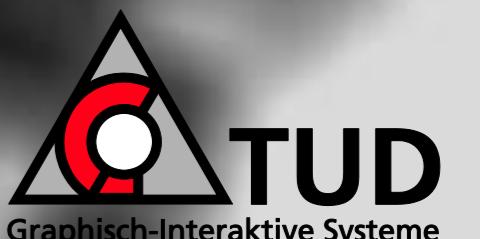
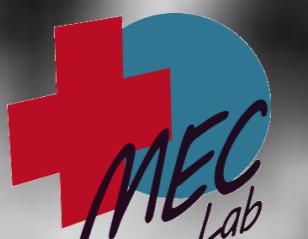


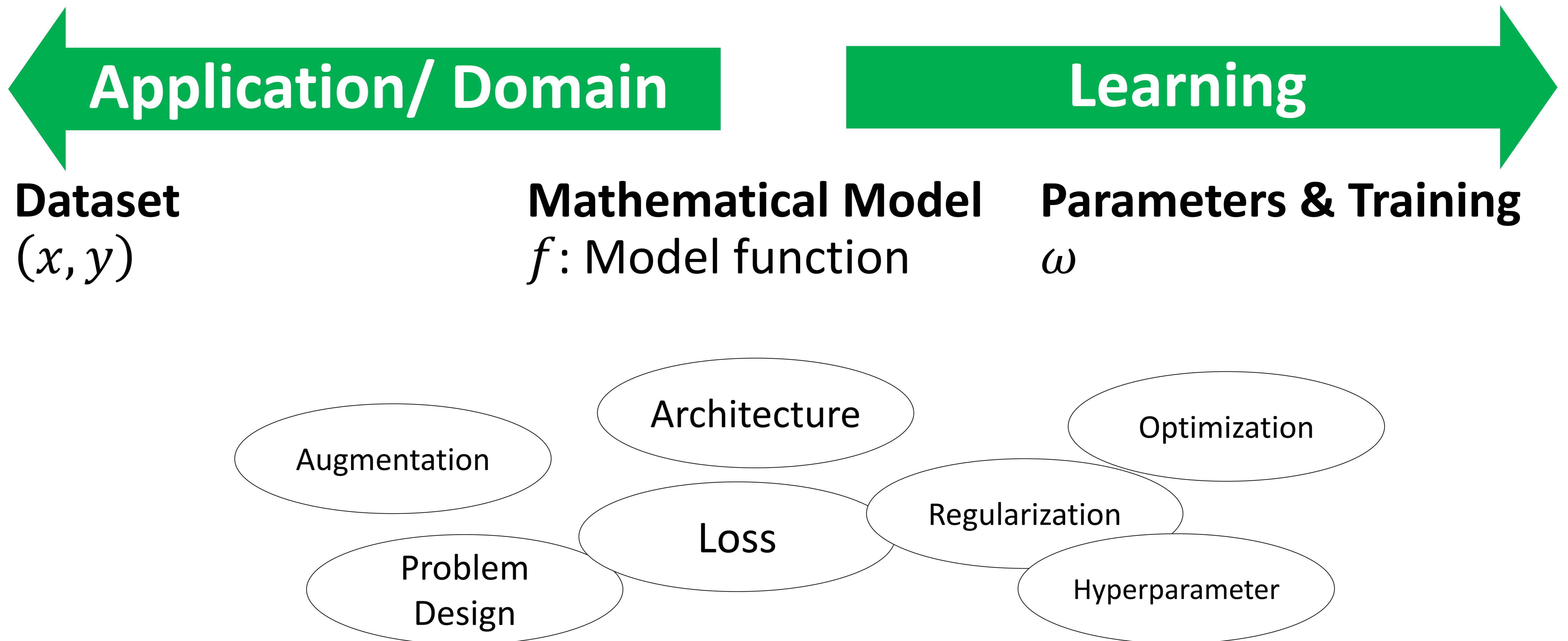
# i3PosNet: instrument pose estimation from X-Ray in temporal bone surgery

David Kögler - Jannik Sehring - Andrei Stefanov  
Igor Stenin - Julia Kristin - Thomas Klenzner  
Jörg Schipper - Anirban Mukhopadhyay



