Computational Surgineering | WS22/23

Robotically-Guided Ultrasound System for 3D Liver Reconstruction

Christian Engel, Mei-Ling Fang, Chengzhi Shen

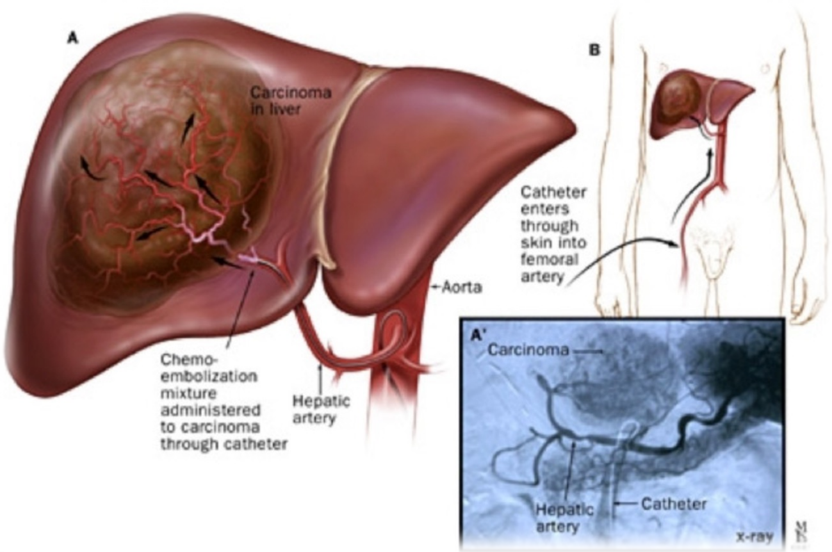
Technische Universität München + Johns Hopkins Whiting School of Engineering

Outline & Work Split

- Problem
- Liver Ultrasound Procedures
- Solution
  - Mei-Ling: Hand-Eye Calibration and Initial Point Localization
  - Chengzhi: Trajectory Planning and Control
  - Christian: Shadow Detection and Escape
- Demo
- Challenges
- Summary and Future Work

Problem Statement

Background



Transcatheter Arterial Chemoembolization (TACE)

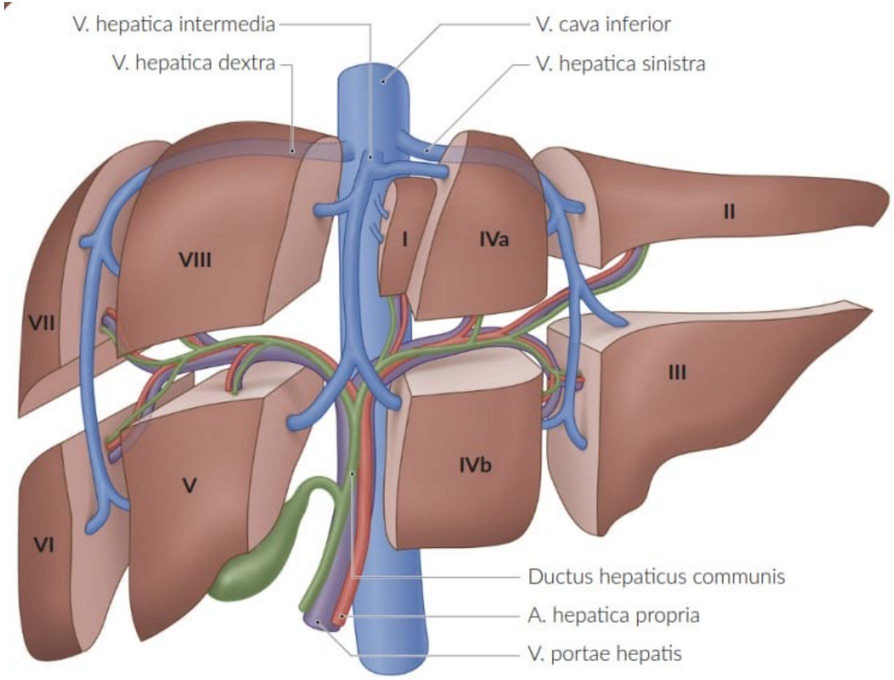
Issues

- **radiation exposure** to medical staff and patient (typical effective dose of CT abdomen: 8 mSv)
- Hand-eye-coordination is challenging

Robotic Arm & Ultrasound to the rescue!

Liver Ultrasound Procedure

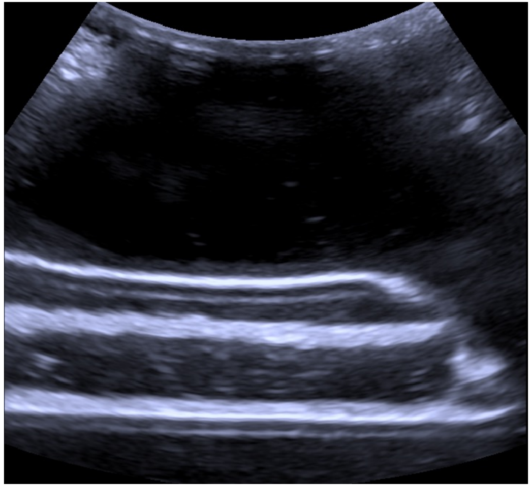
- Liver consists of a left and a right lobe
- Both lobes of the liver must be examined completely
- Clinicians investigate the liver first in sagittal, then transversal
- Challenges include noisy Ultrasound imaging, breathing motion of the patient, body fat

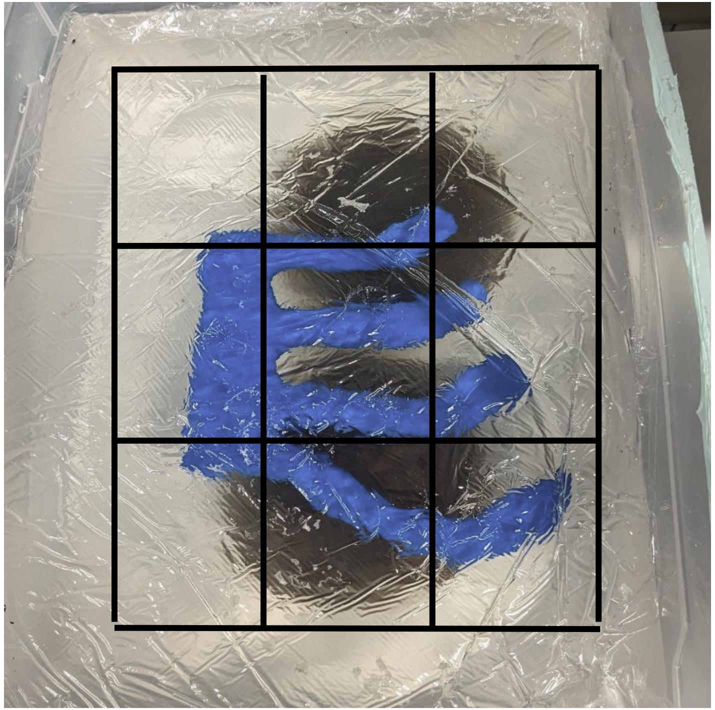


“Sonografische Untersuchung der Leber - AMBOSS.” https://next.amboss.com/de/article/Qq0uyS.

Setup

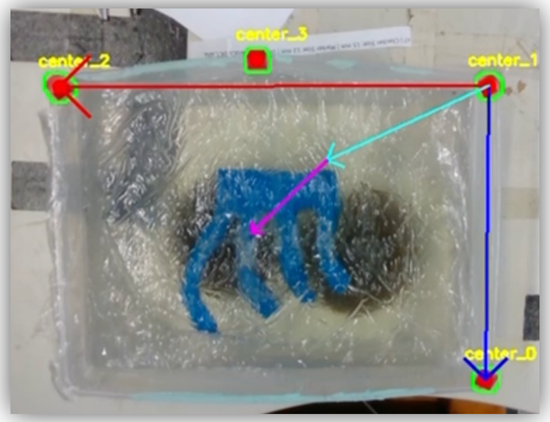
- Our gel phantom mocks the anatomy of a real liver
- We divide it into 9 distinct parts, interpolate a trajectory and move robotically-guided Ultrasound probe

