



Computational Surgineering | WS22/23

# **Robotically-Guided Ultrasound System for 3D Liver Reconstruction**

Christian Engel, Mei-Ling Fang, Chengzhi Shen

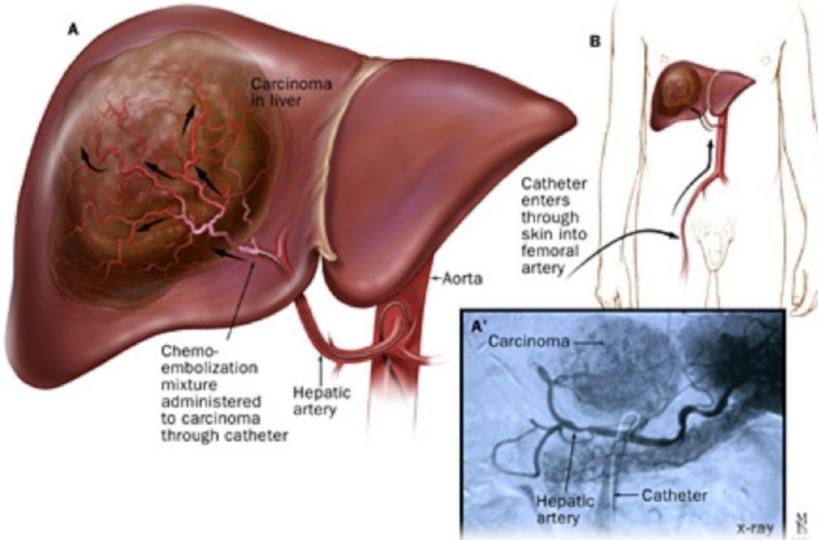
# Outline & Work Split

- 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

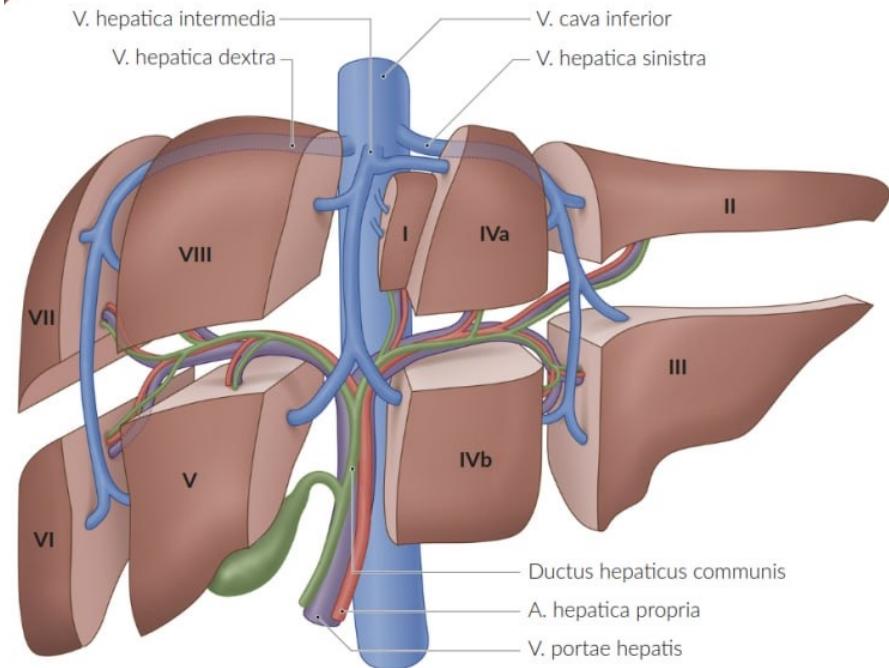
- **radiation exposure** to medical staff and patient (typical effective dose of CT abdomen: 8 mSv)
- Hand-eye-coordination is challenging

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

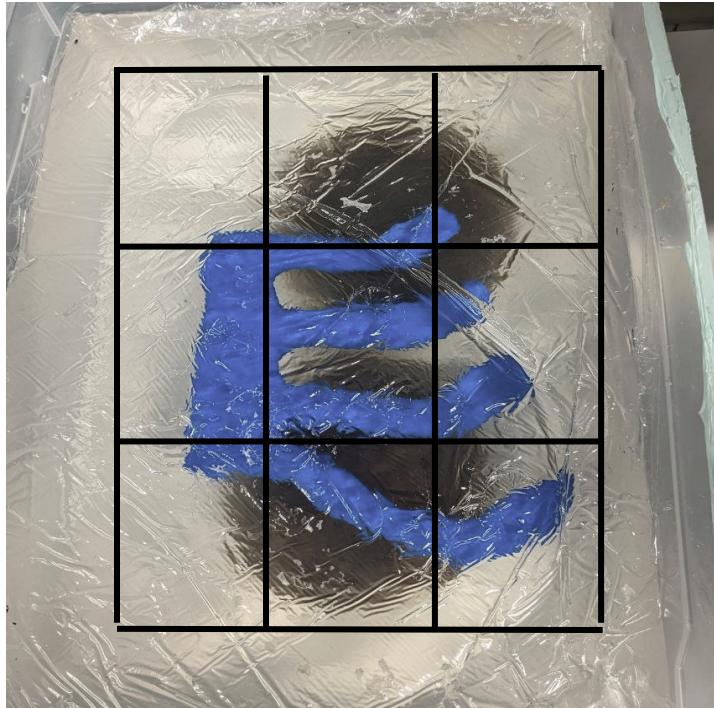
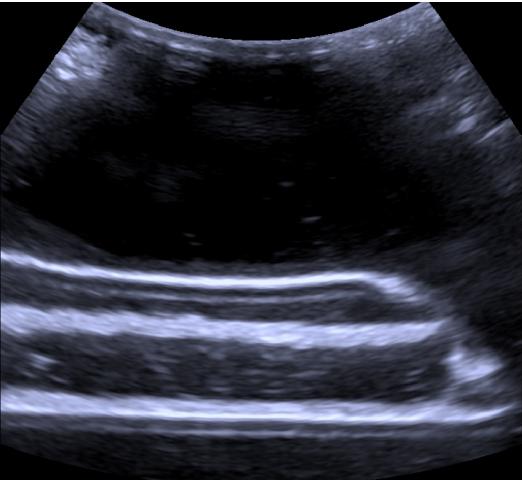


“Sonografische Untersuchung der Leber - AMBOSS.” <https://next.amboss.com/de/article/Qq0uyS>.



# 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

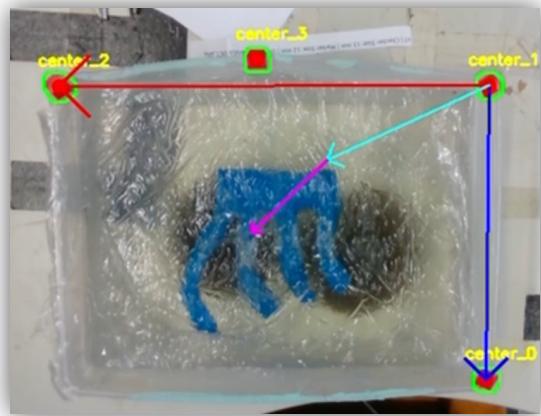




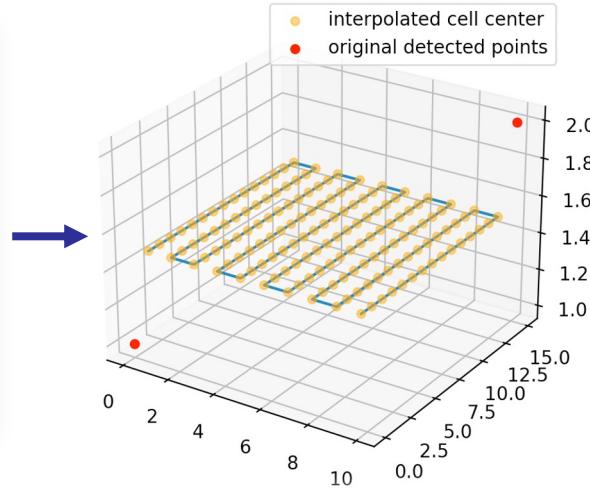
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# Proposed Solution

