
- Solved just as SFM, but with sonar projection model

# Naïve ASFM Solution

**Optimization: Nonlinear least squares**

$$\mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} - \log \prod_{i=1}^{N} p\left(\mathbf{z}_i | \mathbf{x}\right)$$

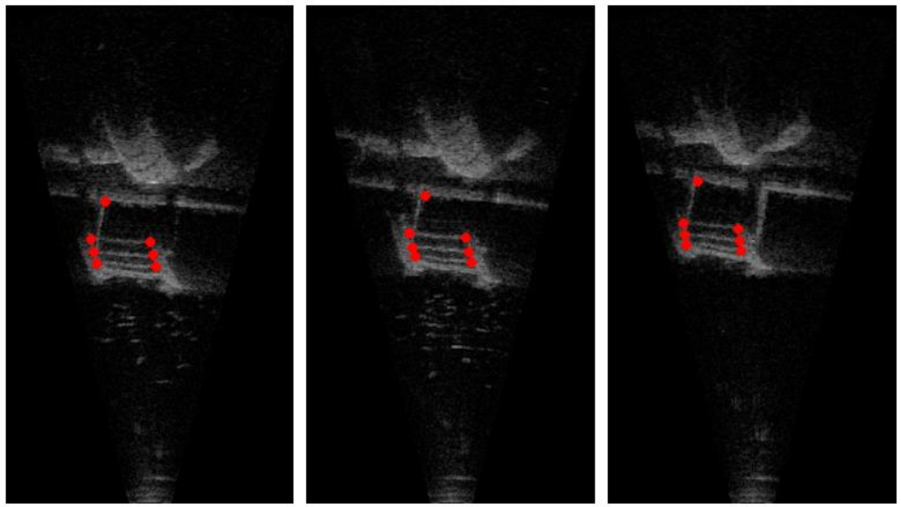
$$= \underset{\mathbf{x}}{\operatorname{argmin}} \sum_{i=1}^{N} \left\| \mathbf{h}_i\left(\mathbf{x}\right) - \mathbf{z}_i \right\|_{\mathbf{\Sigma}_i}^2$$

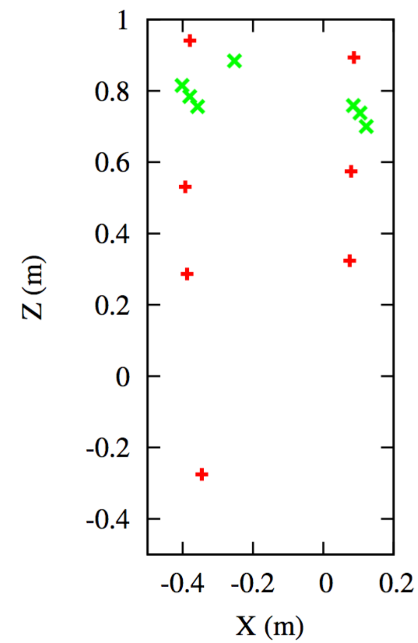
**Solution: Normal Equations**

$$\left(\mathbf{A}^T\mathbf{A}\right)\mathbf{\Delta}^* = \mathbf{A}^T\mathbf{b}$$

$$\mathbf{\Delta}^* = \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{b}$$

# Naïve ASFM Can Recover Structure






x - Before optimization

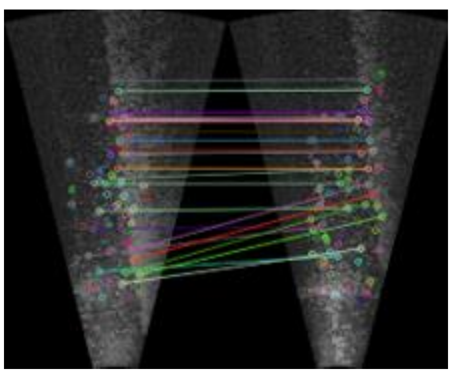
+ - After optimization

# Frontend Improvements

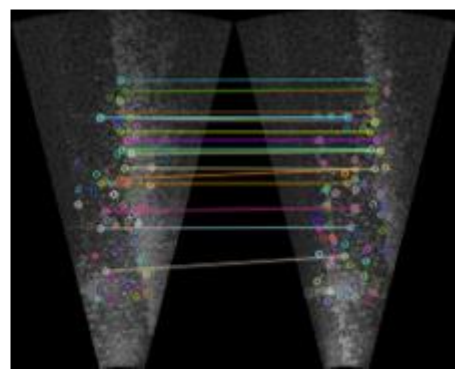
- **A-KAZE features** – diffusion in nonlinear scale space
- **Joint compatibility** feature matching framework

Gaussian diffusion

Anisotropic diffusion



Individual Compatibility



Joint Compatibility

# ASFM Degeneracies

- **Degeneracy:** Gaussian is poor parameterization of elevation

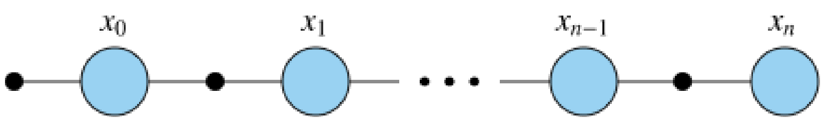
$$\phi \in [\phi_{min}, \phi_{max}]$$

  - **Solution:** non-parametric search over feasible range

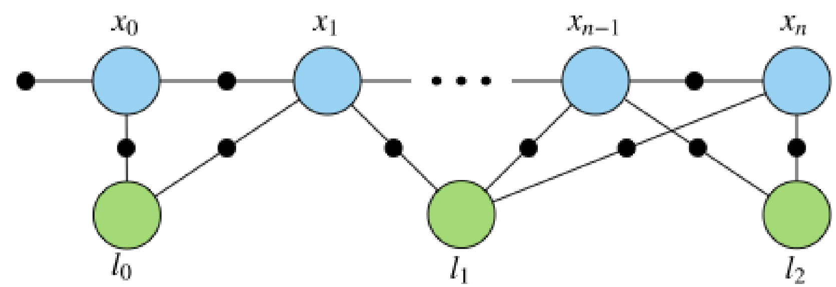
- **Degeneracy:** Certain DOF of motion may not be constrained by feature correspondences
  - **Solution:** degeneracy-aware state updates