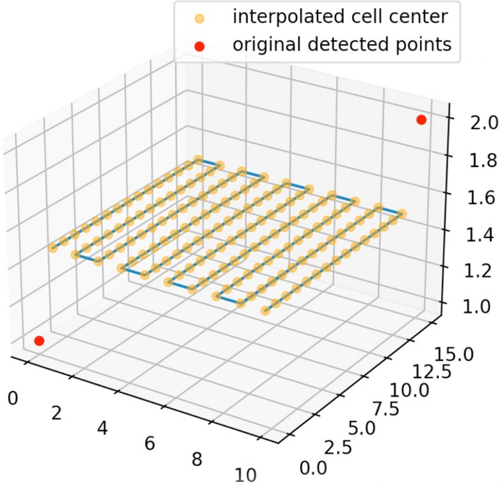




Proposed Solution

Components Overview



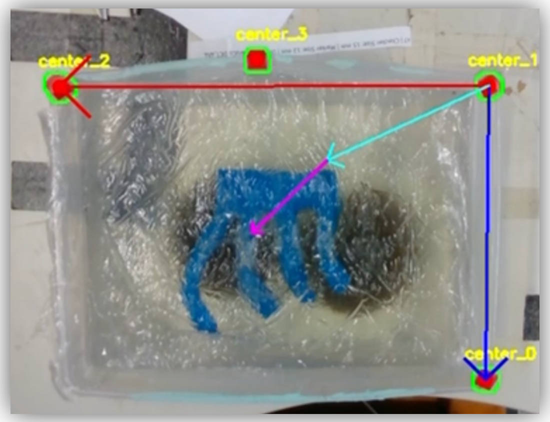


Initial Point Detection

Trajectory Planning

Shadow Detection

Components Overview



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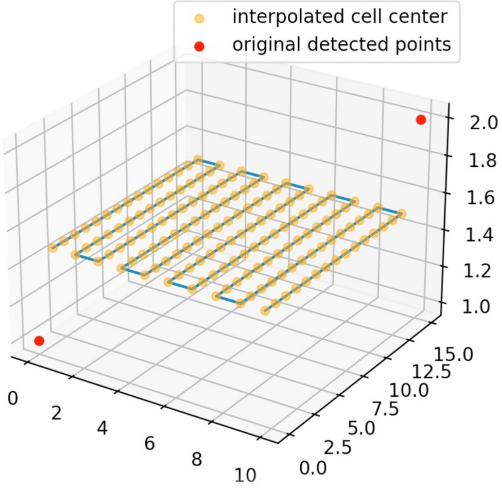
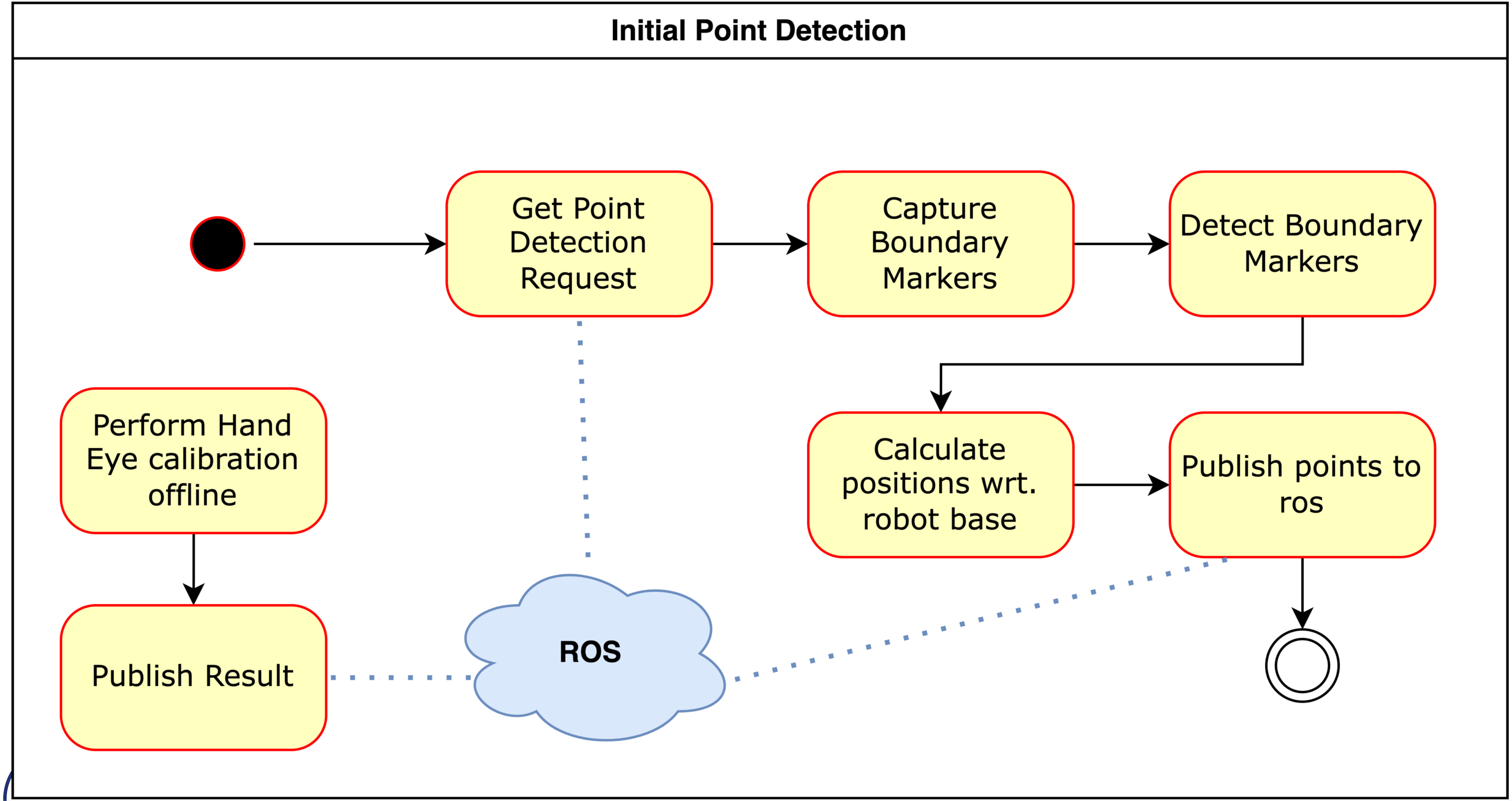
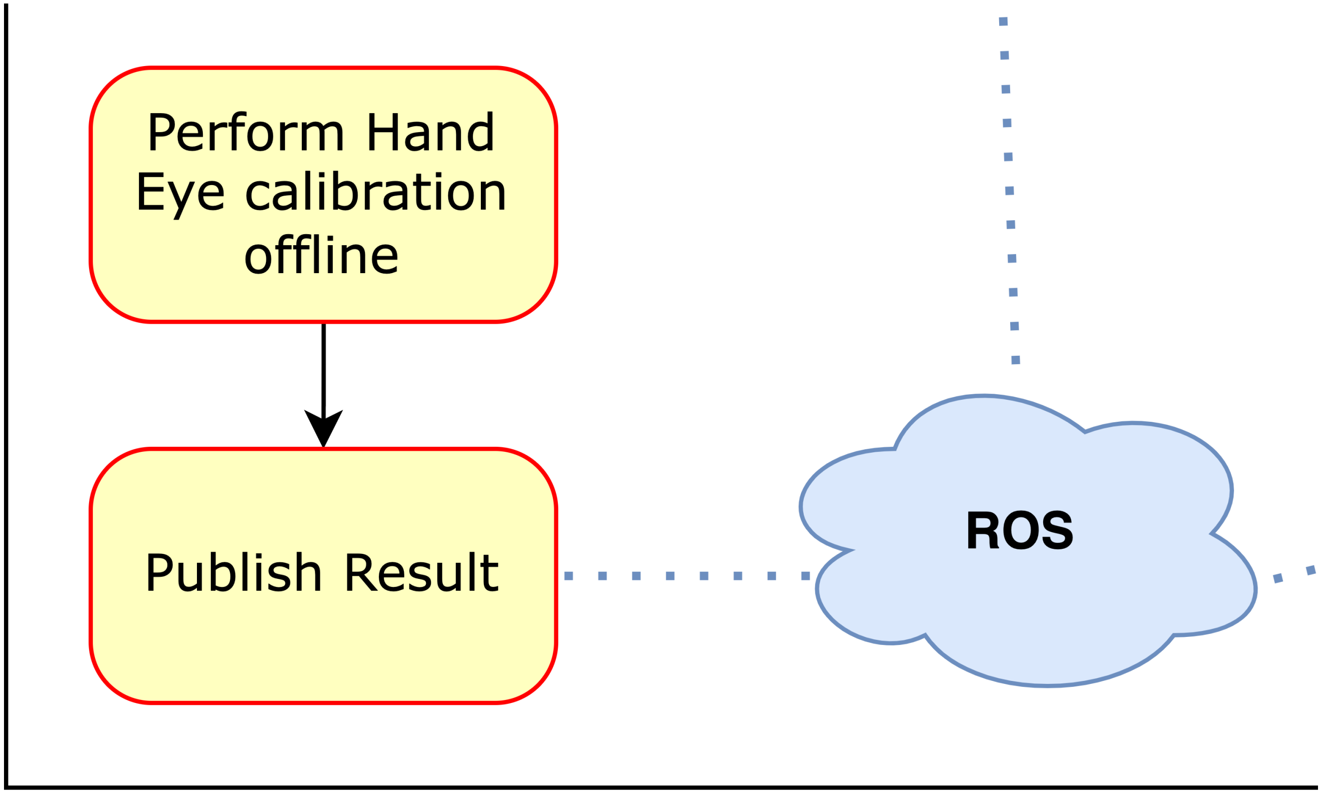


Trajectory Planning

Shadow Detection


Initial Point Detection
Get Point Detection Request
Capture Boundary Markers
Detect Boundary Markers
Perform Hand Eye calibration offline
Calculate positions wrt. robot base
Publish points to ros
Publish Result
ROS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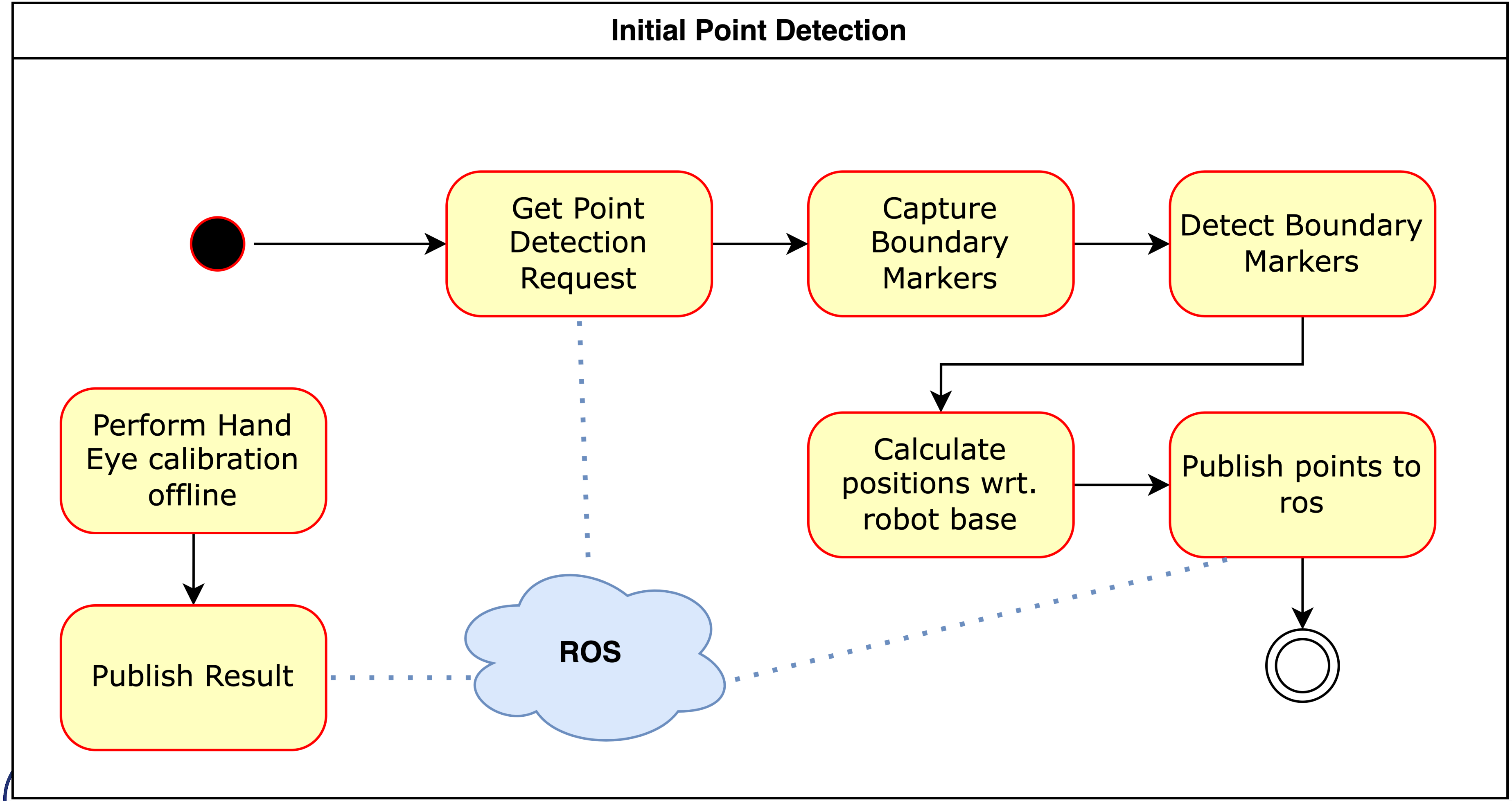
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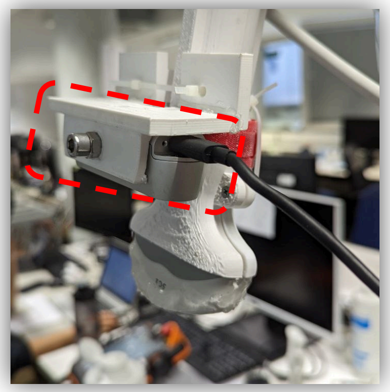
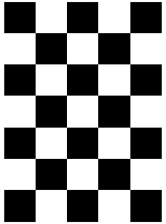
Components: Initial Point Detection