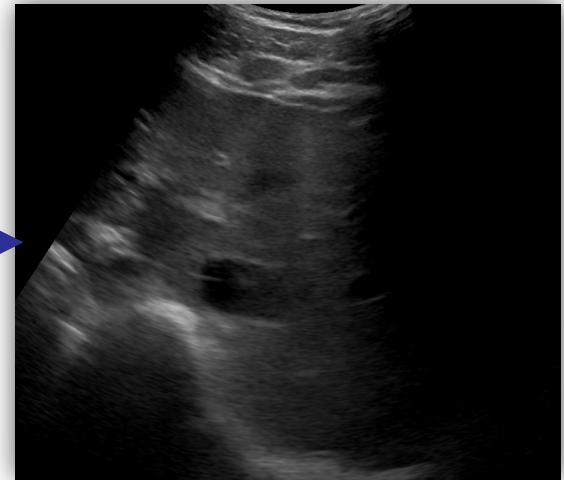
# Components Overview



Initial Point Detection



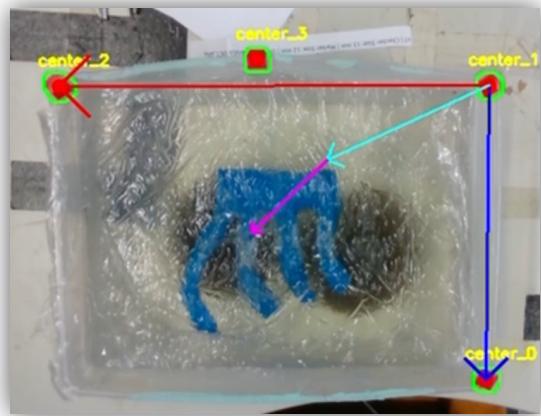
Trajectory Planning



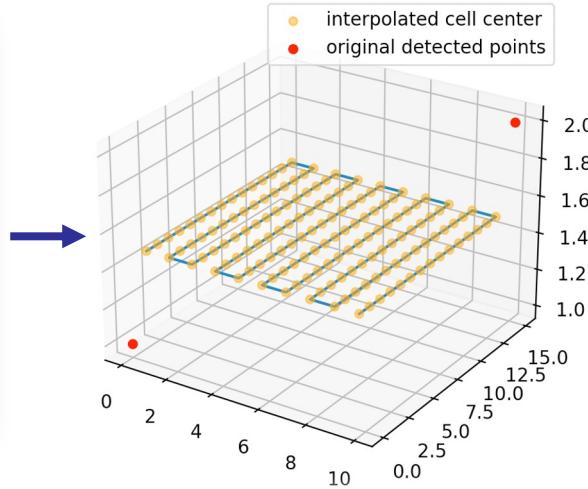
Shadow Detection



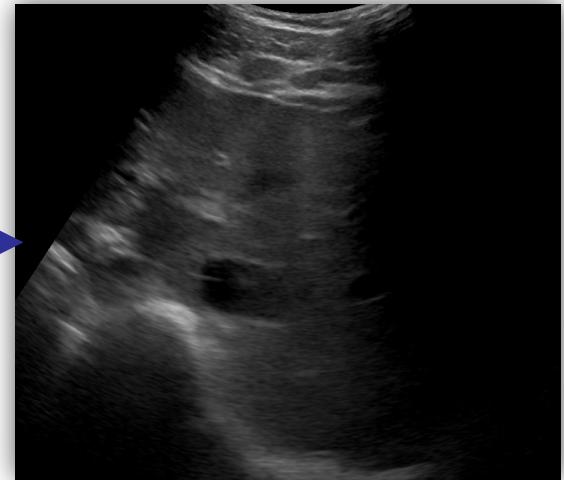
# Components Overview



Initial Point Detection

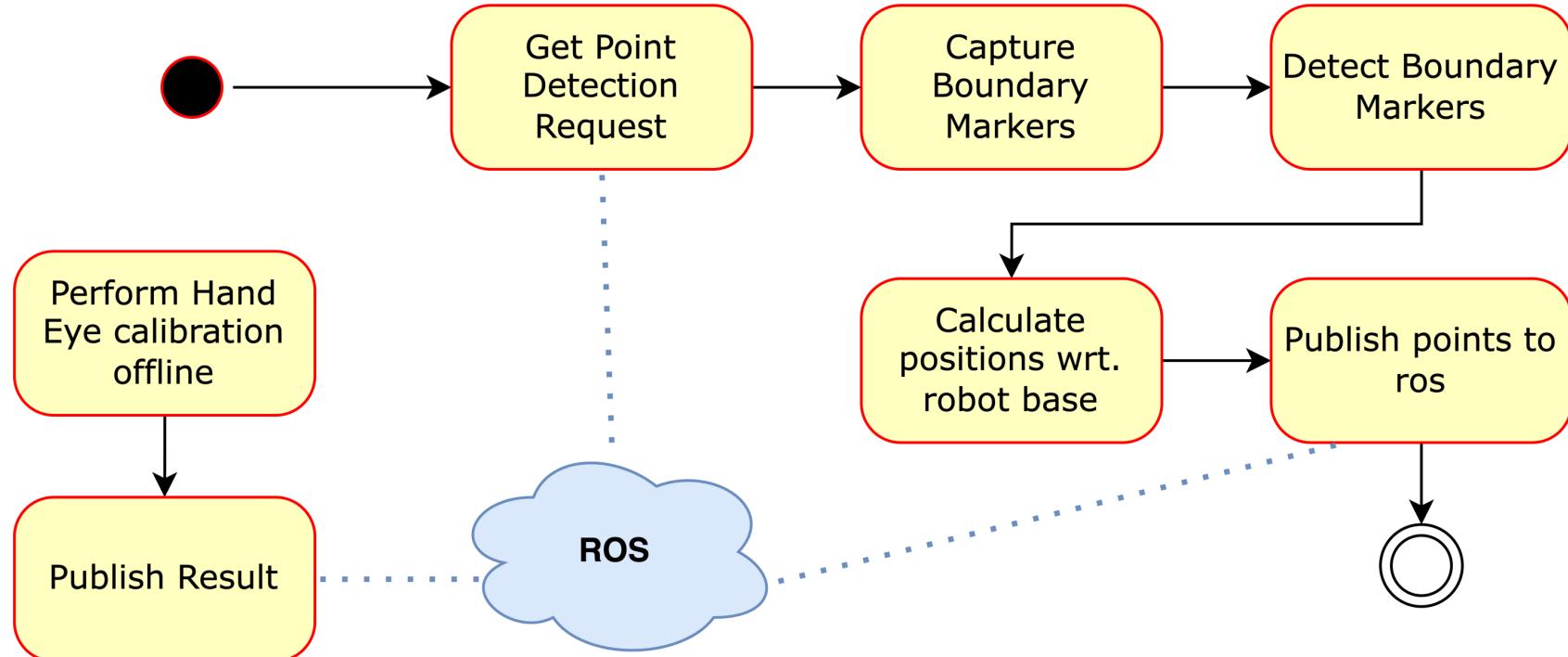


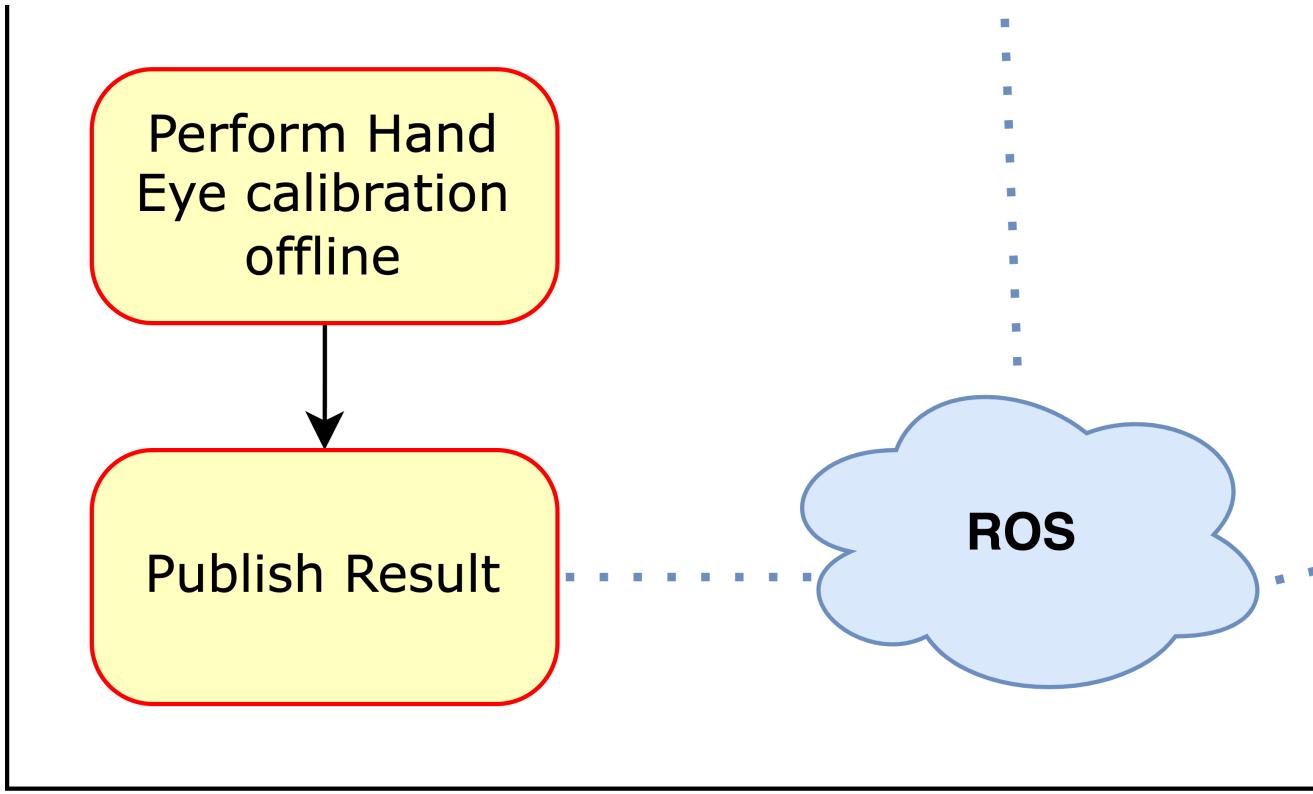