# ASFM Formulations

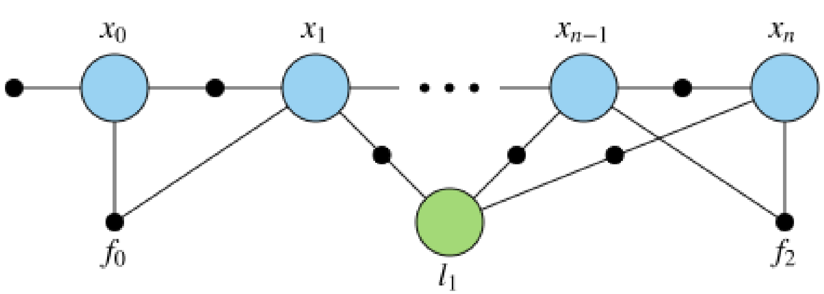
Dead Reckoning



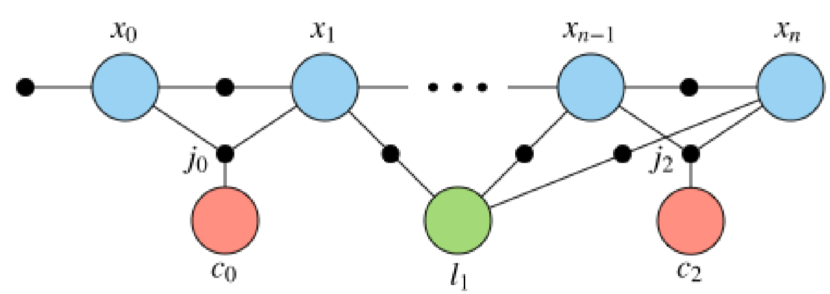

Original ASFM




**Method 1**:
Non-Parametric Factors




**Method 2**:
Mixed 2D Nodes



# Degeneracy-aware Updates

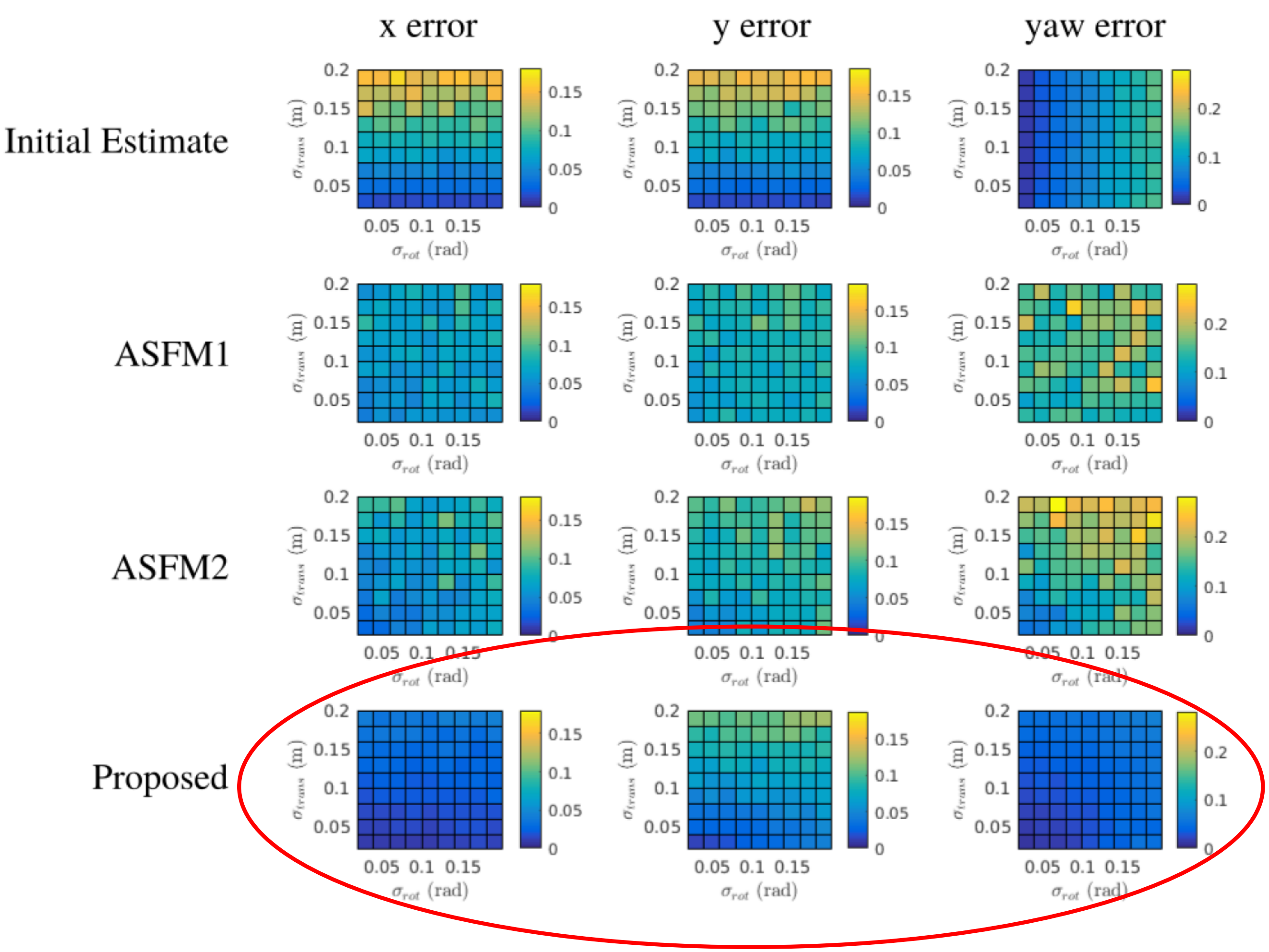
- Robot pose can also be affected by degeneracy
- Update state based on **singular value decomposition**