Attach RGB-D Camera to End Effector

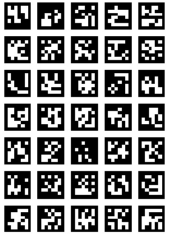
+

Hand Eye Calibration



Chessboard

+



ArUco

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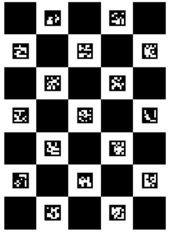
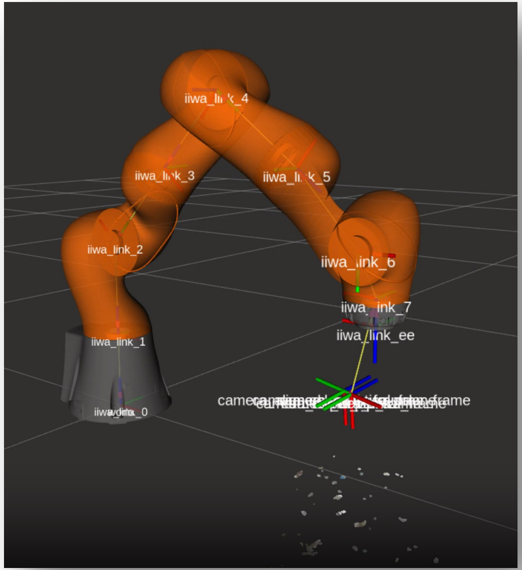