Trajectory Planning



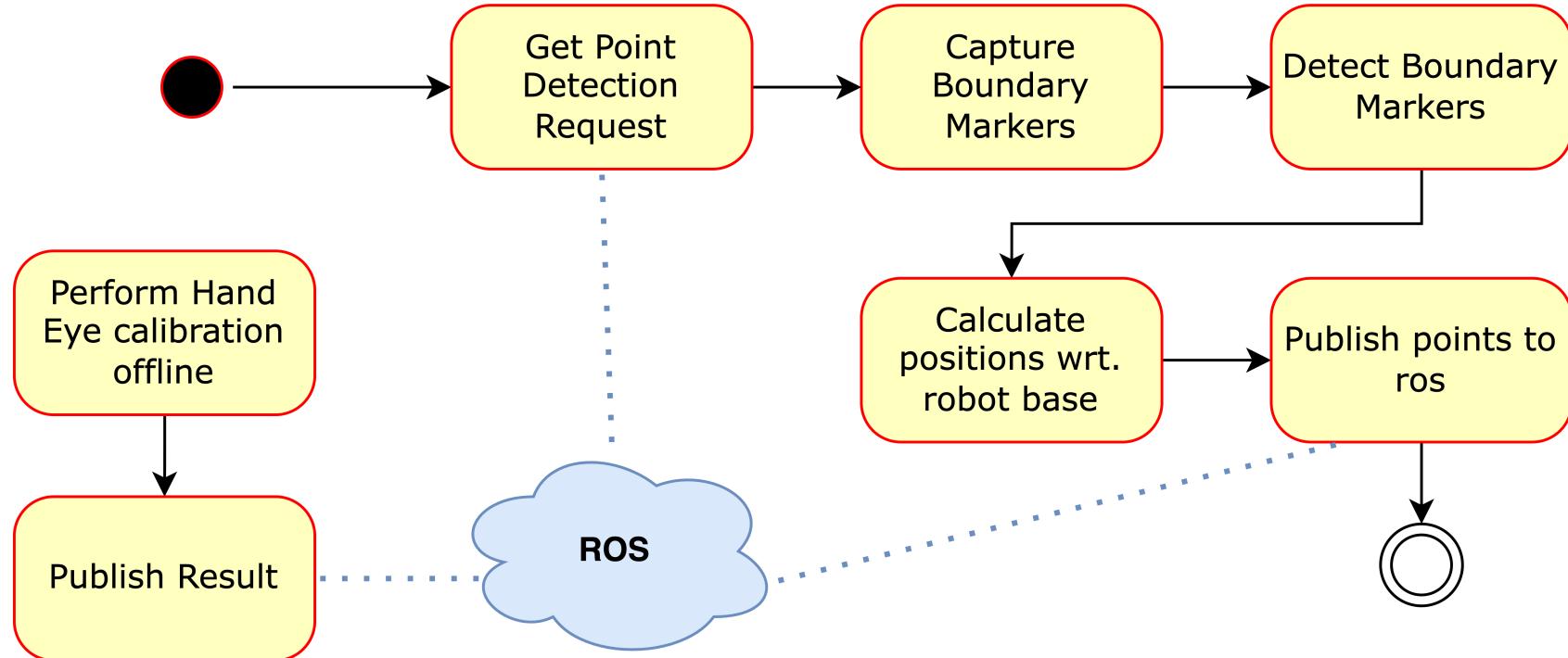
Shadow Detection

## Initial Point Detection





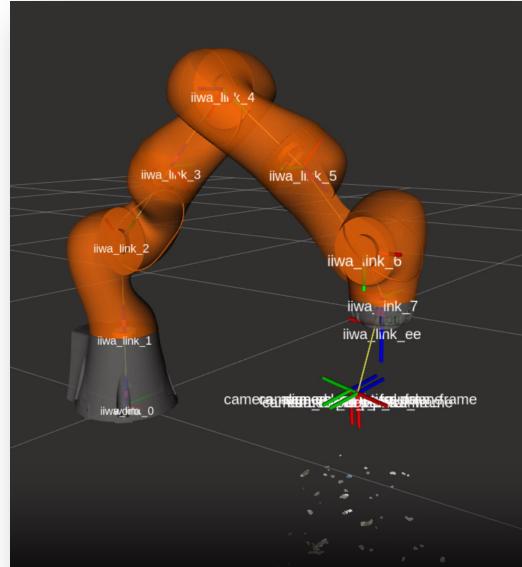
## Initial Point Detection



# Components: Initial Point Detection

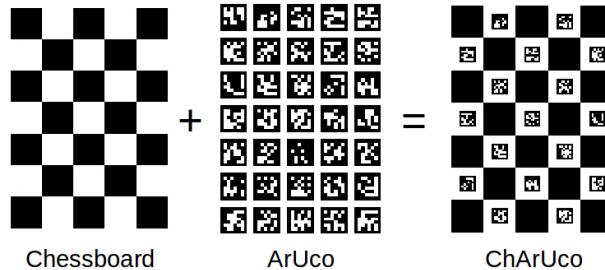


Hand Eye  
Calibration



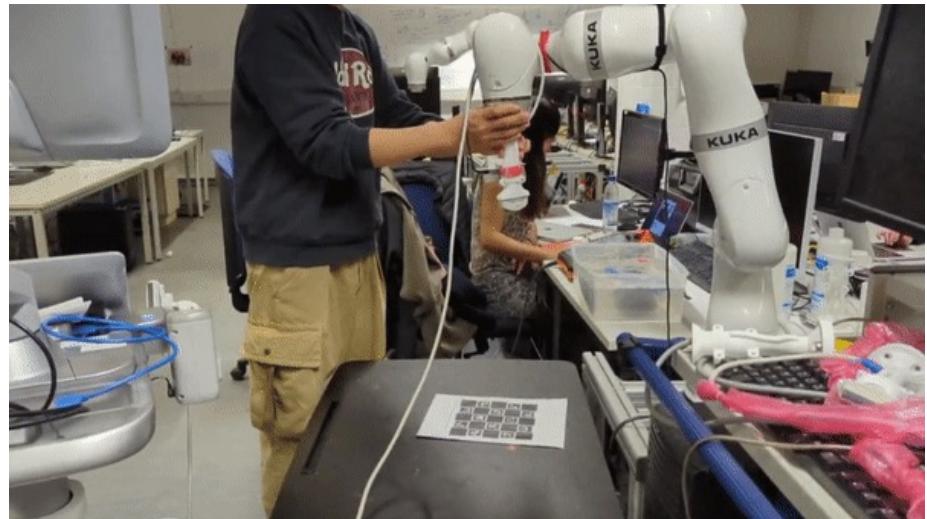
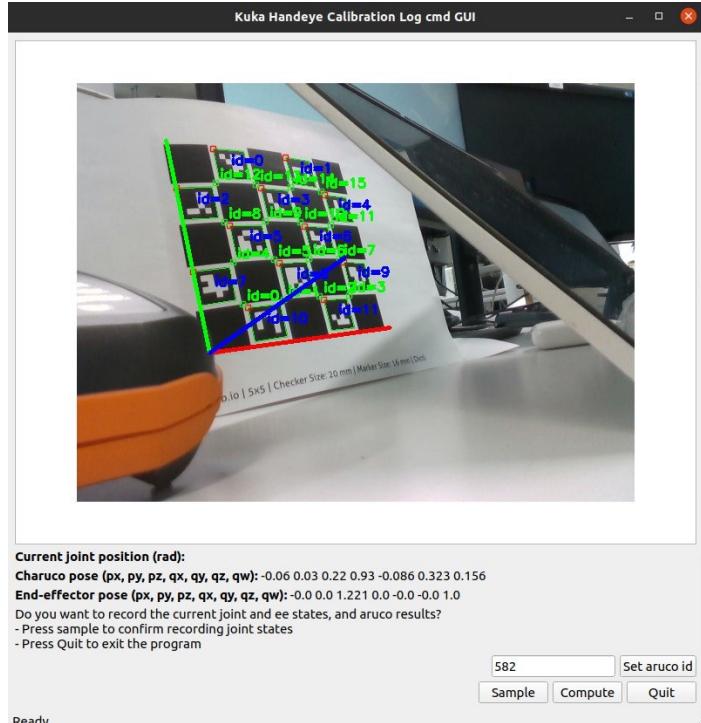
Build & Visualize  
Coordinate System