$$\mathbf{\Delta}^* = \mathbf{A}_D^\dagger \mathbf{b} = \mathbf{V}\mathbf{S}_D^\dagger \mathbf{U}^T \mathbf{b}$$

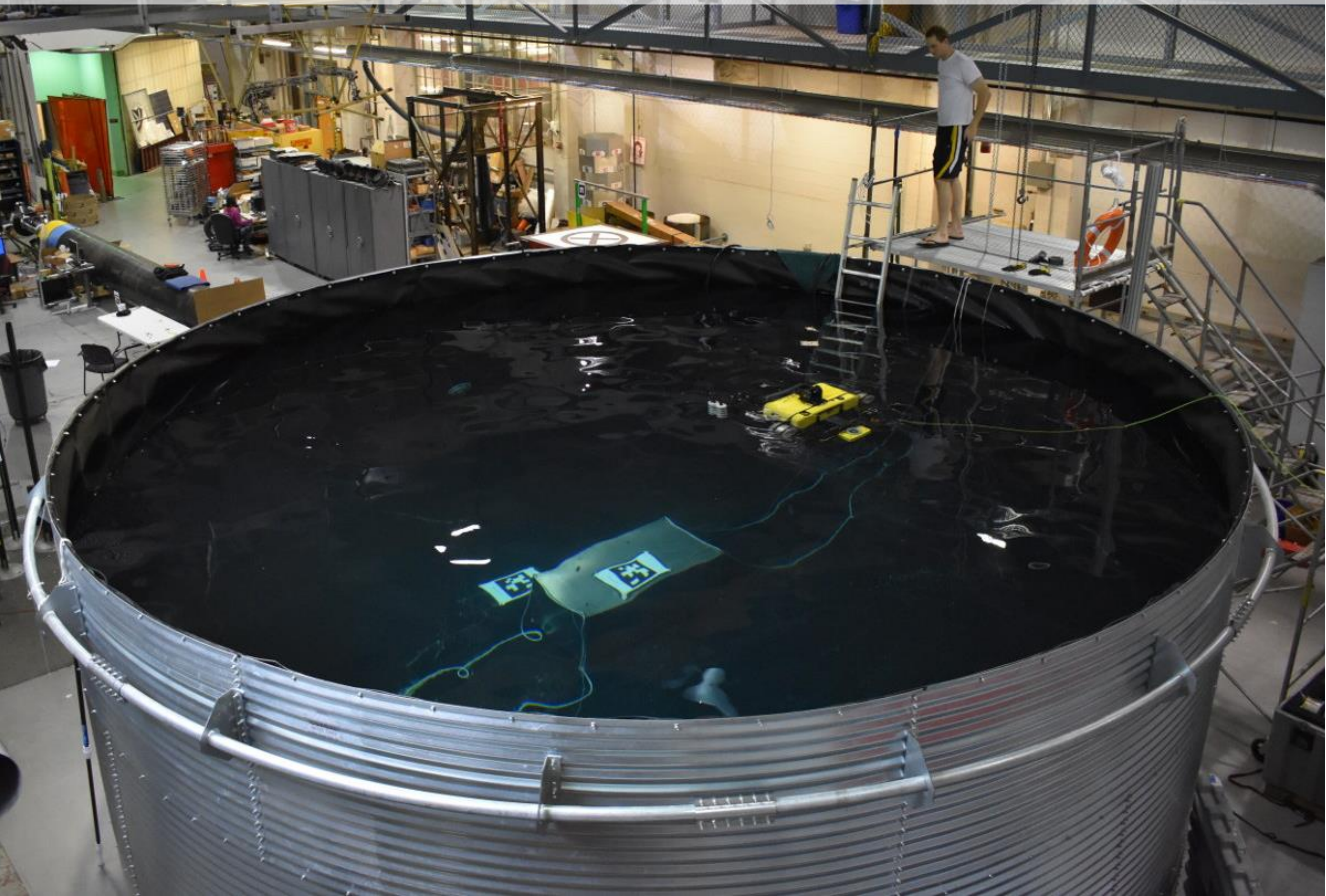
$$\mathbf{S}_D^\dagger = \mathrm{diag}\left([0, \ldots, 1/\sigma_s, \ldots, 1/\sigma_n]\right)$$

- Only update in directions that are **sufficiently constrained**
- Straight-forward Gauss-Newton style optimization
  - No need to heuristically "dampen" system as in Levenberg-Marquardt