ChArUco

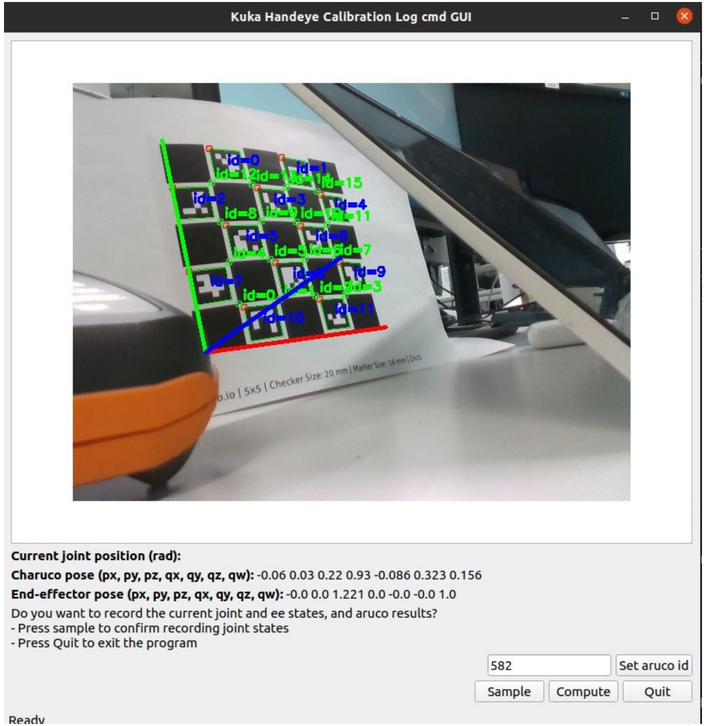
=

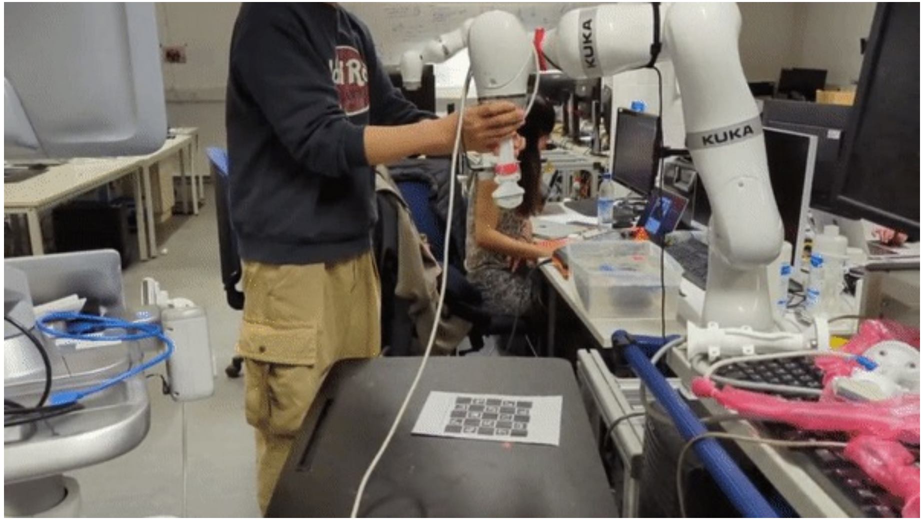


Build & Visualize Coordinate System

Components: Initial Point Detection

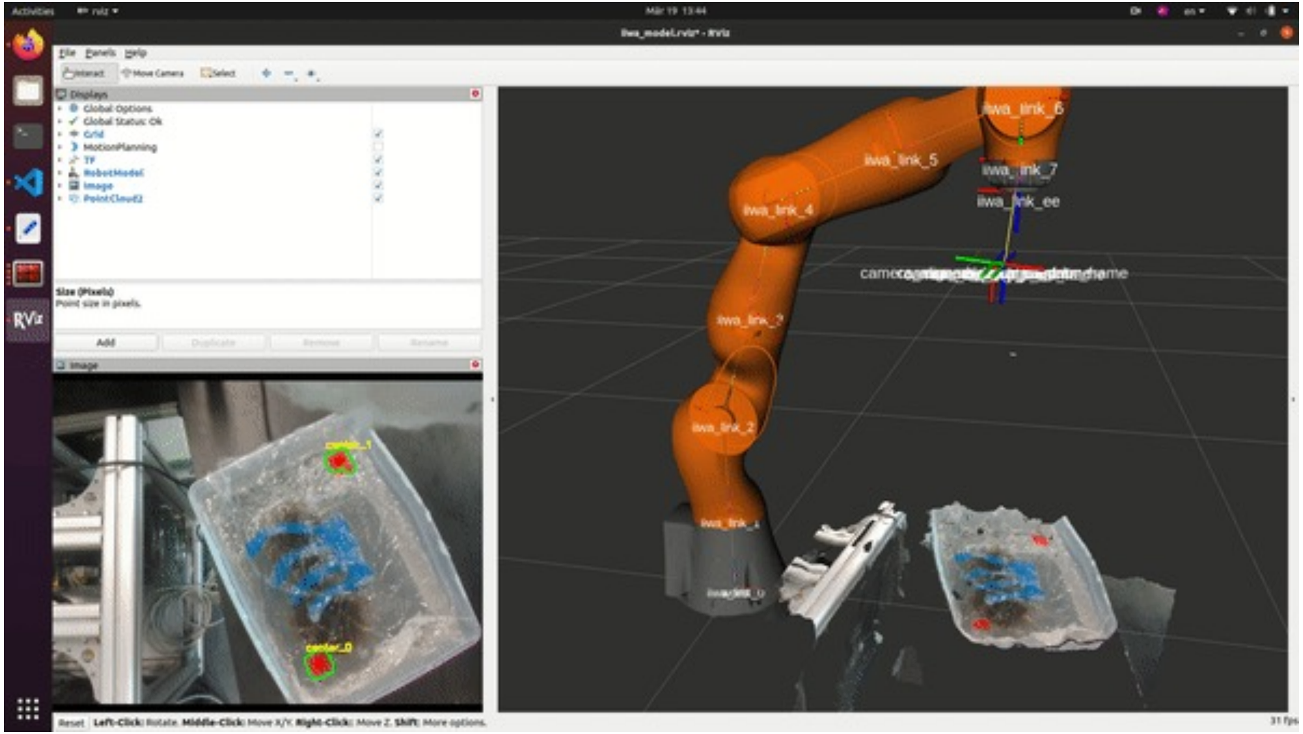
Hand Eye Calibration





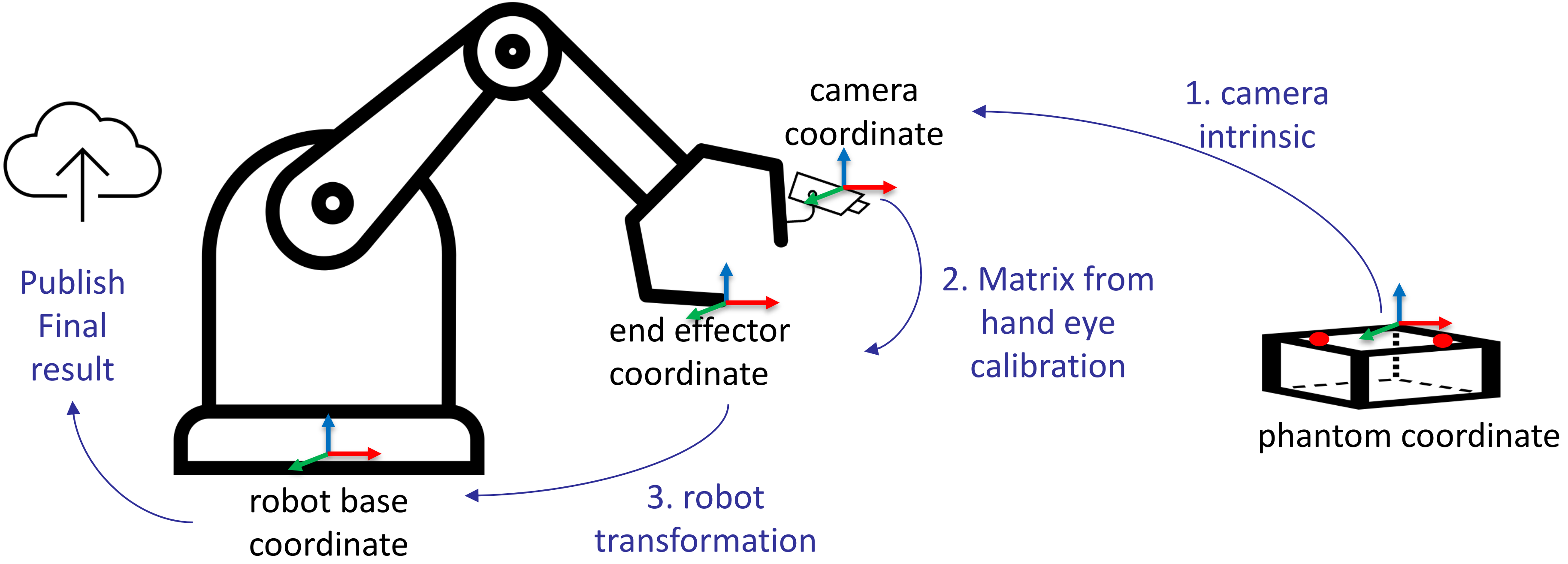
Components: Initial Point Localization

Detect Markers

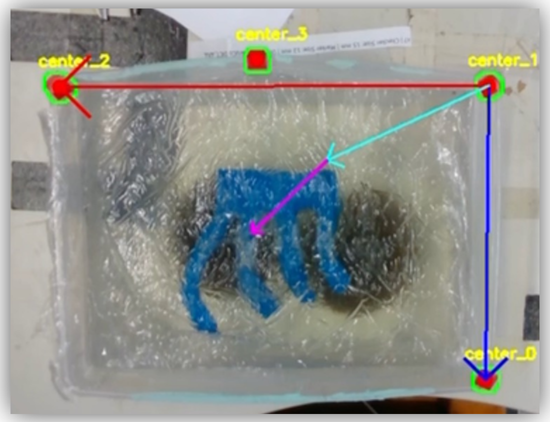


Components: Initial Point Localization

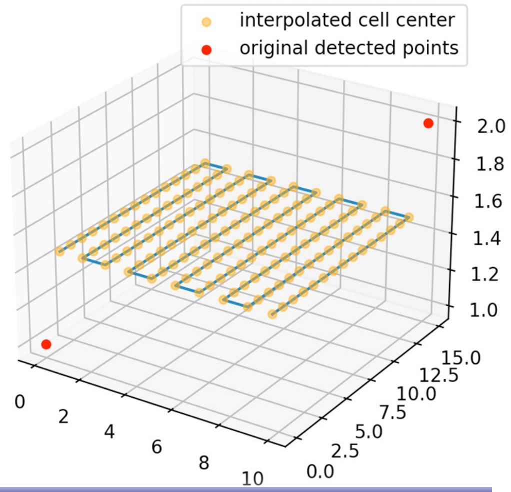
Transformations



Components Overview



Initial Point Detection



Trajectory Planning

Shadow Detection

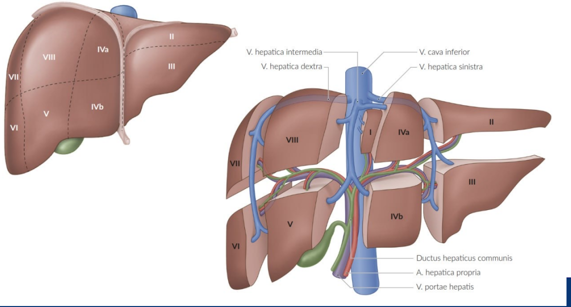
Trajectory Planning: Medical Approximation

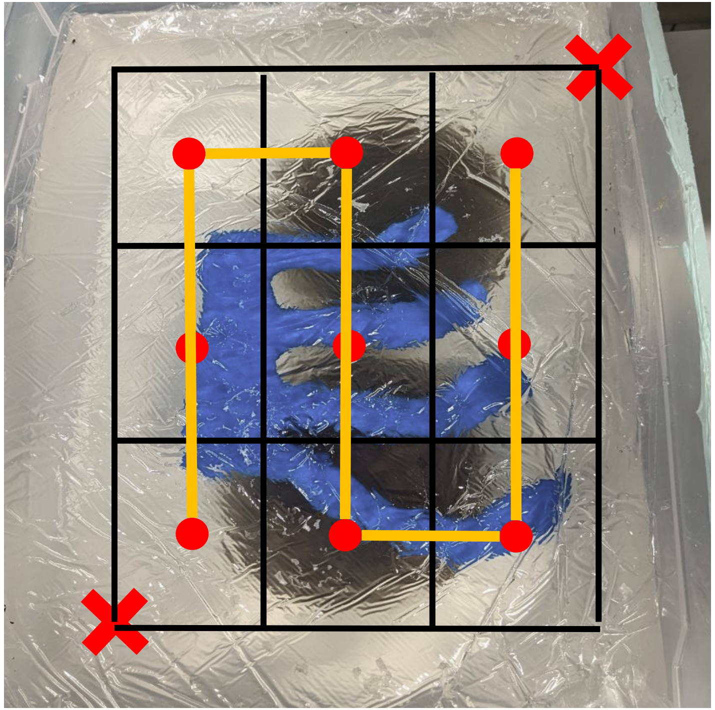
Medical liver scan protocol:

- Doctors scan liver into regions
- **We approximate doctor’s workflow**

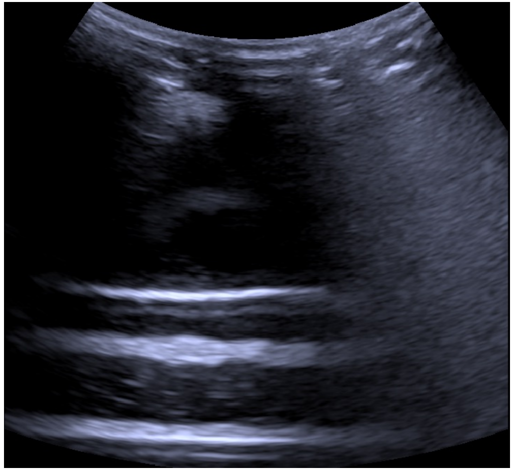
Given 2 detected points in diagonal:

- Divide into 3x3 cells
- Extract the cell centers
- Interpolate with fixed step size (1cm)

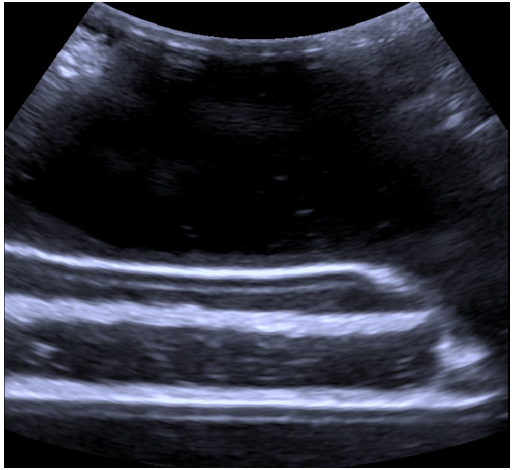




Trajectory Planning: Tradeoff Image Quality and Safety



Poor image quality
Poor contact force



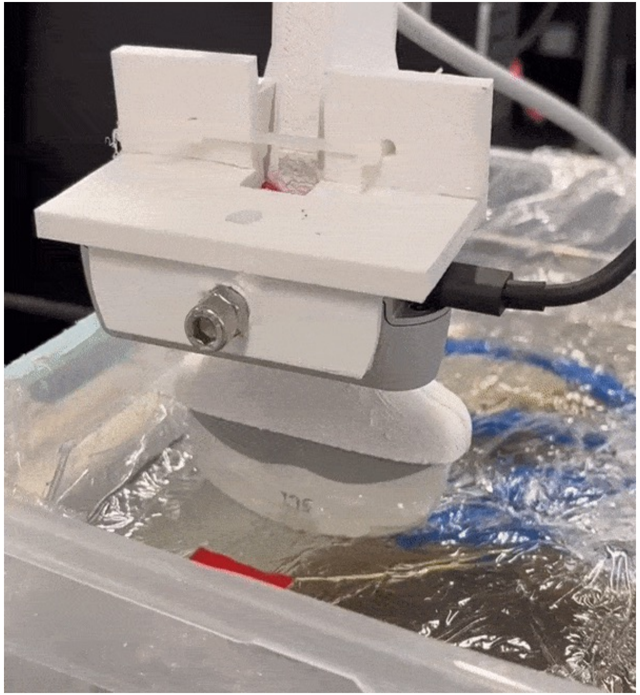
Good image quality
Optimal contact force

Too much force
Danger!

Trajectory Planning: Force Adaptation

Force adaptation:

- Keep the robot contact force within optimal range
- Adjust to the optimal contact on the scanning target
- Maximize US scanning quality
- Avoid harming the patient



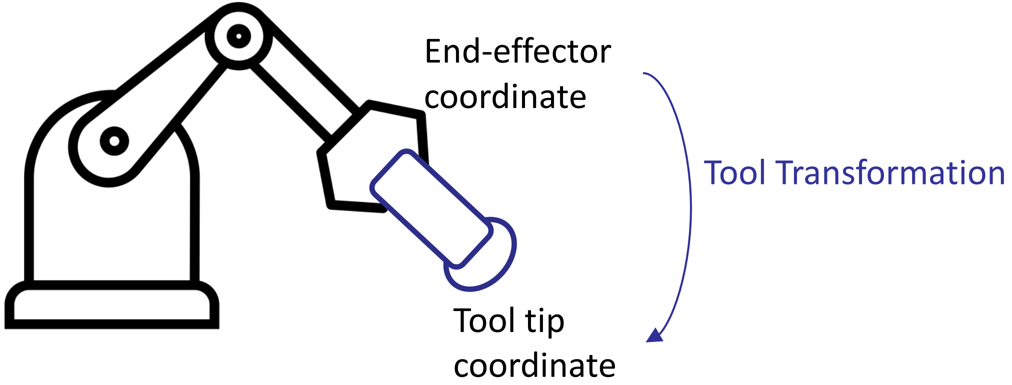
Oscillation-aware:

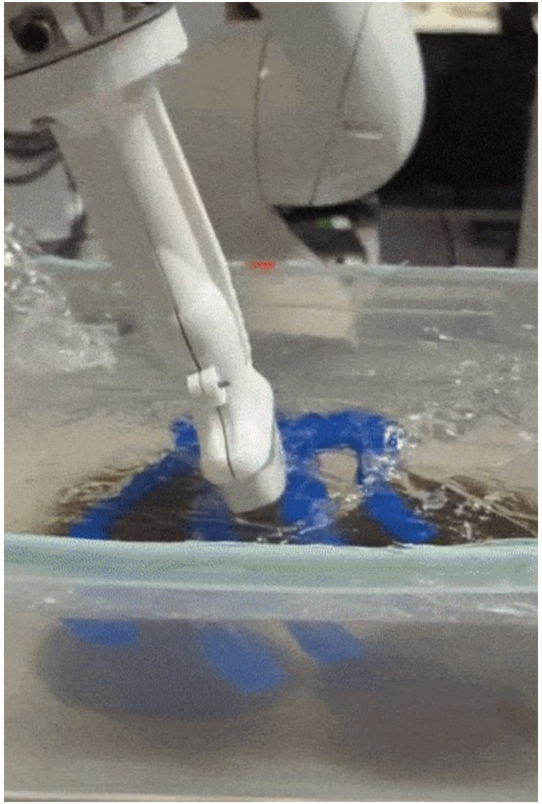
- Start with larger step-size
- Reduce the z-axis step-size if oscillation detected
- Enables faster movement and finer control