Attach RGB-D Camera  
to End Effector



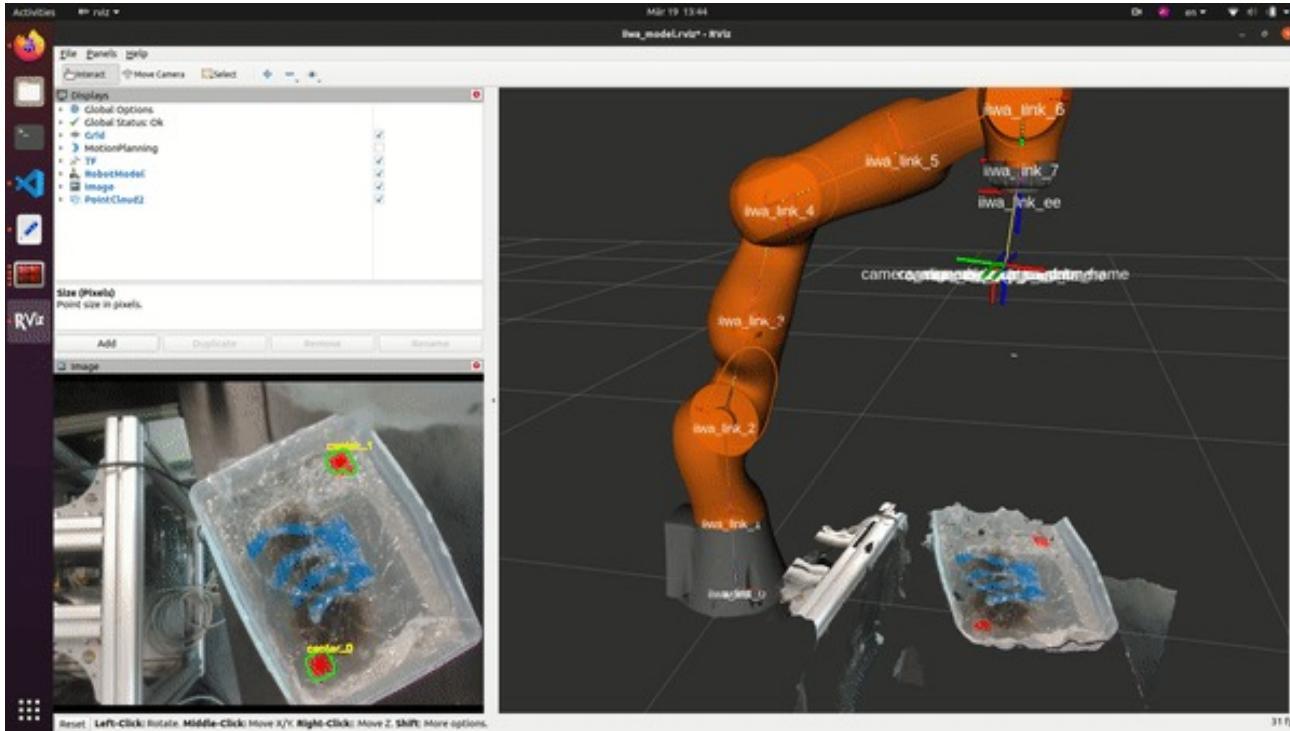
# Components: Initial Point Detection

Hand Eye Calibration



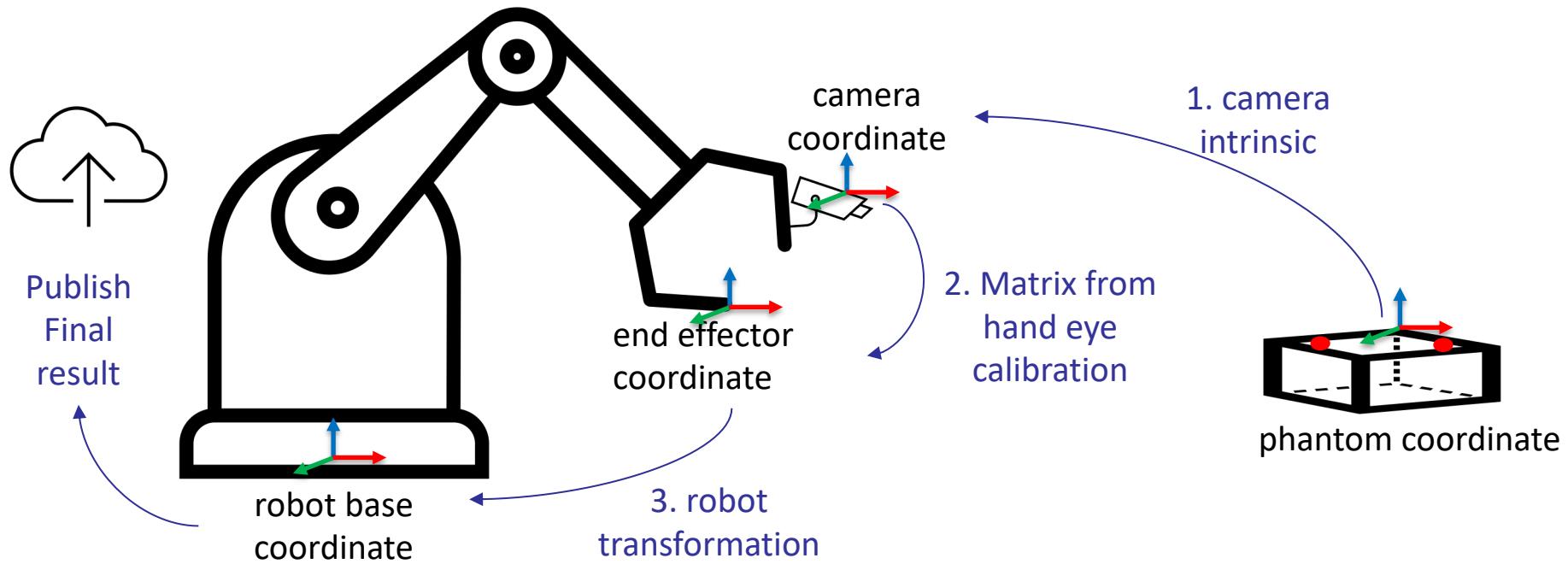
# Components: Initial Point Localization

Detect Markers

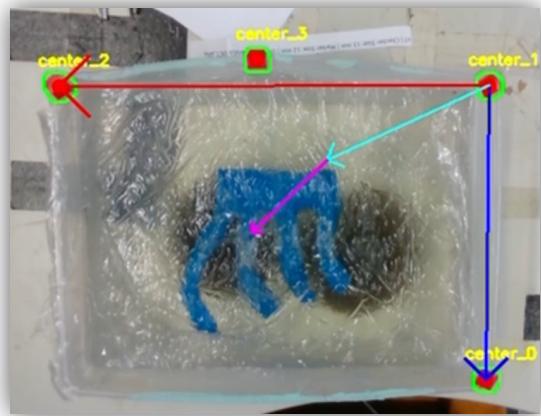


# Components: Initial Point Localization

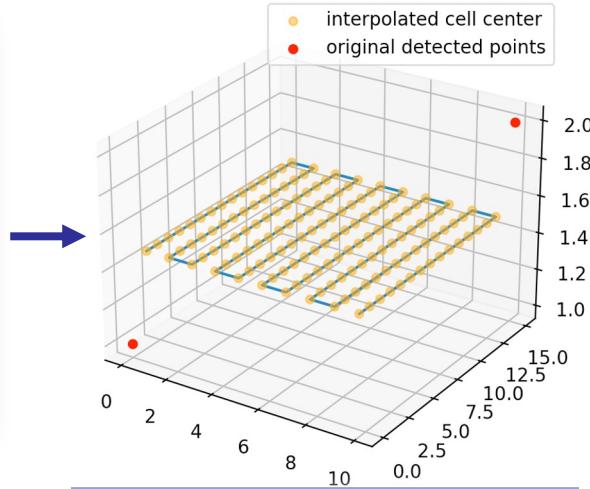
Transformations



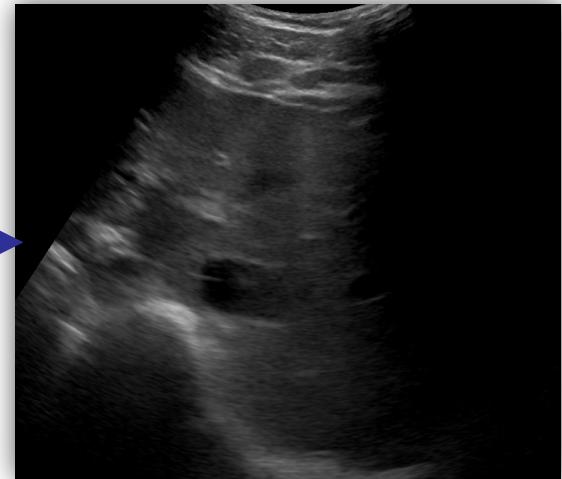
# Components Overview



Initial Point Detection



Trajectory Planning



Shadow Detection

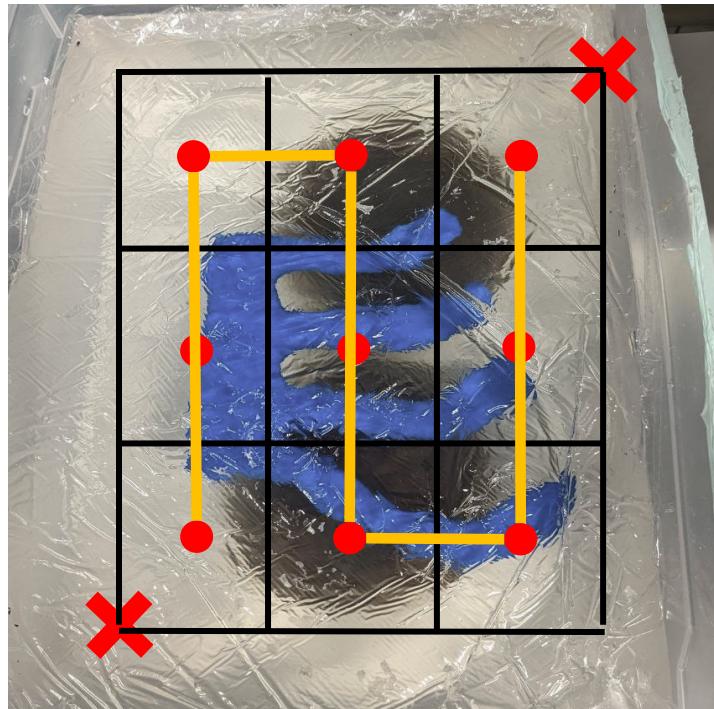
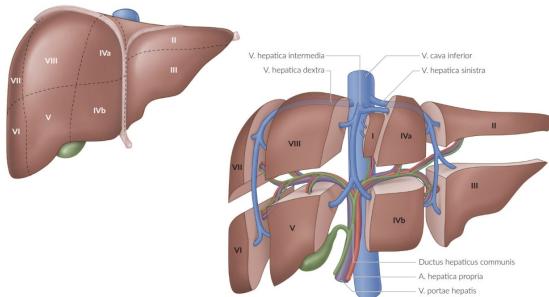
# Trajectory Planning: Medical Approximation

## Medical liver scan protocol:

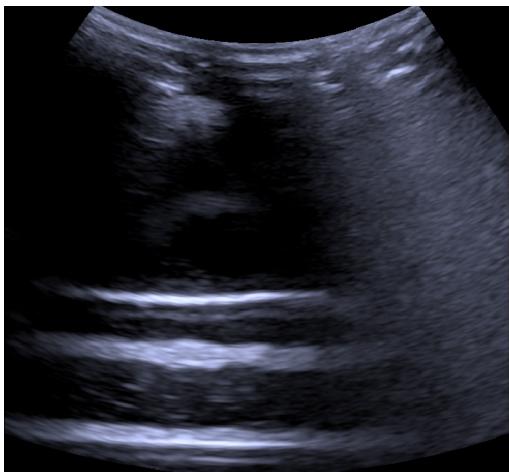
- Doctors scan liver into regions
- We approximate doctor's workflow

## Given 2 detected points in diagonal:

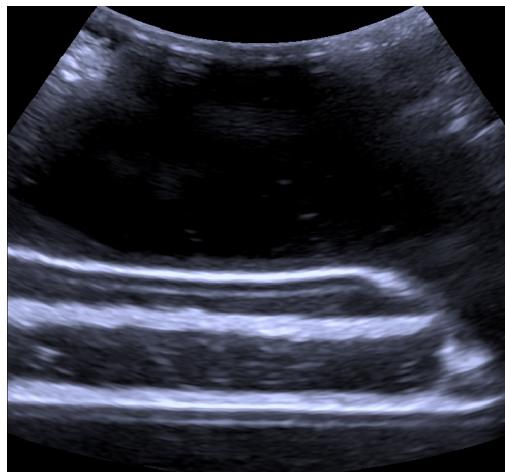
- Divide into 3x3 cells
- Extract the cell centers
- Interpolate with fixed step size (1cm)