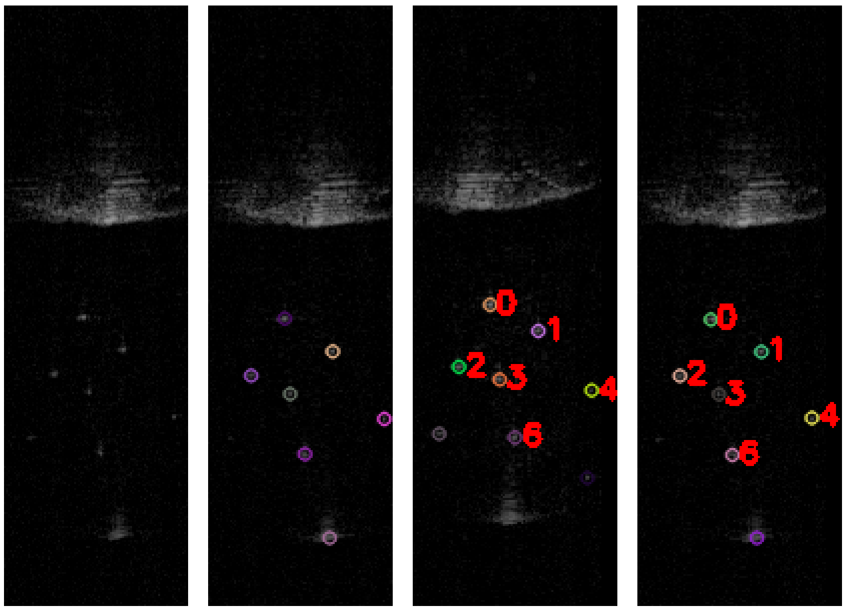
# Simulation Results

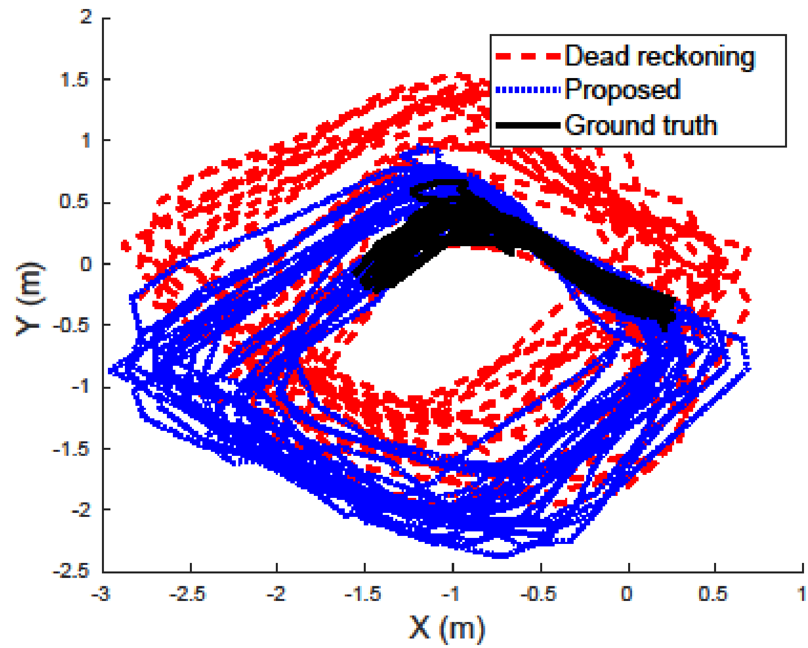


# Test Tank



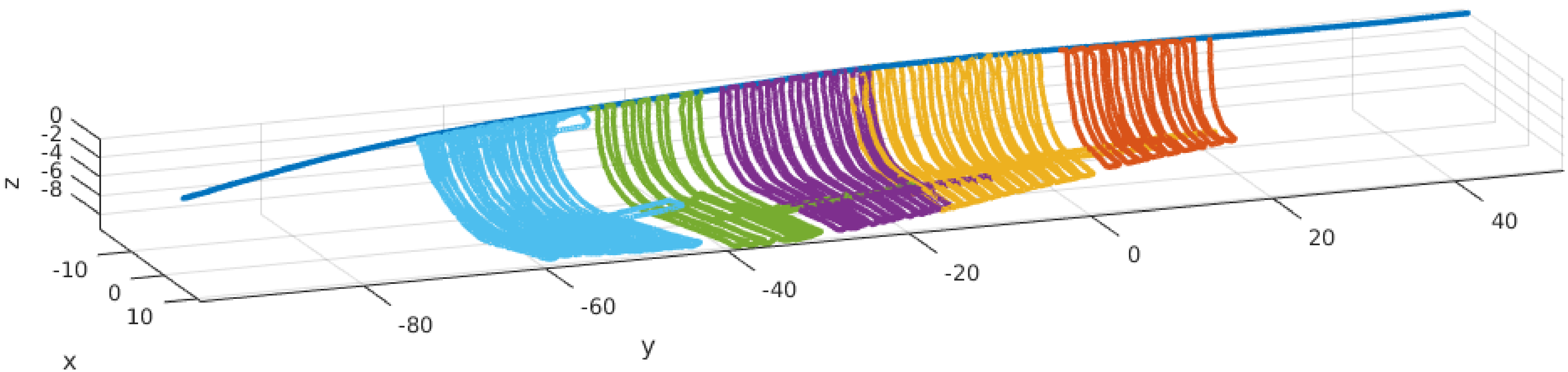
# Experimental Results – Test Tank



# Experimental Results – Ship Hull

Ground truth trajectories

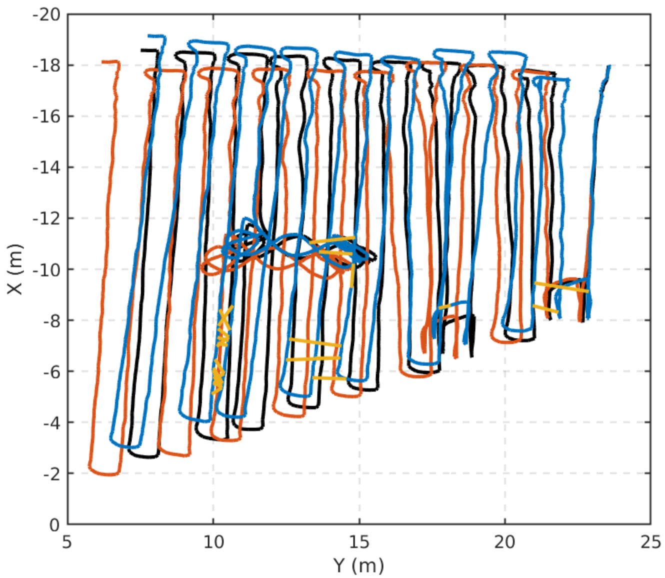


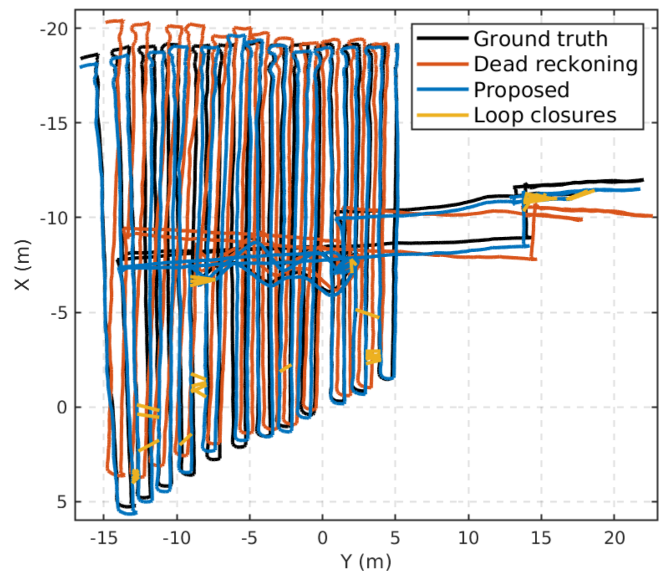

J. Li, M. Kaess, R. Eustice, and M. Johnson-Roberson, “Pose-graph SLAM using forward-looking sonar”, IEEE Robotics and Automation Letters (RA-L), vol.3, no. 3, pp. 2330-2337, Jul. 2018.

# Experimental Results – Ship Hull

Ship hull localization error

| Mission | | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| Error in X [m] | DR | 0.587 | 0.354 | 0.662 | **0.234** | 0.357 | 0.783 |
| | Li | 0.606 | **0.270** | 1.595 | 1.367 | 0.547 | 1.500 |
| | Prop. | **0.579** | 0.603 | **0.389** | 0.427 | **0.356** | **0.457** |
| Error in Y [m] | DR | 0.352 | 0.687 | 0.565 | 0.406 | 0.414 | 0.496 |
| | Li | 0.350 | 0.771 | 0.615 | 0.489 | 0.530 | 1.625 |
| | Prop. | **0.344** | **0.291** | **0.370** | **0.288** | **0.285** | **0.484** |
| Error in yaw [degrees] | DR | 0.383 | **0.579** | 2.842 | 1.803 | 3.177 | **1.918** |
| | Li | 0.392 | 0.852 | 3.392 | 2.941 | 2.792 | 4.149 |
| | Prop. | **0.381** | 1.21 | **2.029** | **1.479** | **1.647** | 1.998 |