Trajectory Planning: Sweeping Motion

Sweeping motion:

- Sweep around the fixed point (tool tip)
- To obtain more information from different angles
- Transformation needed: robot end-effector -> tool tip

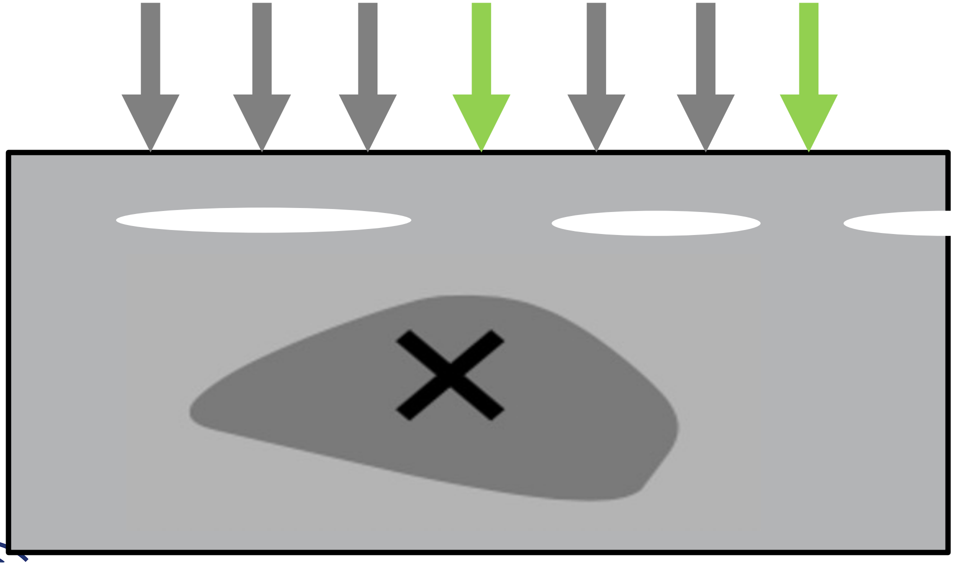


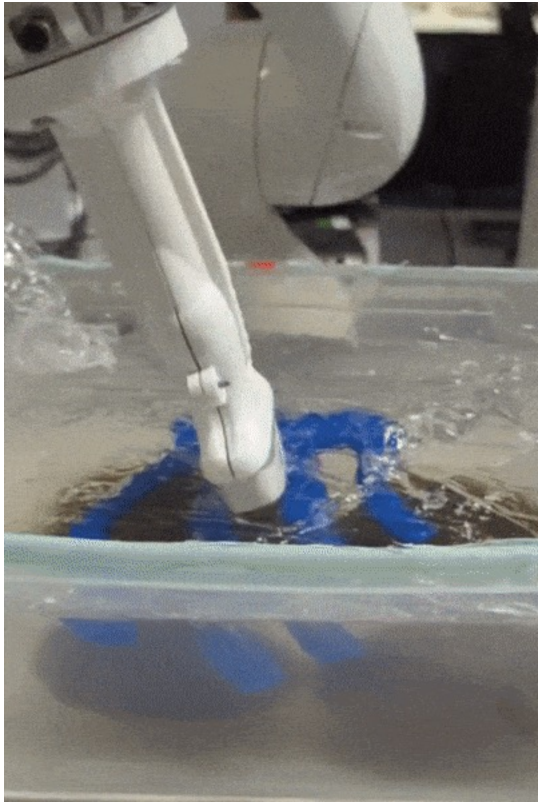


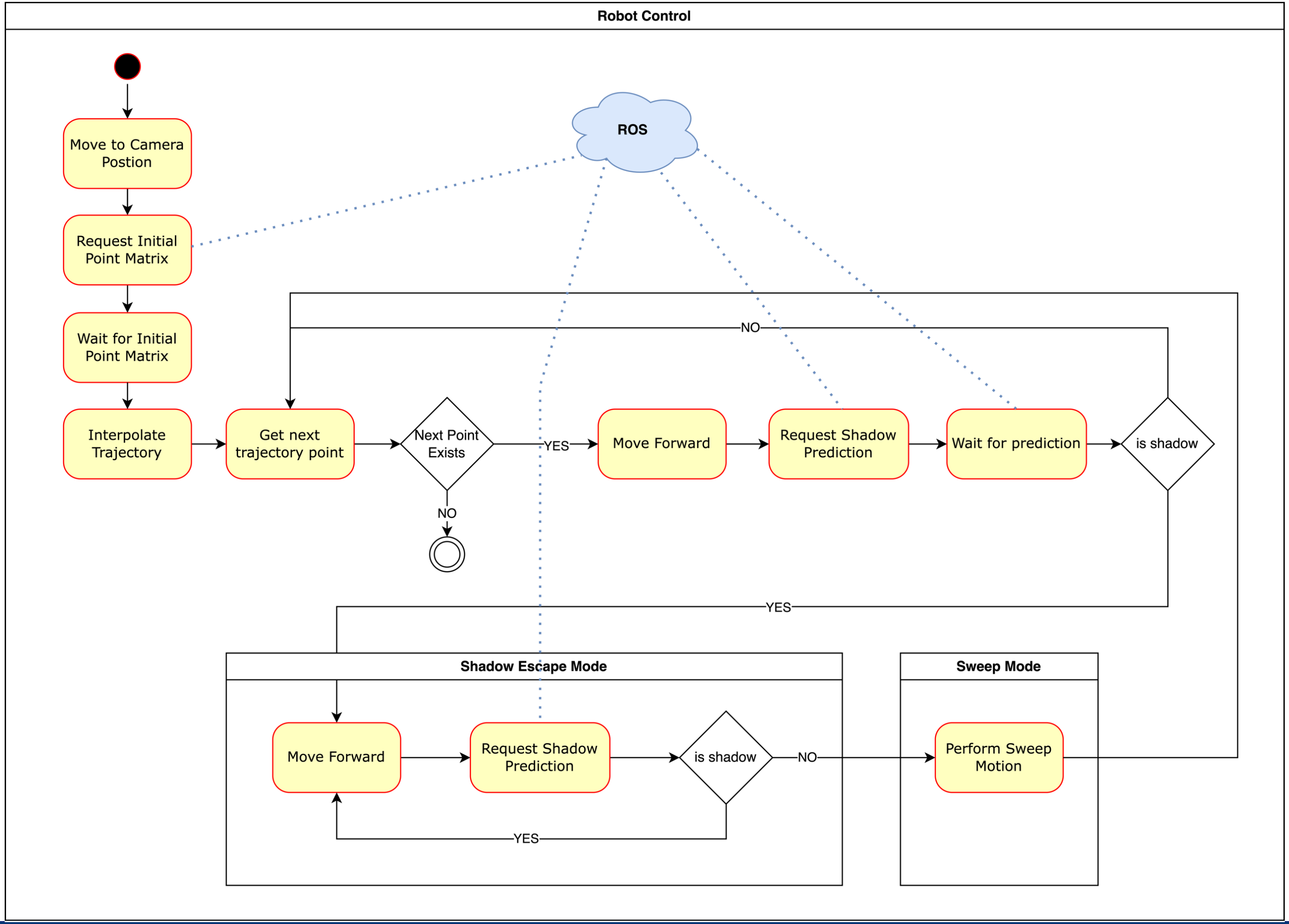
Trajectory Planning: Sweeping Strategy

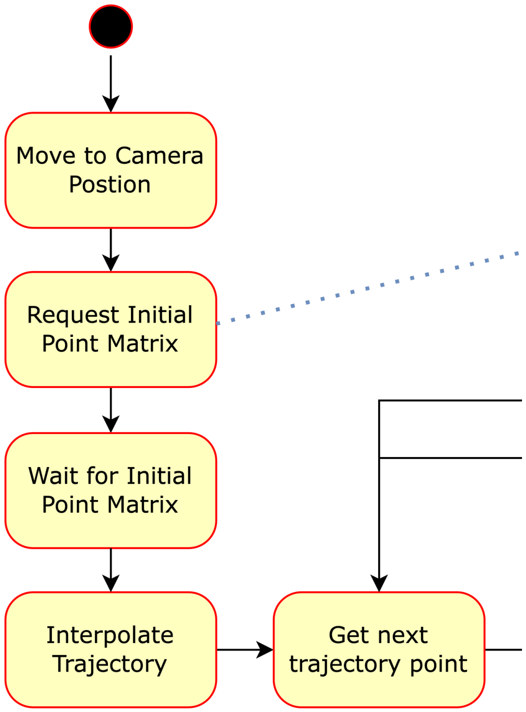
Where is the best location to sweep?