# Trajectory Planning: Tradeoff Image Quality and Safety



**Poor image quality  
Poor contact force**



**Good image quality  
Optimal contact force**



**Too much force  
Danger!**



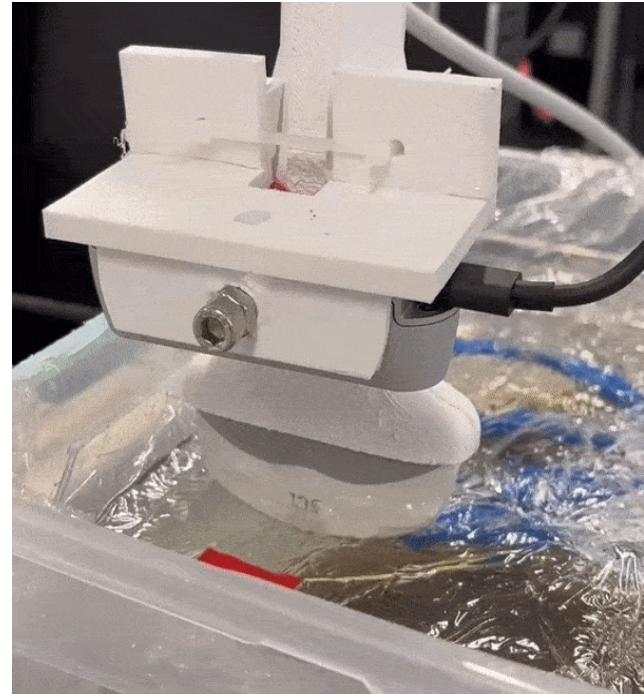
# Trajectory Planning: Force Adaptation

## 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:

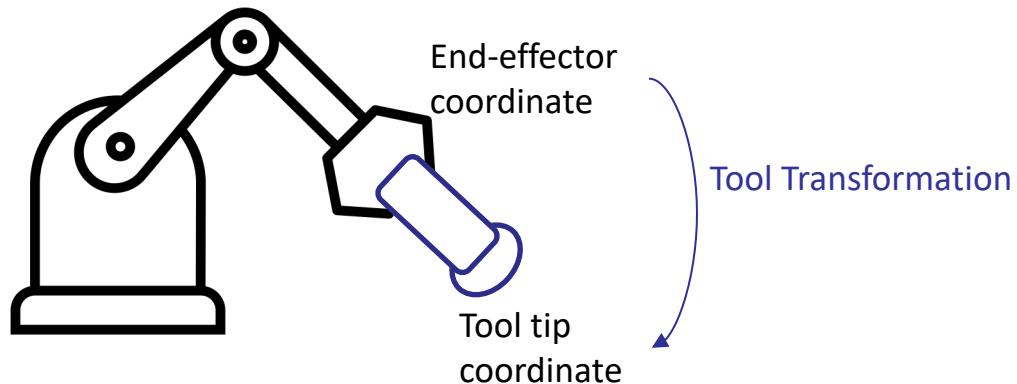
- Start with larger step-size
- Reduce the z-axis step-size if oscillation detected
- Enables faster movement and finer control



# Trajectory Planning: Sweeping Motion

## Sweeping motion:

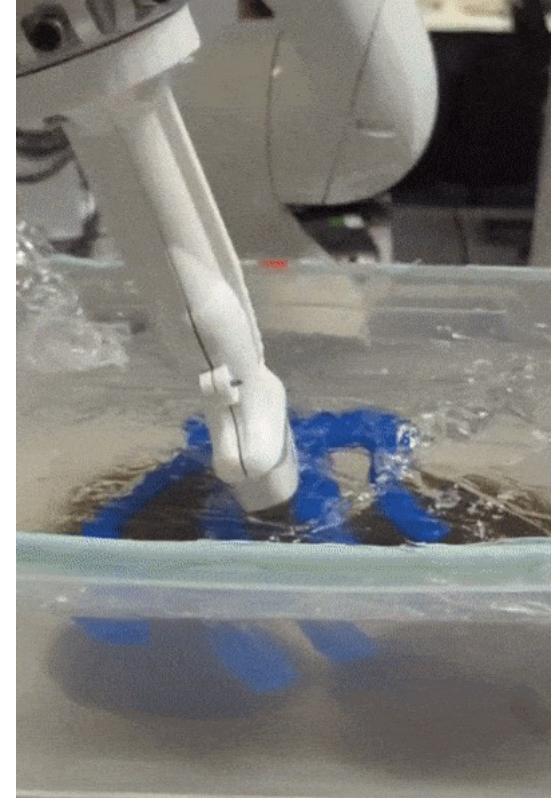
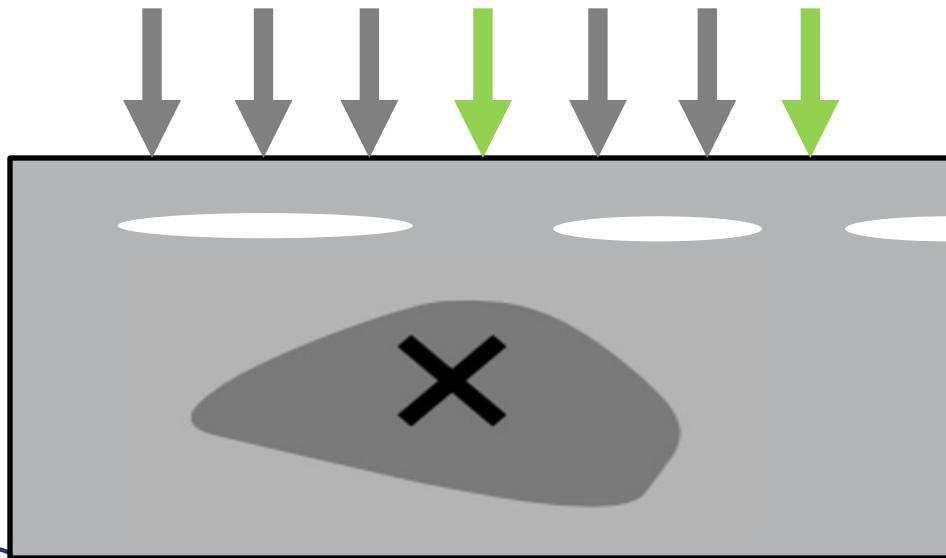
- Sweep around the fixed point (tool tip)
- To obtain more information from different angles
- Transformation needed: robot end-effector -> tool tip