@kueglerd @anirbanakash

# Learning for X



# Learning for CAI

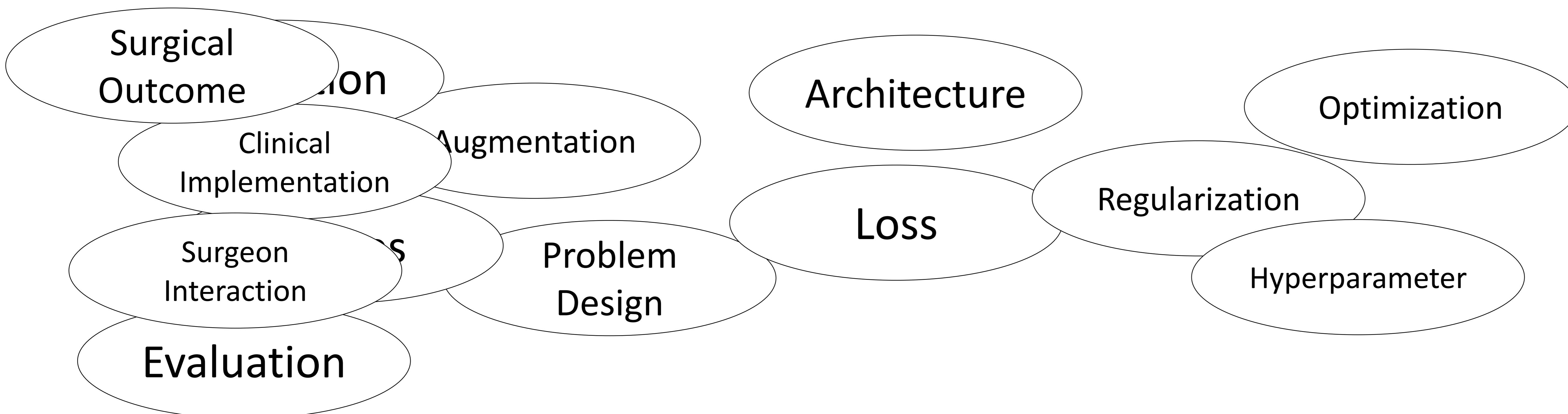
Application/ Domain

Learning

~~Dataset~~  
Application

Mathematical Model  
 $f$ : Model function