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# Dense Reconstruction

# Dense Reconstruction – Related Work

- Profiling sonar
  - Teixeira, Kaess, Hover, and Leonard, IROS 2016
  - e.g. lens with 1 degree opening, approximated as single line scanner
- Space carving
  - Aykin and Negahdaripour, JOE 2016
  - Feasible object region mask (FORM), alpha-shapes
  - Only simple objects, known poses, discards most information from sonar
- Min-filtering
  - Guerneve, Subr, and Petillot, JFR 2018
  - Needs wide variety of viewpoints
- Occupancy grid mapping
  - Wang, Ji, Woo, Tamura, Yamashita, and Hajime, SYROCO 2018
  - Inverse sensor model, needs wide variety of viewpoints
- Inference with generative sensor models

# Dense Reconstruction Using Generative Models

- Linear approximation of elevation aperture
  - Guerneve, Subr, Petillot, JFR 2018
  - Blind deconvolution with spatially-varying kernel
  - Requires precise motion along z axis.
- Objects on seafloor
  - Aykin and Negahdaripour, JOE 2016
  - Directly estimates elevation angle of each pixel, similar to our approach
- Our goal
  - Arbitrary scenes
  - Arbitrary sensor motion
  - Applicable to wide aperture sonar

# Reflection Model

Simple diffuse reflection model:

$$I\left(r,\theta\right)=k\cos^{m}\left(\alpha\right)$$

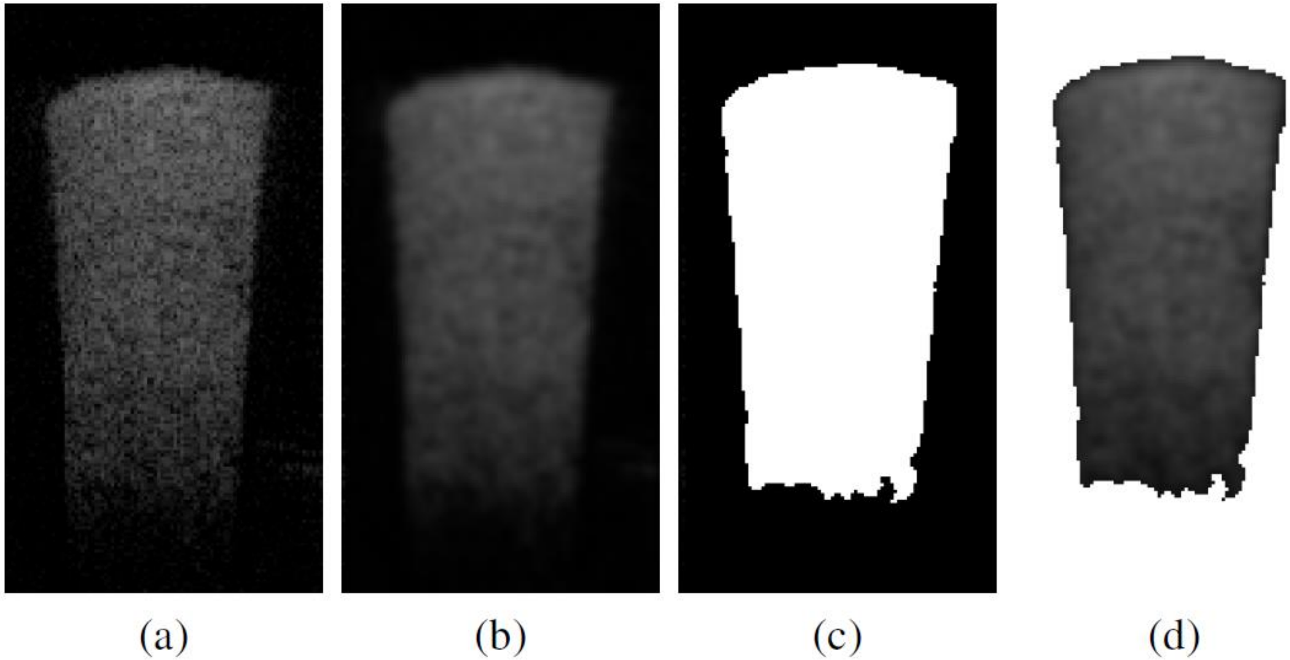
- k: normalization constant
- $1 \leq m \leq 2$
- $\alpha$: angle of incidence between incoming acoustic beam and surface normal

Assumptions:

- Specular reflection negligible due to rough surfaces and grazing incident angles
- Time/range varying gain (TVG/RVG) applied to raw image

More general models could be used with proposed algorithm

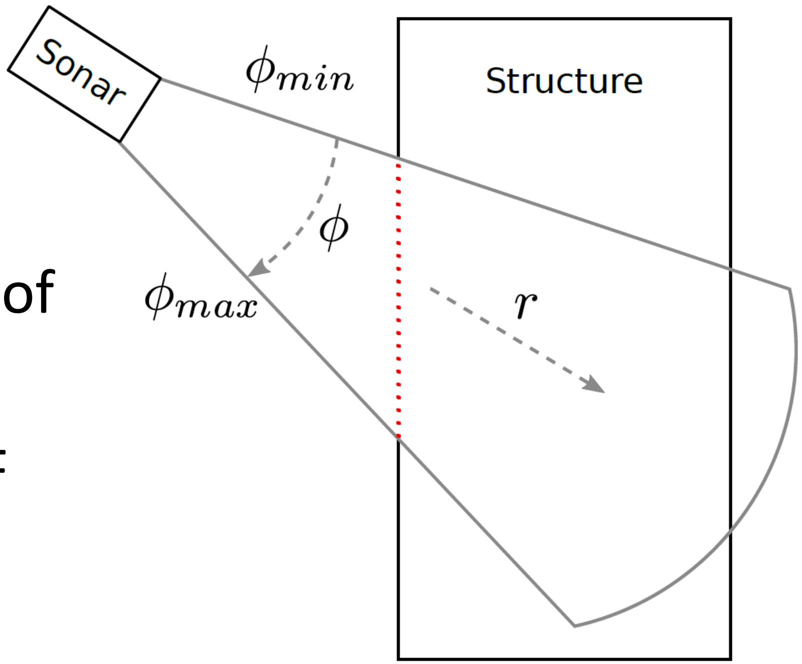
# Image Preprocessing




a) Raw polar coordinate sonar image
b) Denoising with anisotropic diffusion
c) Surface segmentation using MSER
d) Mask applied to denoised image