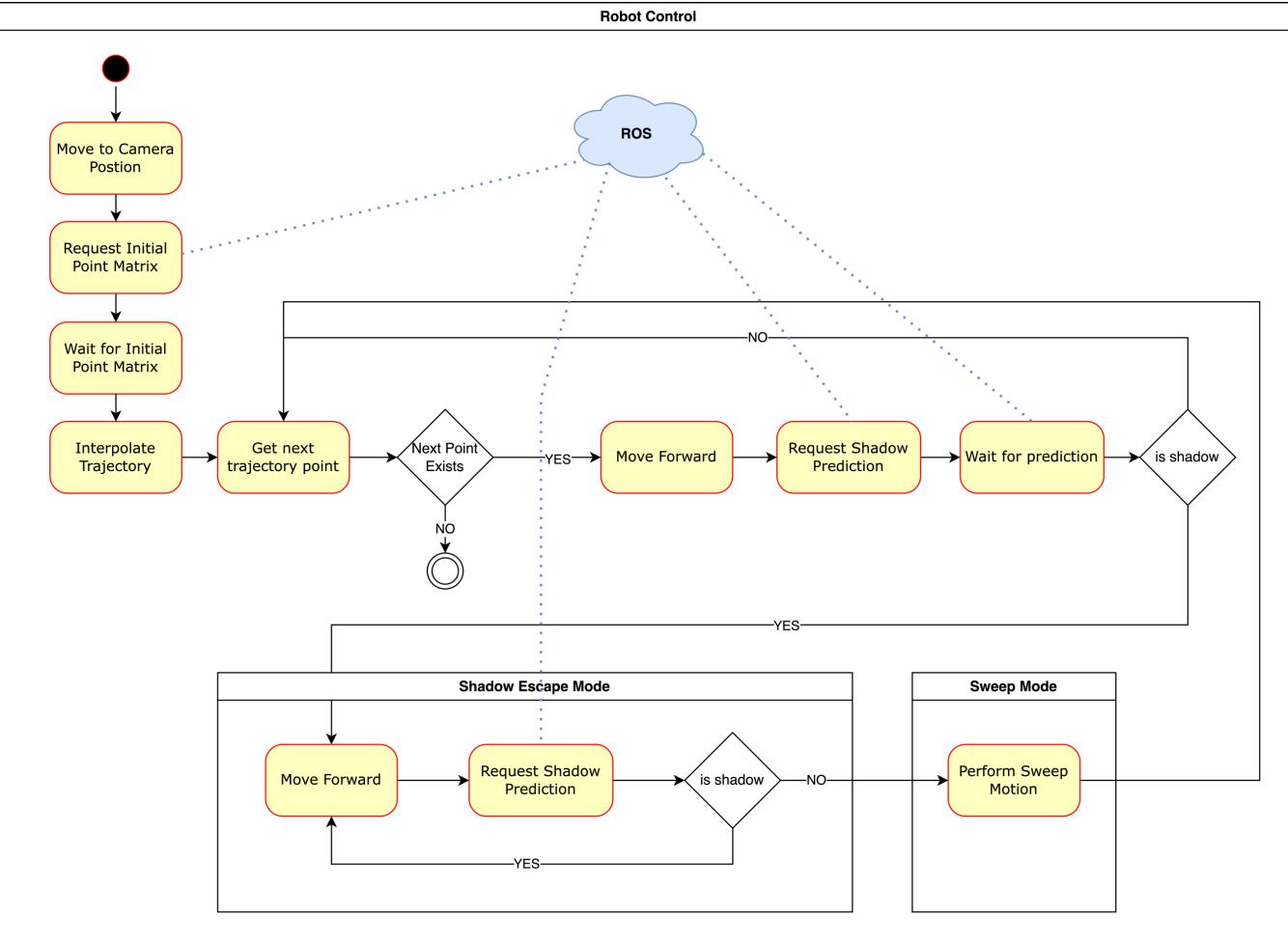


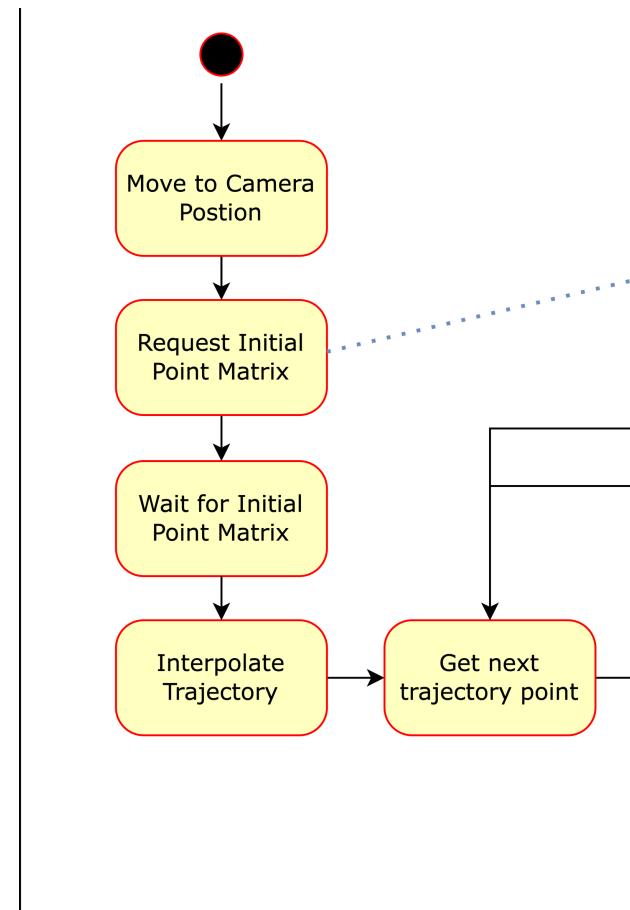
# Trajectory Planning: Sweeping Strategy

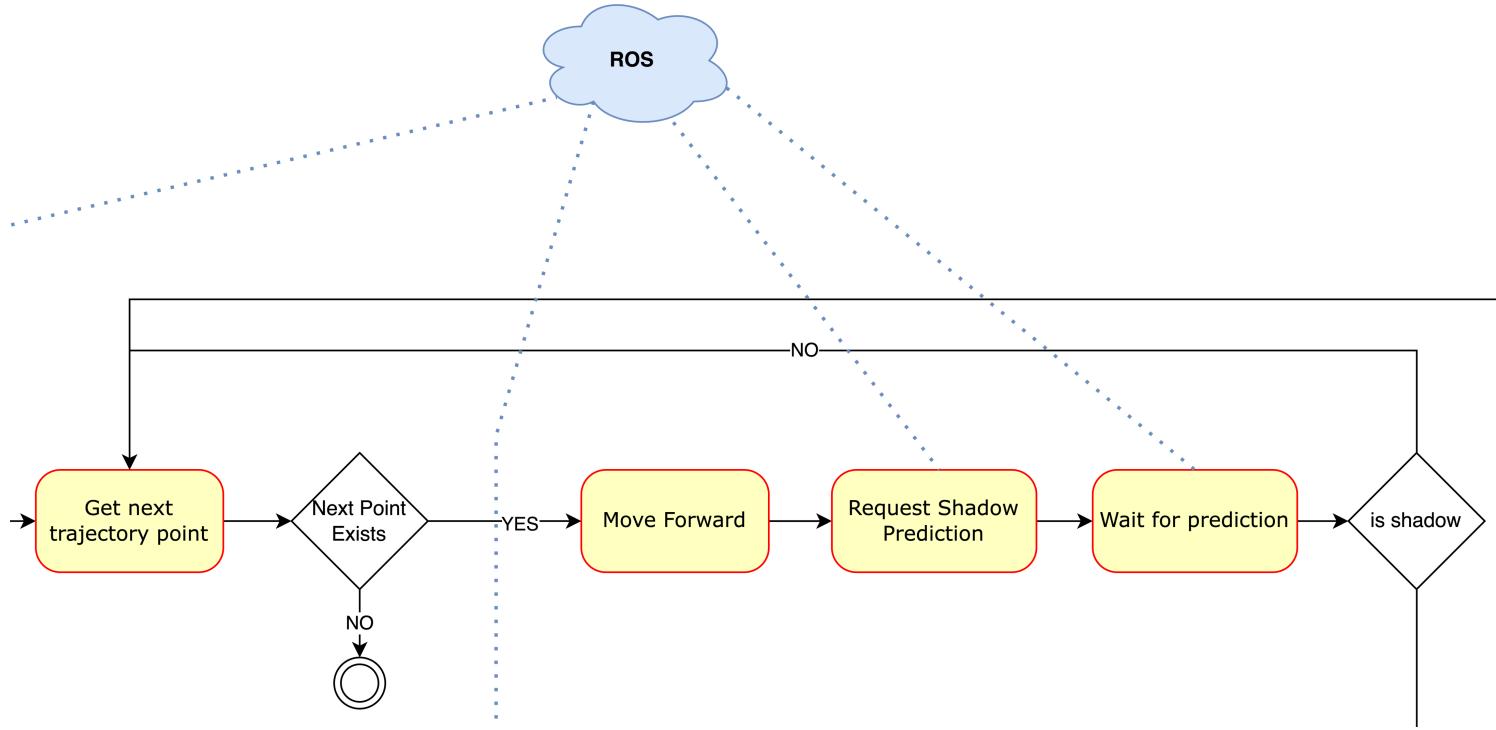
Where is the best location to sweep?