- Shadow detection






Robot Control
ROS
Move to Camera Postion
Request Initial Point Matrix
Wait for Initial Point Matrix
Interpolate Trajectory
Get next trajectory point
Next Point Exists
YES
NO
Move Forward
Request Shadow Prediction
Wait for prediction
is shadow
NO
YES
Shadow Escape Mode
Move Forward
Request Shadow Prediction
is shadow
NO
YES
Sweep Mode
Perform Sweep Motion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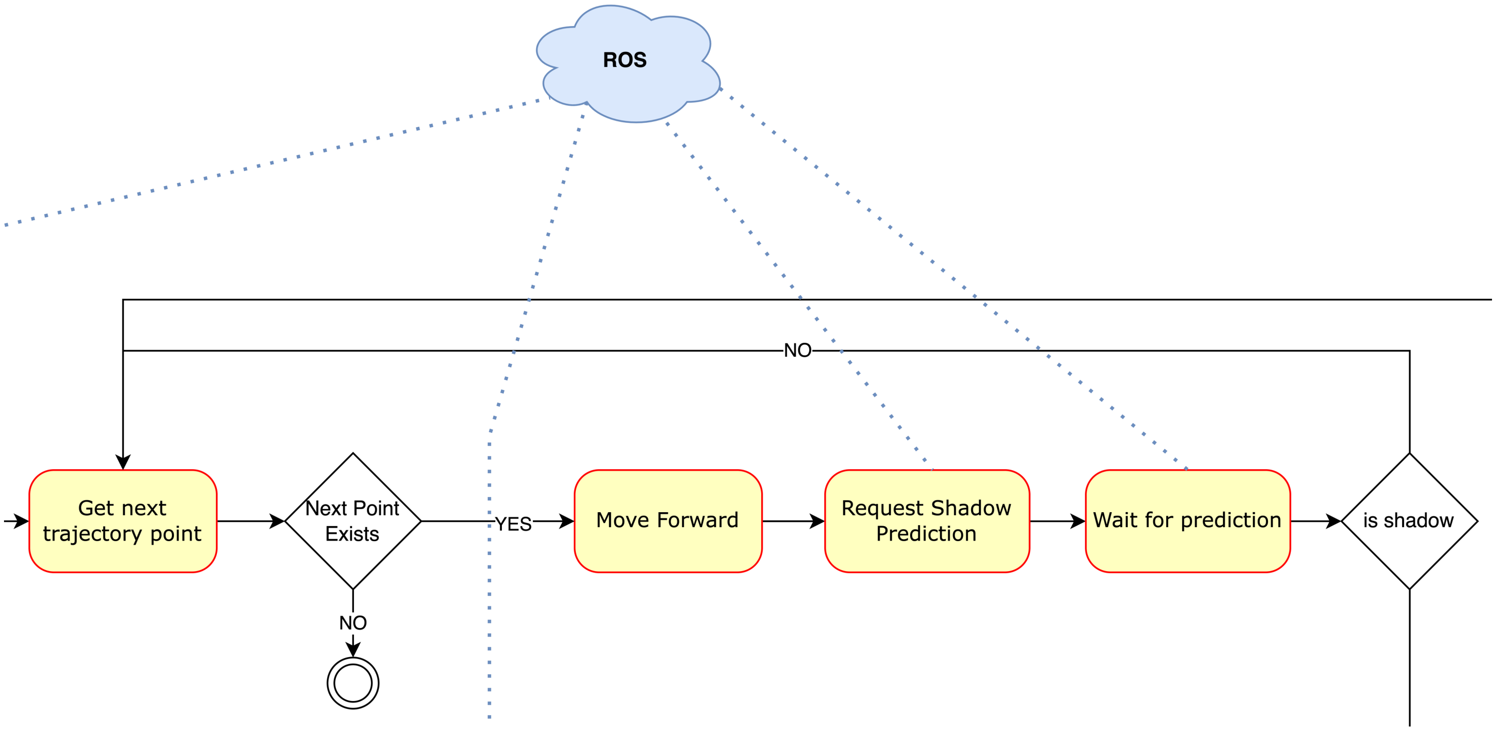
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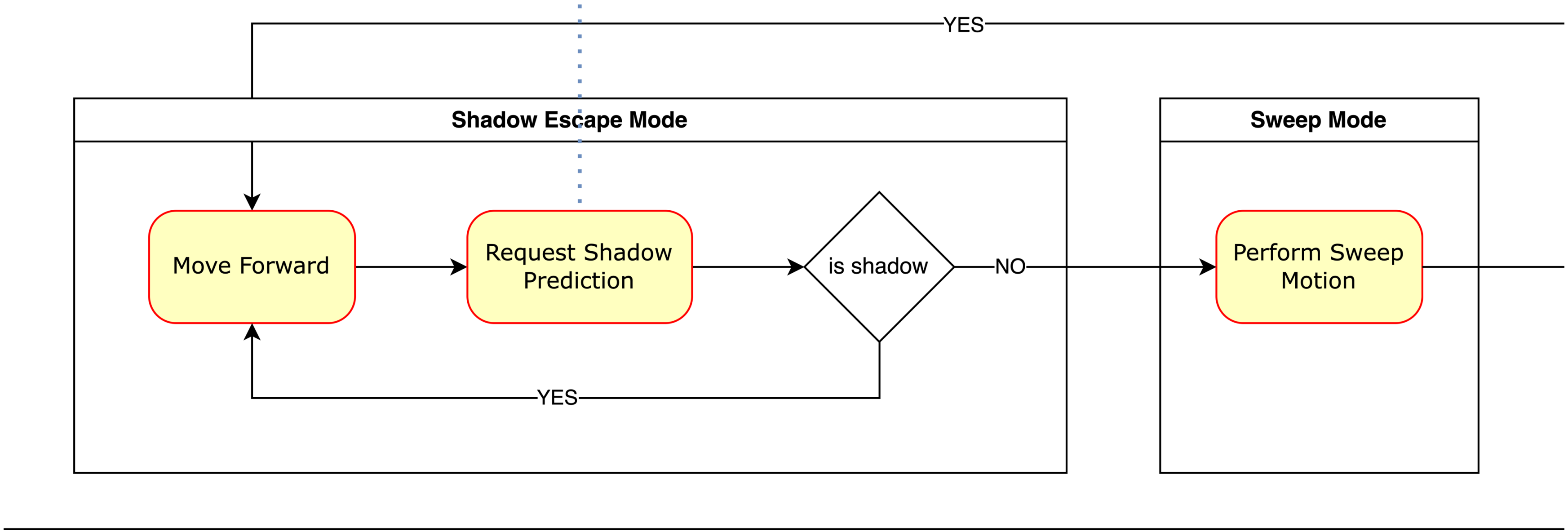
YES
Shadow Escape Mode
Sweep Mode
Move Forward
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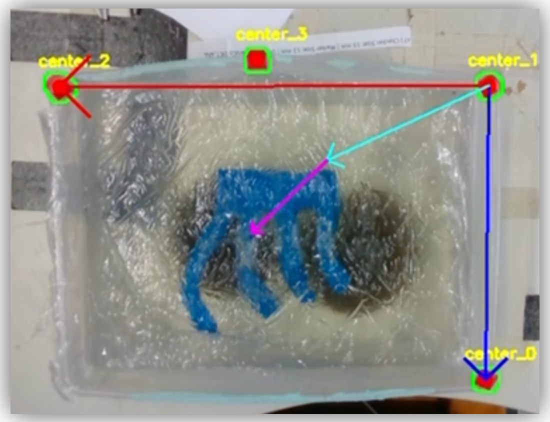
is shadow
NO
Perform Sweep Motion
YES

Components Overview



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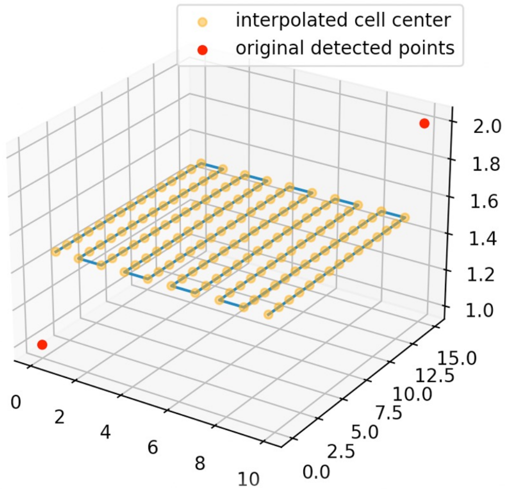
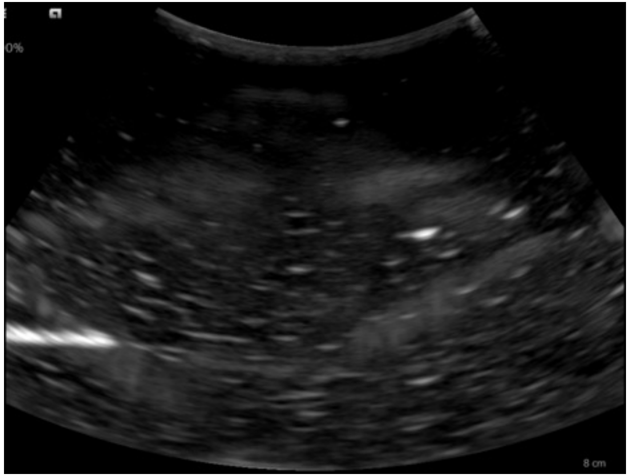


Trajectory Planning

Shadow Detection

Components: Shadow Detection



Main Idea

- Train deep learning classifier
- Receives live stream of Ultrasound images
- Listen to requests/ publish predictions via ROS
- Enable real-time predictions (without noticeable latency)

Problems

- Manual labeling is time consuming
- Keeping labeling consistency is hard
- CNNs struggle with noisy Ultrasound images
- Model size must be reasonable

Components: Shadow Detection

Approaches Overview

1. Uncertainty-Aware Pseudo-Labeling Classifier
   - use small labeled subset to fully label dataset and train classifier
   - leverages uncertainty of predictions and negative labels
   - problem: included noisy training through ambiguous labels
2. Confidence Maps-based Classifier
   - improved pseudo-labeling approach
   - problem: processing too expensive, no real-time ability
3. Embedding-based Clustering
   - fully unsupervised training
   - based on Autoencoder, PCA, k-means clustering
   - proved to work reliably in action

Components: Shadow Detection

First Approach

- use small labeled dataset
- perform uncertainty-aware pseudo-labeling approach
- leverages confidence of a prediction with Monte Carlo Dropout
- iteratively label full dataset and train classifier in one go
- use Resnet-like architecture

$$g_c^{(i)} = \mathbb{1}\left[u\left(p_c^{(i)}\right) \leq \kappa_p\right] \mathbb{1}\left[p_c^{(i)} \geq \tau_p\right] + \mathbb{1}\left[u\left(p_c^{(i)}\right) \leq \kappa_n\right] \mathbb{1}\left[p_c^{(i)} \leq \tau_n\right]$$

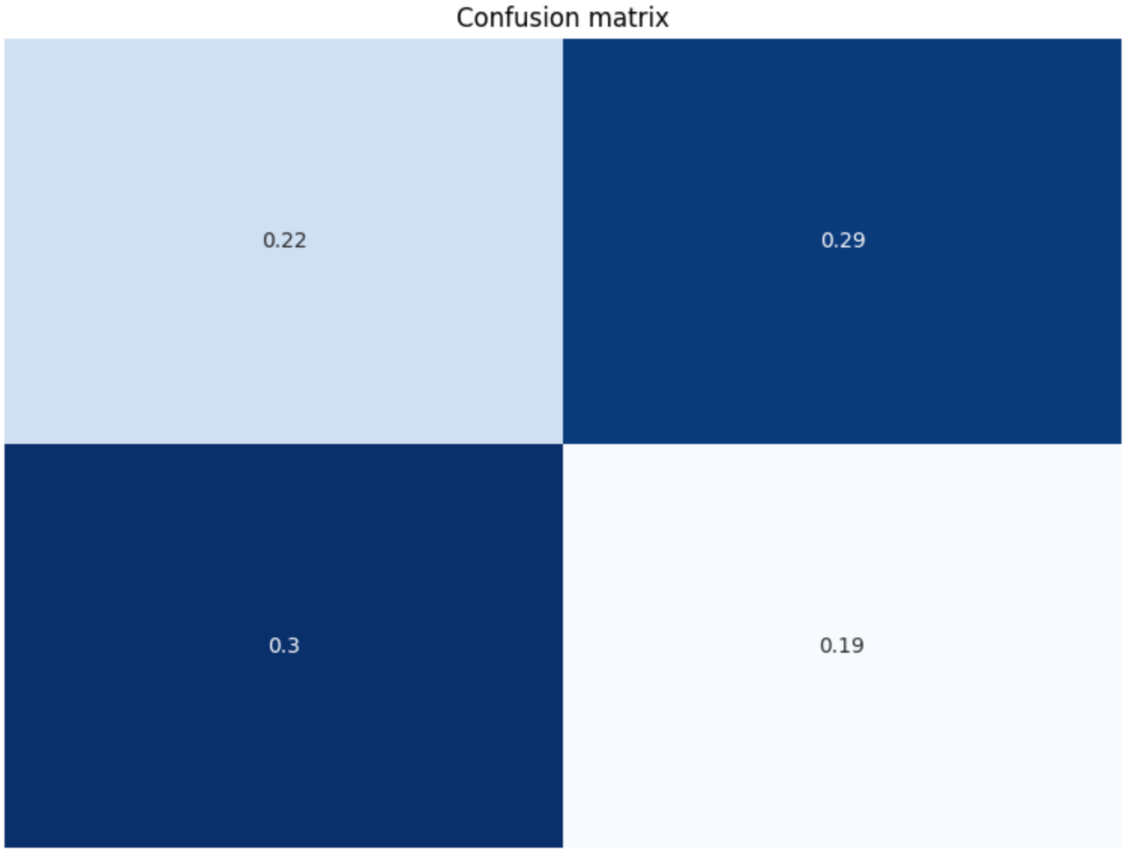
M. N. Rizve, K. Duarte, Y. S. Rawat, and M. Shah, "IN DEFENSE OF PSEUDO-LABELING: AN UNCERTAINTY-AWARE PSEUDO-LABEL SELECTION FRAMEWORK FOR SEMI-SUPERVISED LEARNING," p. 20, 2021.