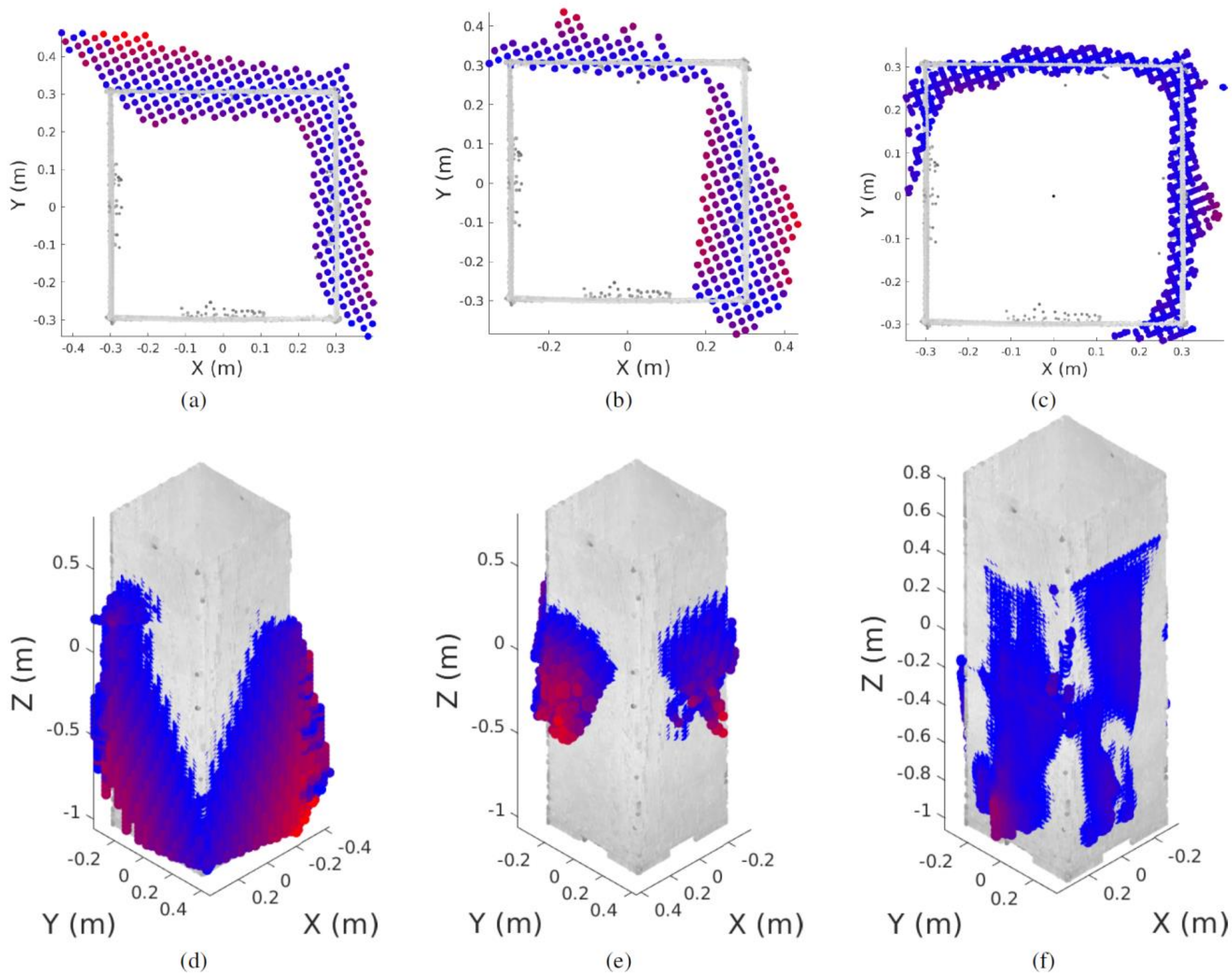
# High-level Approach

1. Initialize from first range (top)
2. Recover 3D of each frame using generative model (from change of surface normal)
3. Fuse multiple frames using TSDF