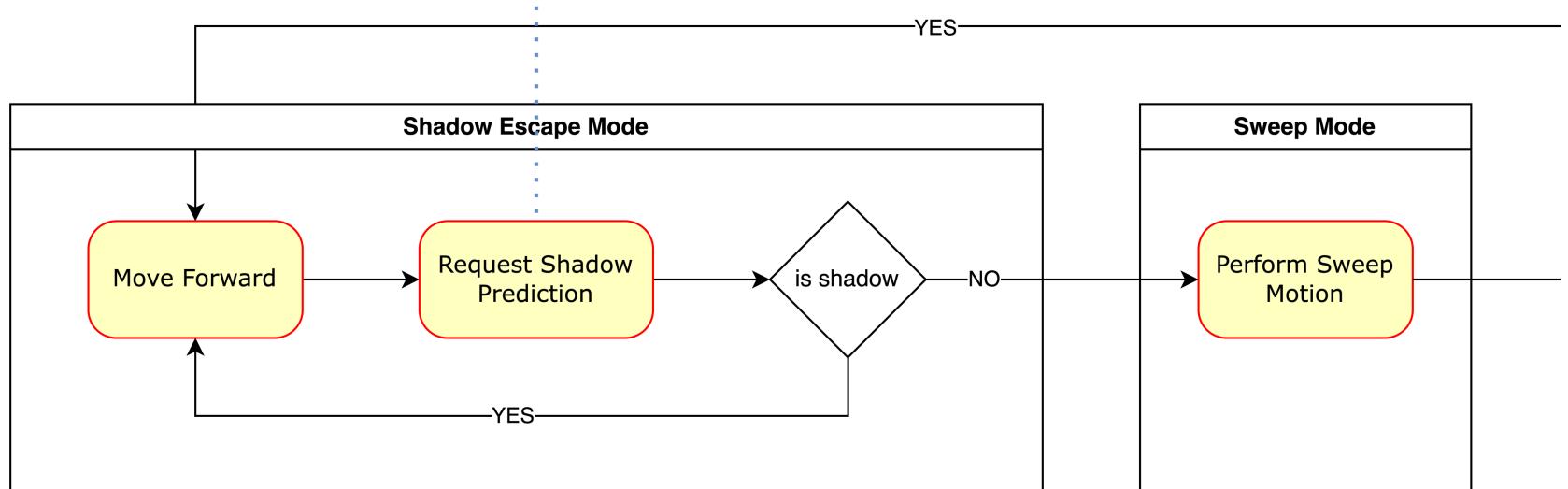
- Shadow detection



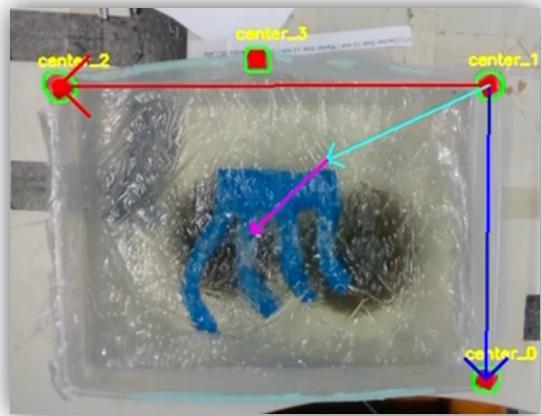




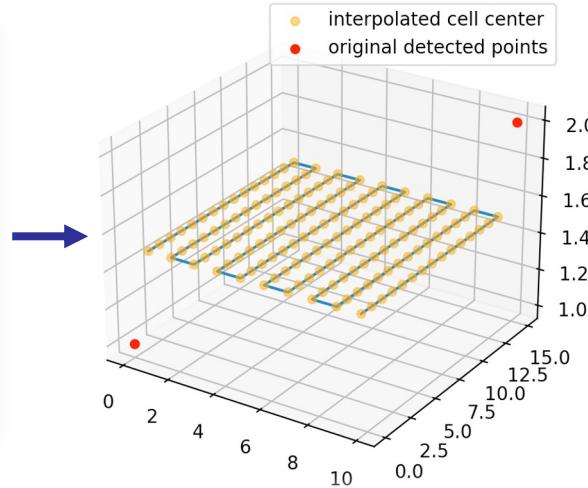




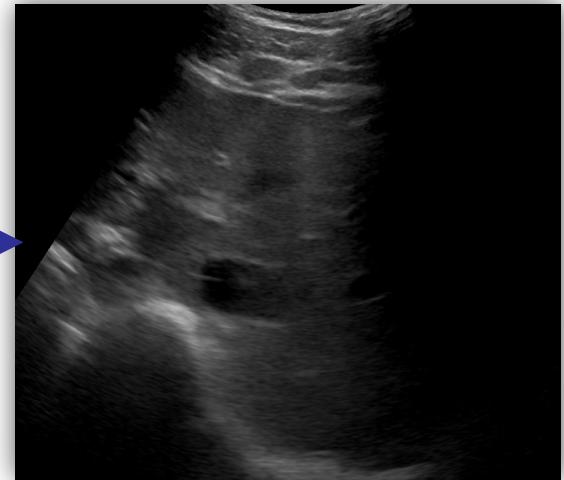
# Components Overview



Initial Point Detection



Trajectory Planning

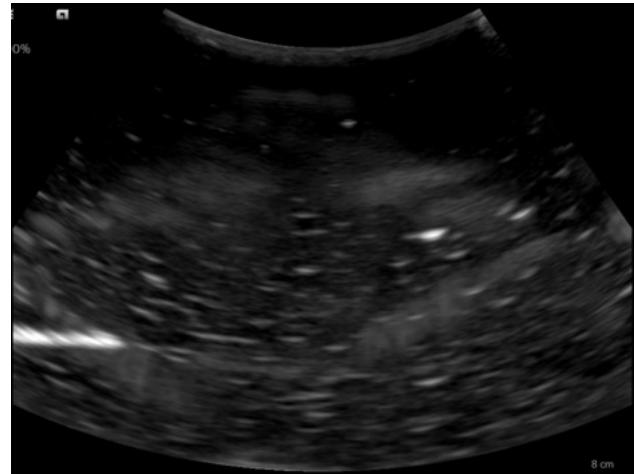


Shadow Detection

# 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

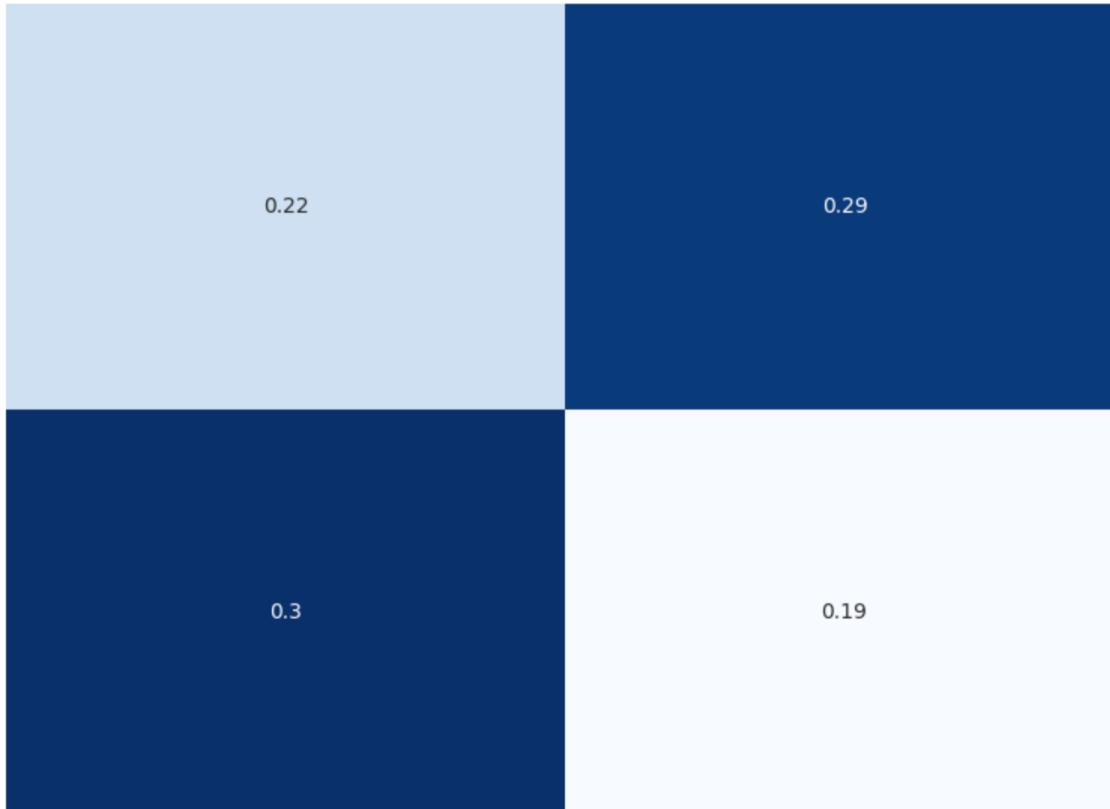


Liver or Shadow?



# Components: Shadow Detection

Confusion matrix



# 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



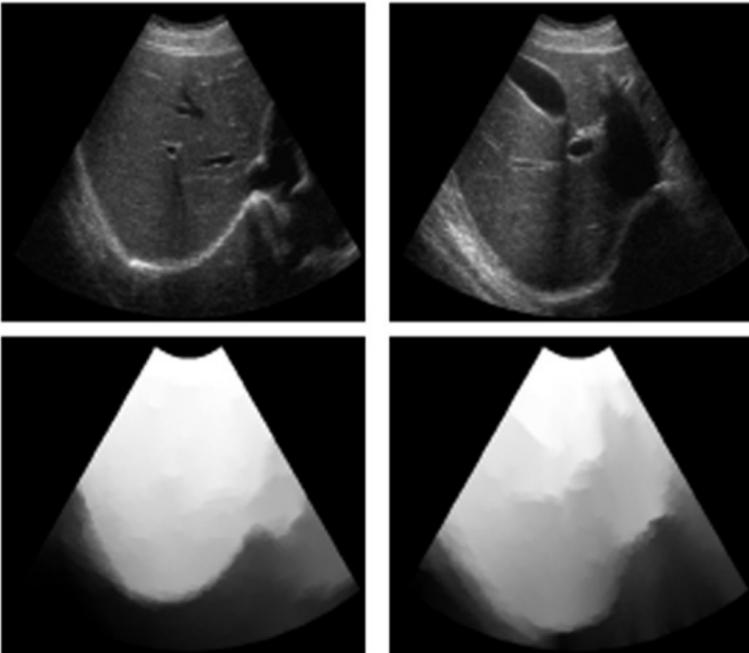
# Components: Shadow Detection

## 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](https://doi.org/10.1016/j.media.2012.07.005).



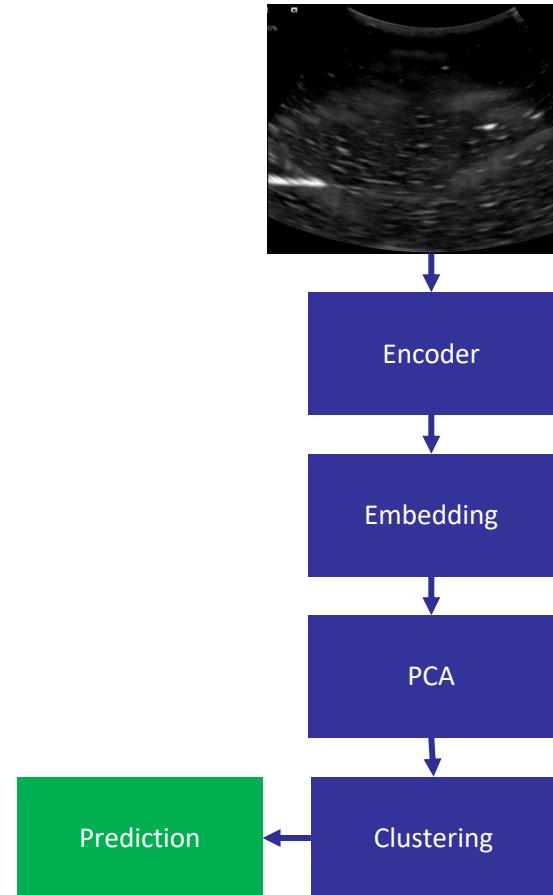
# Components: Shadow Detection

## Final Approach

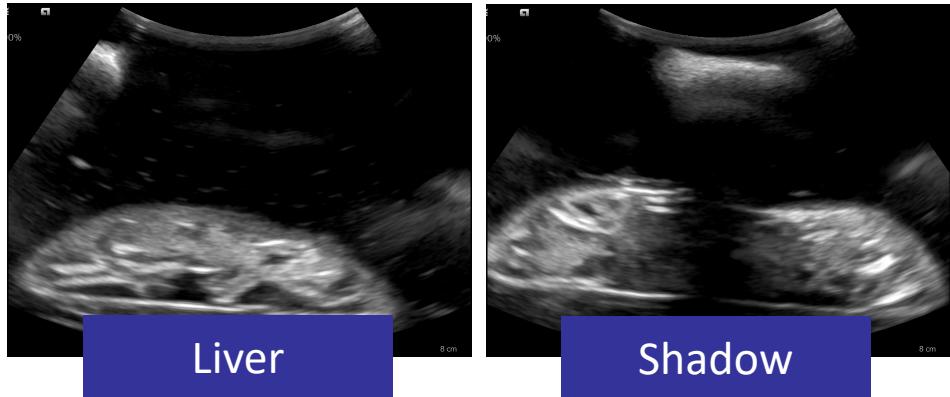
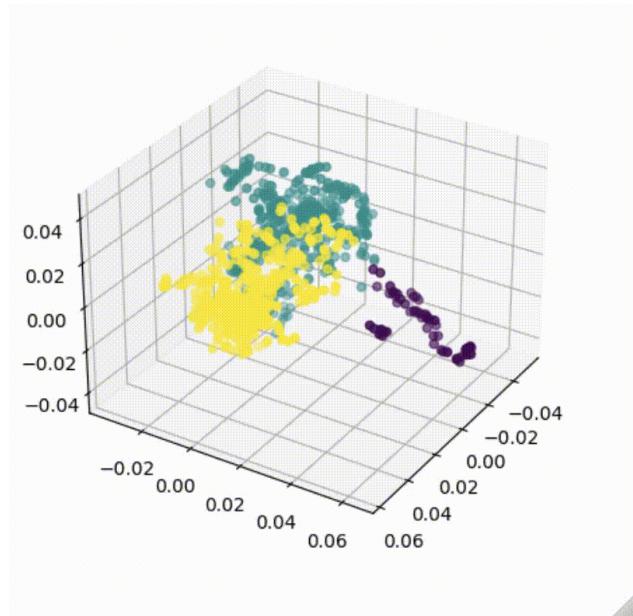
- Use Autoencoder to learn meaningful embeddings
- Reduce dimensionality using PCA
- Cluster reduced embeddings
- Perform classification based on cluster id