Parameters & Training  
 $\omega$



# Clinical Scenario

- Cochlear implant
- Tumor removal:  
Vestibular schwannoma

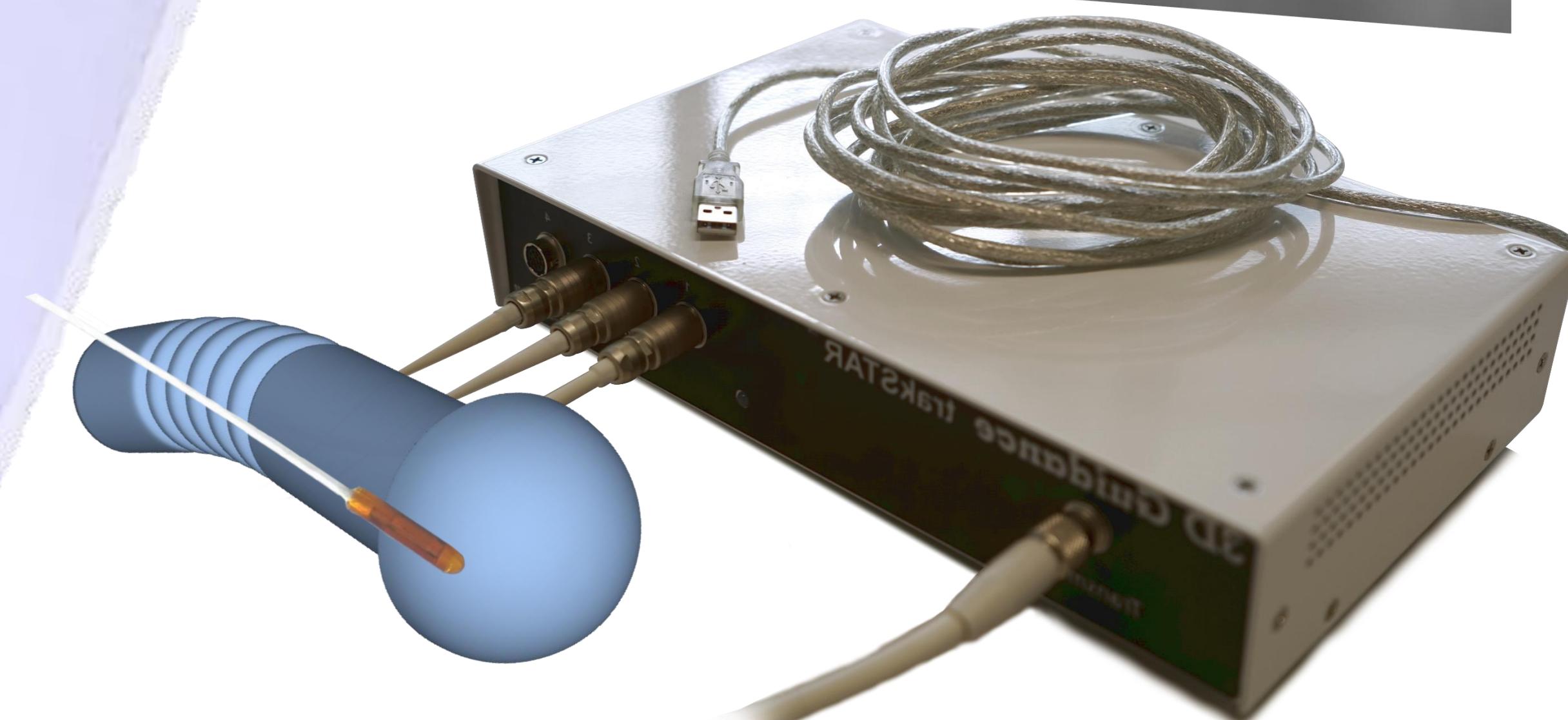
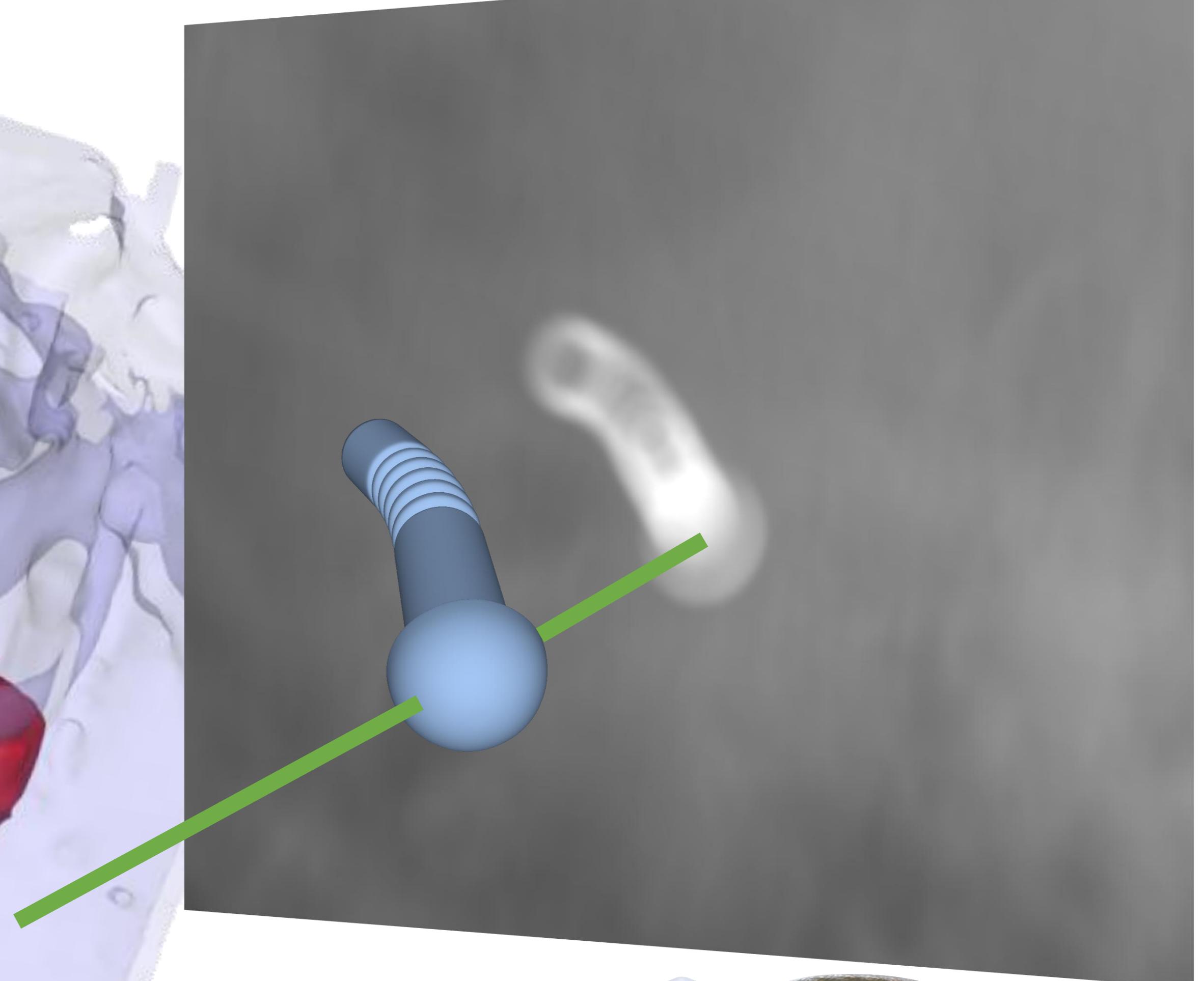
# Workflow