Assumption: Each pixel (intensity measurements) arises from single surface patch

# Reconstruction of Mockup Piling in Tank



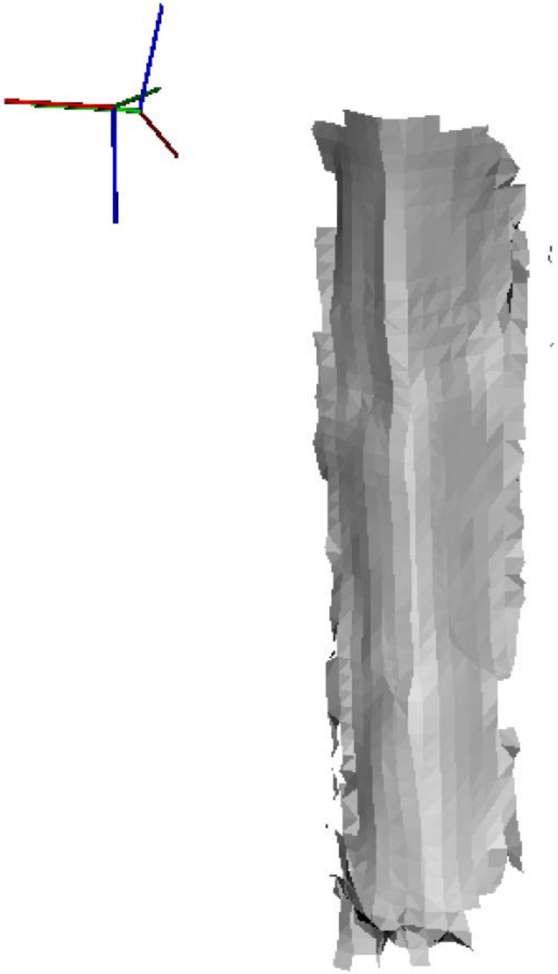

Ground truth: Faro survey lidar scan of mockup

Space Carving

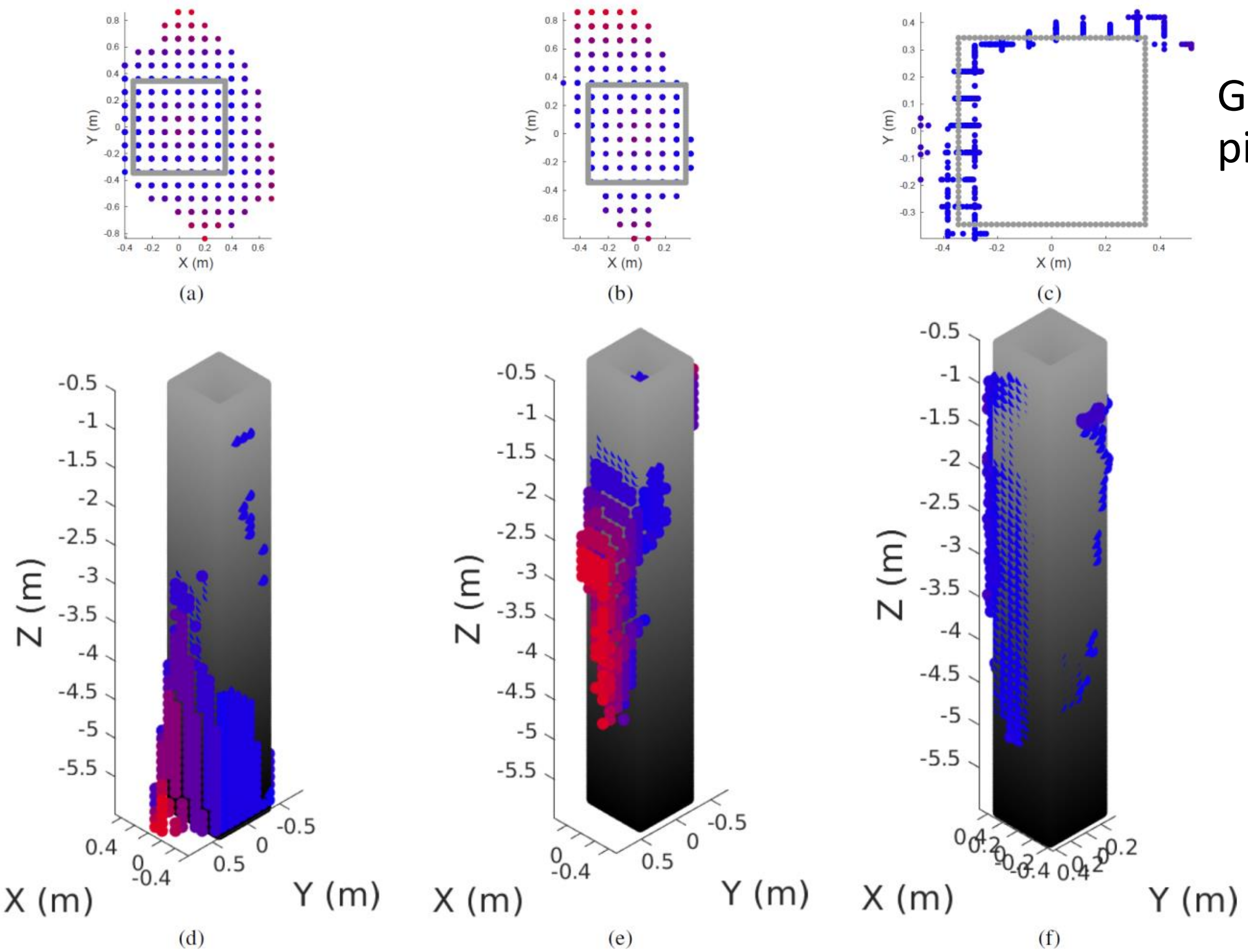
Occupancy Grid

Our Method

# Reconstruction of Piling (San Diego)



# Reconstruction of Piling (San Diego)




Ground truth: measured piling dimensions

Space Carving    Occupancy Grid    Our Method

# Quantitative Results

Average absolute distance error

Root mean square error

| | AADE (m) | | | RMSE (m) | | |
|---|---|---|---|---|---|---|
| Dataset | SC | OGM | Ours | SC | OGM | Ours |
| Tank piling | 0.033 | 0.038 | **0.0176** | 0.035 | 0.047 | **0.022** |
| Field piling | 0.136 | 0.152 | **0.039** | 0.168 | 0.207 | **0.047** |

# Conclusion & Future Work

- Sparse: helps vehicle localization, requires good features
- Dense: still basic research

Next steps:

- More general initialization
- Calibration: Automatically derive generative sonar model
- Alternative surface reconstruction methods
- How to handle multiple surfaces projecting to same pixel
- Beyond diffuse reflection
- Tightly coupled IMU integration

# Publications


1. E. Westman and M. Kaess, “Wide aperture imaging sonar reconstruction using Generative Models”, in IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS), Macao, submitted.
2. E. Westman and M. Kaess, “Degeneracy-aware imaging sonar SLAM”, IEEE Journal of Oceanic Engineering (JOE), submitted.
3. E. Westman and M. Kaess, “Underwater AprilTag SLAM and calibration for high precision robot localization,” Robotics Institute, Carnegie Mellon University, Tech. Rep. CMU-RI-TR-18-43, Oct. 2018.
4. P. Teixeira, M. Kaess, F. Hover, and J. Leonard, “Multibeam data processing for underwater mapping,” in IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS), Madrid, Spain, Oct. 2018.
5. J. Li, M. Kaess, R. Eustice, and M. Johnson-Roberson, “Pose-graph SLAM using forward-looking sonar”, IEEE Robotics and Automation Letters (RA-L), vol.3, no. 3, pp. 2330-2337, Jul. 2018.
6. E. Westman, A. Hinduja, and M. Kaess, “Feature-based SLAM for imaging sonar with under-constrained landmarks”, in IEEE Intl. Conf. on Robotics and Automation (ICRA), Brisbane, Australia, May 2018.
7. T. Huang and M. Kaess, “Incremental Data Association for Acoustic Structure from Motion”, in IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS), Daejeon, Korea, Oct. 2016.
8. T. Huang and M. Kaess, “Towards Acoustic Structure from Motion for Imaging Sonar”, in IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS), Hamburg, Germany, Sep. 2015.
9. F. Hover, R. Eustice, A. Kim, B. Englot, H. Johannsson, M. Kaess, and J. Leonard, “Advanced Perception, Navigation and Planning for Autonomous In-Water Ship Hull Inspection”, Intl. J. on Robotics Research (IJRR), Oct. 2012
10. H. Johannsson, M. Kaess, B. Englot, F. Hover, and J. Leonard, “Imaging Sonar-Aided Navigation for Autonomous Underwater Harbor Surveillance”, in IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS), Taipei, Taiwan, 2010.