## Benefits

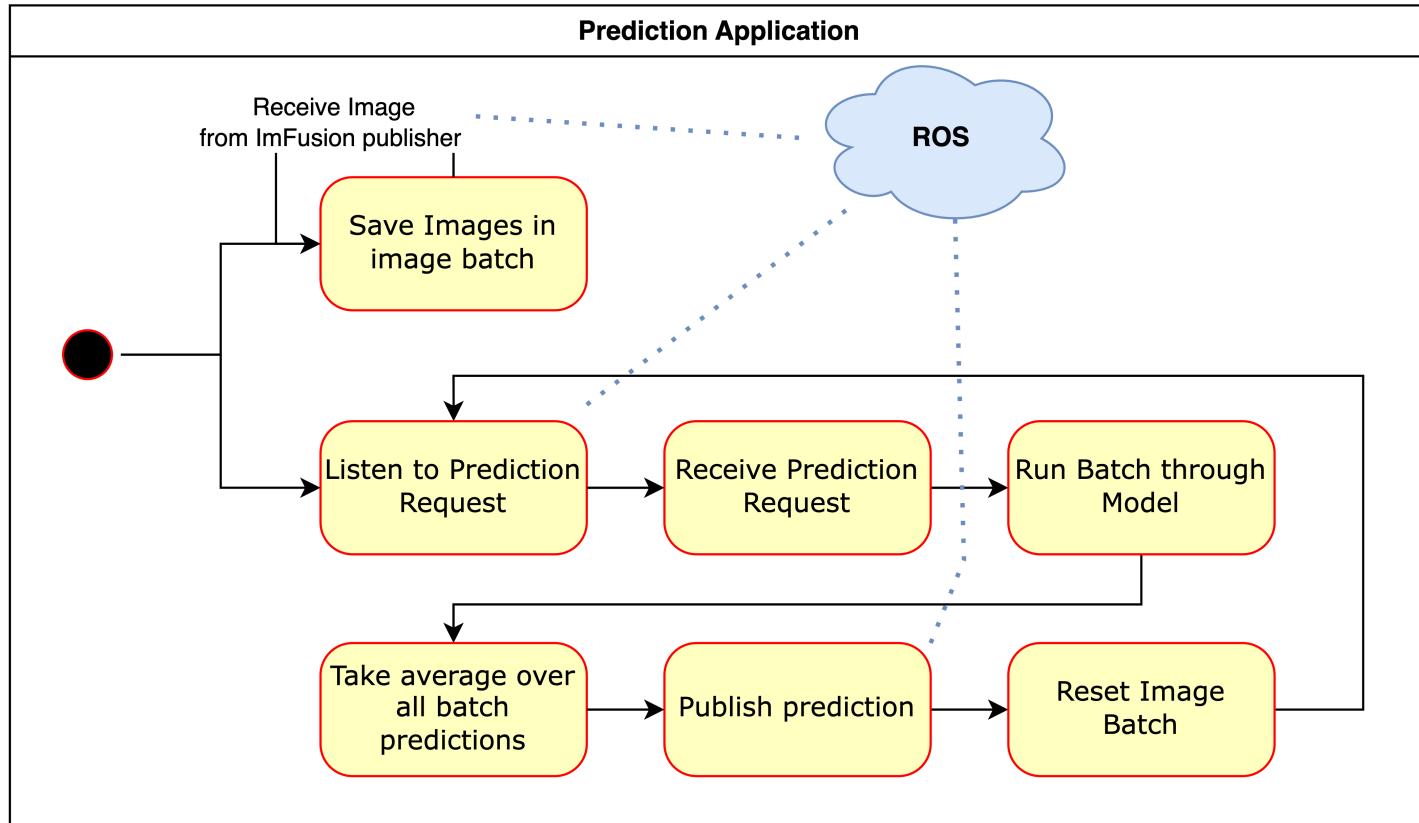
- unsupervised training => no labeling task
- fast training
- real-time application possible without noticeable latency, even for large batches up to 512 images



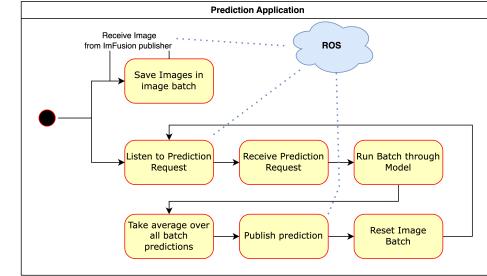
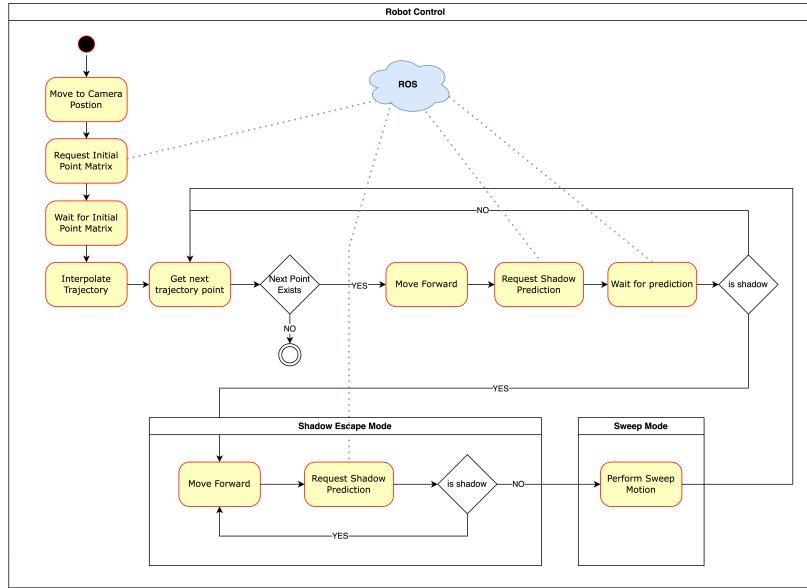
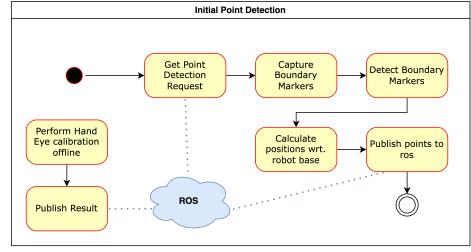
# Components: Shadow Detection



# Components: Shadow Detection



# Components: The bigger picture





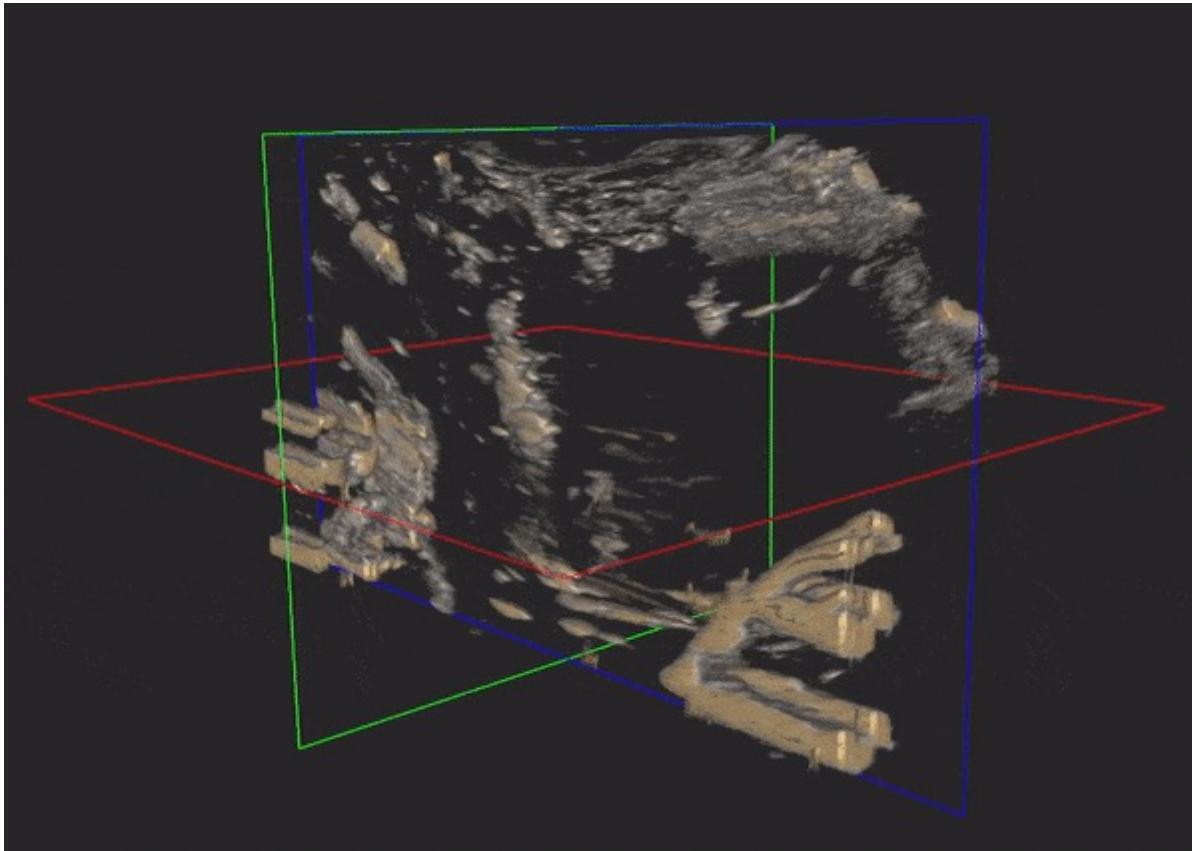
# Demo



# 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





Thank you for your attention.