Components: Shadow Detection

Liver

Liver or Shadow?

Components: Shadow Detection



Components: Shadow Detection

Problems

- CNNs struggle with noisy Ultrasound images
- finding useful data augmentations is complicated
  - first approach highly relies on augmentations
  - most used augmentation types in Computer Vision are not applicable in this domain
- Training quickly becomes too noisy through wrong labels
- Result: Unusable classifier

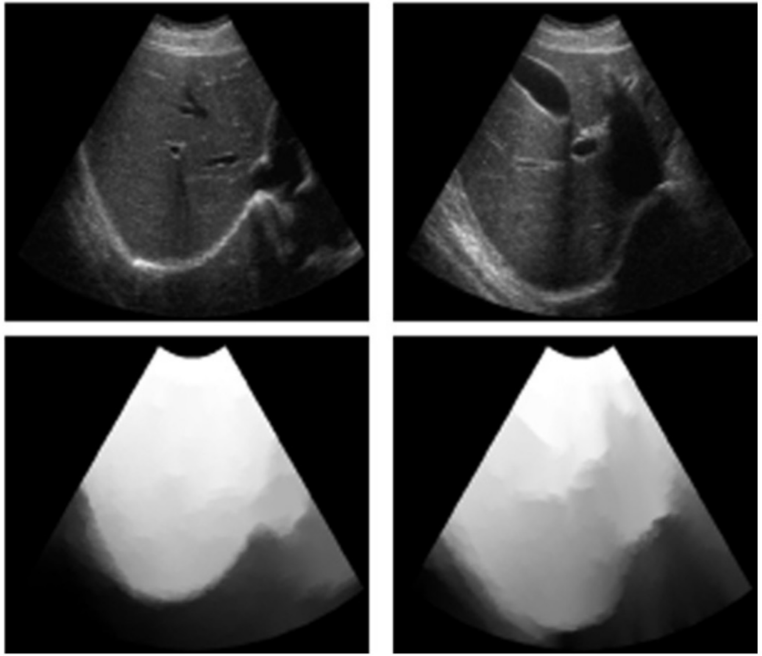
Components: Shadow Detection

Second Approach

- use confidence maps as basis for pseudo-labeling/ classification
- measures uncertainty in ultrasound images caused by shadowing (per-pixel)
- natively supported in ImFusion!

Problems

- no real-time computation possible
- processing of single batch with 10 images took 40 seconds



A. Karamalis, W. Wein, T. Klein, and N. Navab, “Ultrasound confidence maps using random walks,” *Medical Image Analysis*, vol. 16, no. 6, pp. 1101–1112, Aug. 2012, doi: 10.1016/j.media.2012.07.005.

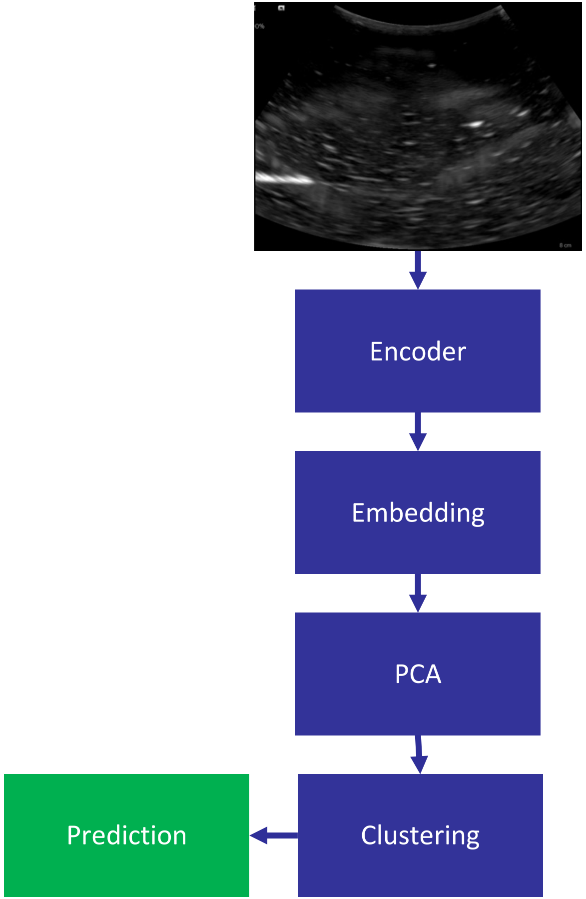
Components: Shadow Detection

Final Approach

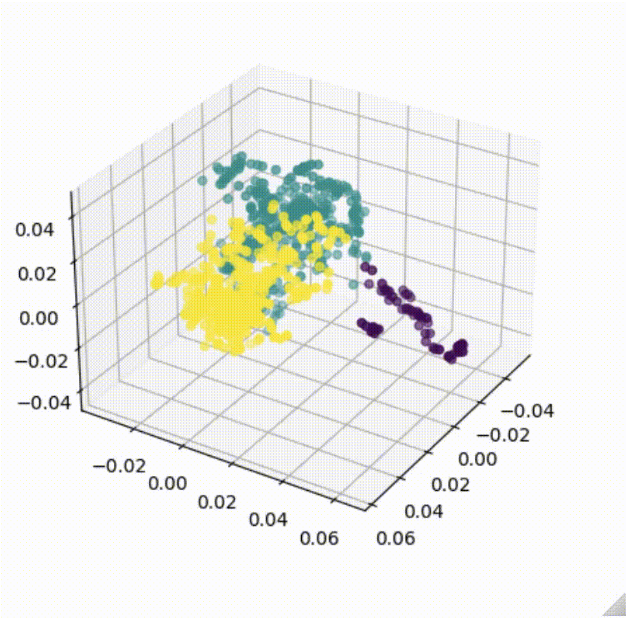
- Use Autoencoder to learn meaningful embeddings
- Reduce dimensionality using PCA
- Cluster reduced embeddings
- Perform classification based on cluster id

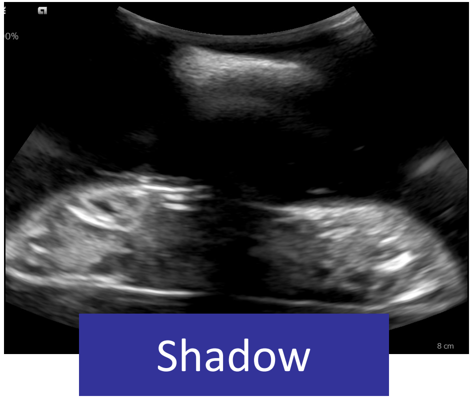
Benefits

- unsupervised training => no labeling task
- fast training
- real-time application possible without noticeable latency, even for large batches up to 512 images

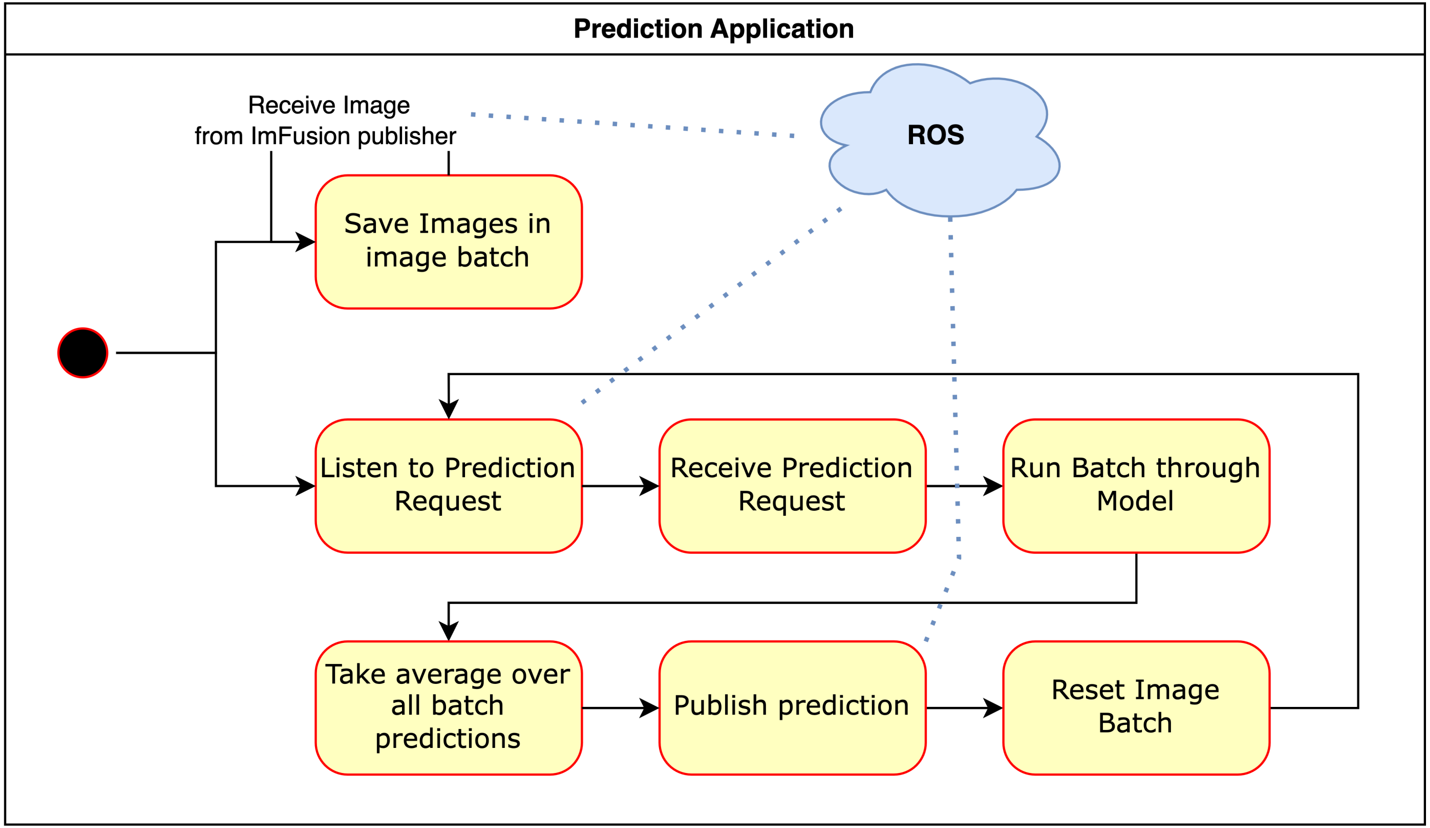


Components: Shadow Detection

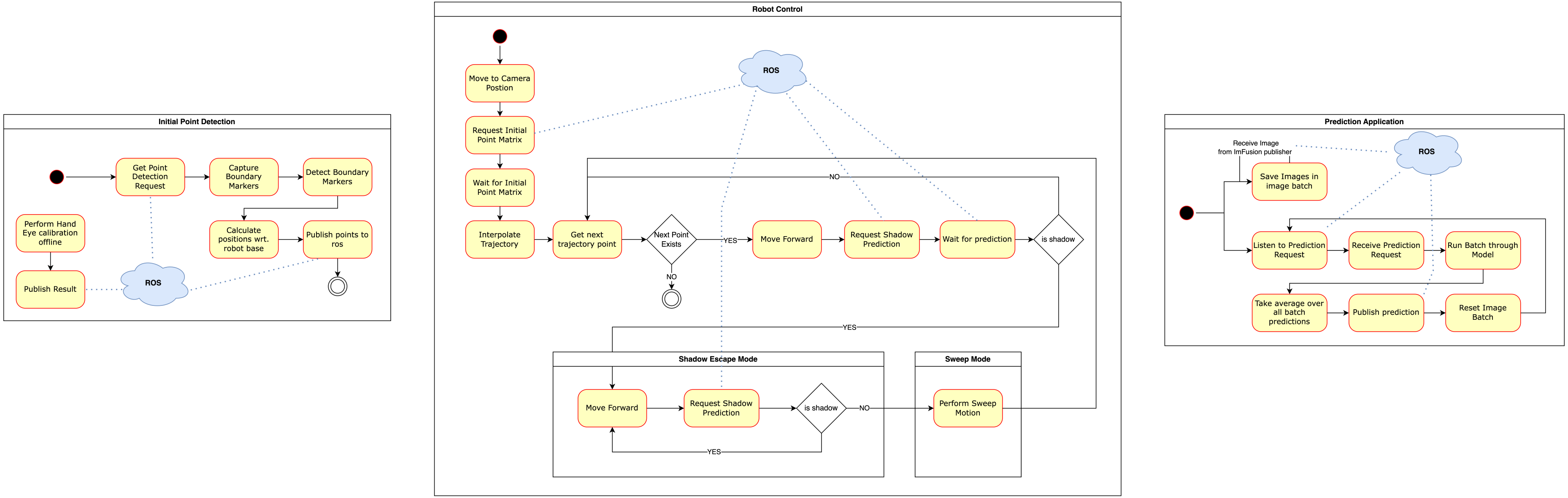




Components: Shadow Detection

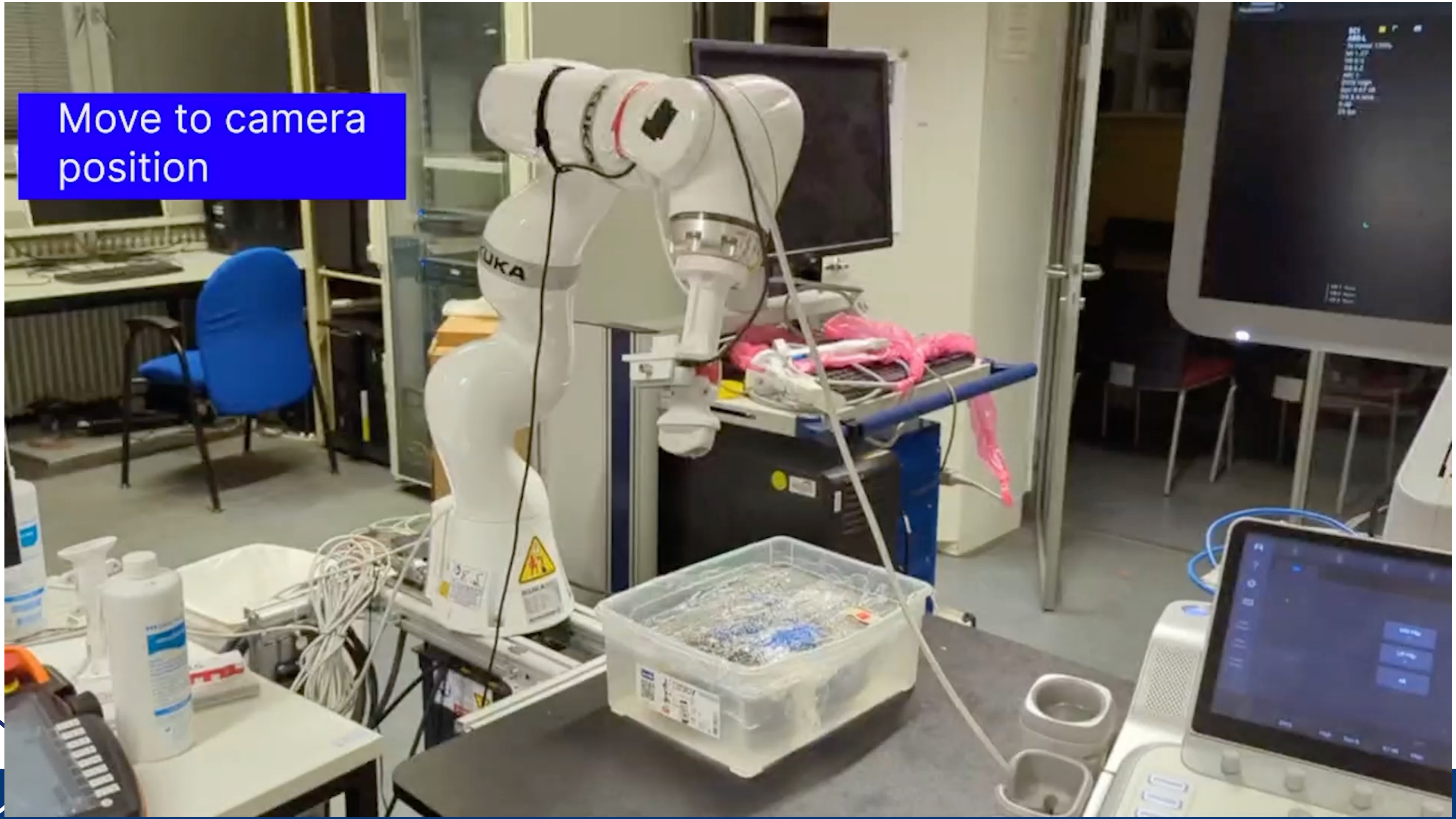


Components: The bigger picture

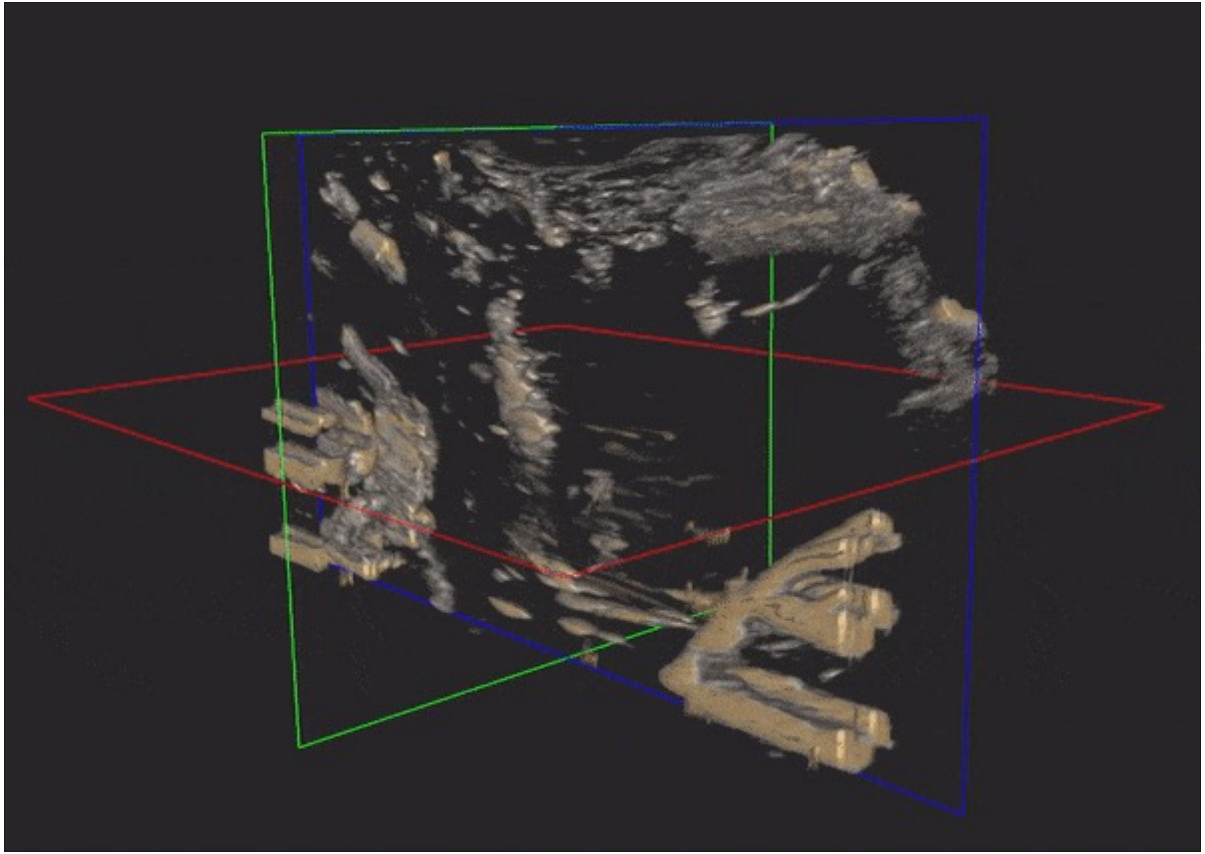


Demo

Demo



3D Compounding



Summary

Current Limitations & Challenges

Limitations

- Proposed solution is functional only on the provided phantom
- The solution requires a lot of configuration
- The phantom is fully flat, which makes trajectory planning and adjusting easier

Main challenges

- Understanding transformation chain for point detection
- Implementation of communication requests between applications
- Testing multiple deep learning approaches for shadow detection
- ImFusion crashes

Summary and Outlook

- Proposed solution for phantom is fully functional
  - Initial point detection
  - Trajectory control
  - Shadow detection
- Outlook
  - Move from phantom to real body
  - Investigate clustering approach with human anatomy

Thank you for your attention.

Technische Universität München

JOHNS HOPKINS
WHITING SCHOOL
of ENGINEERING