EMT

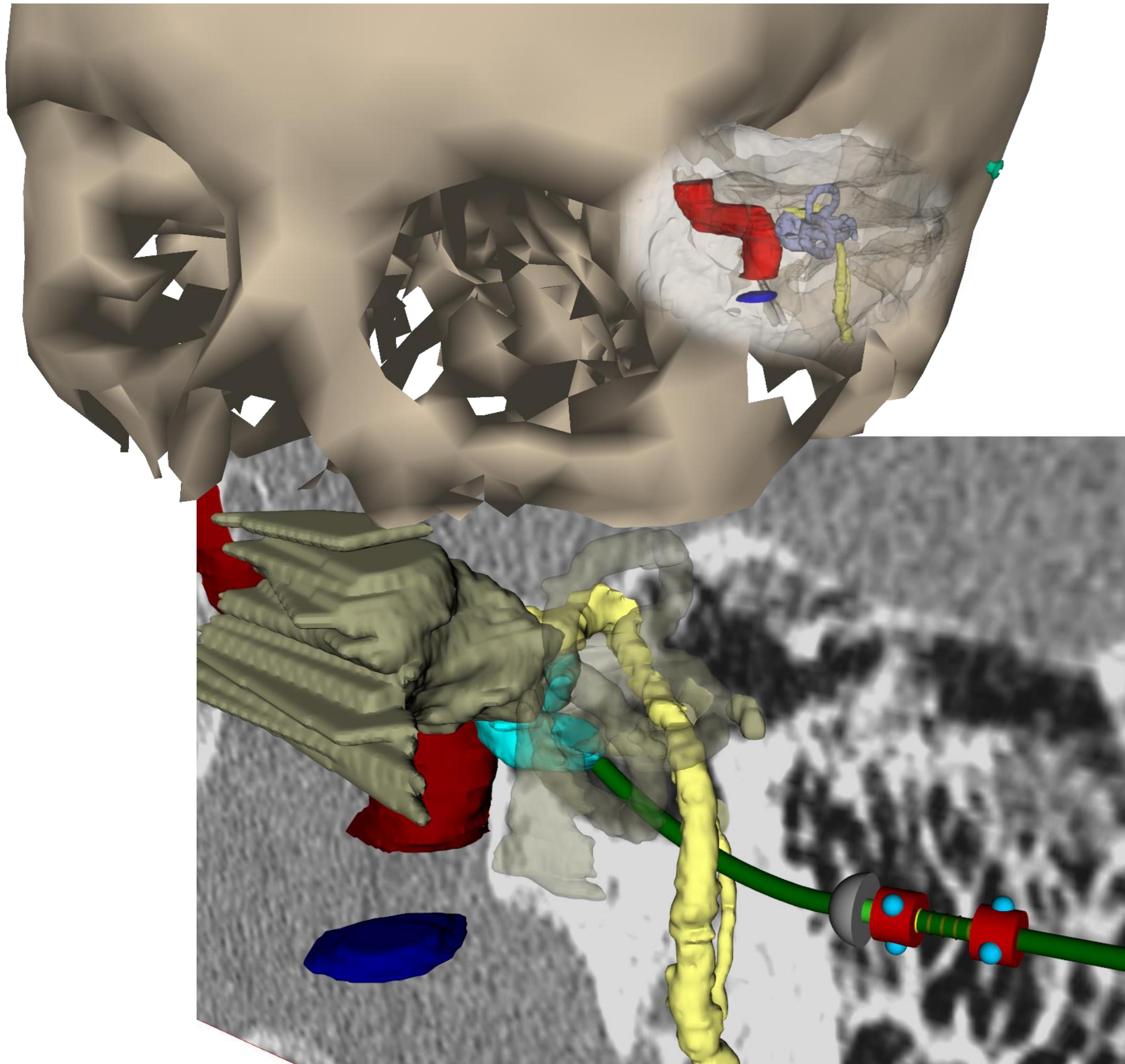


Imaging & Planning - Pose Estimation / Tracking - Navigation

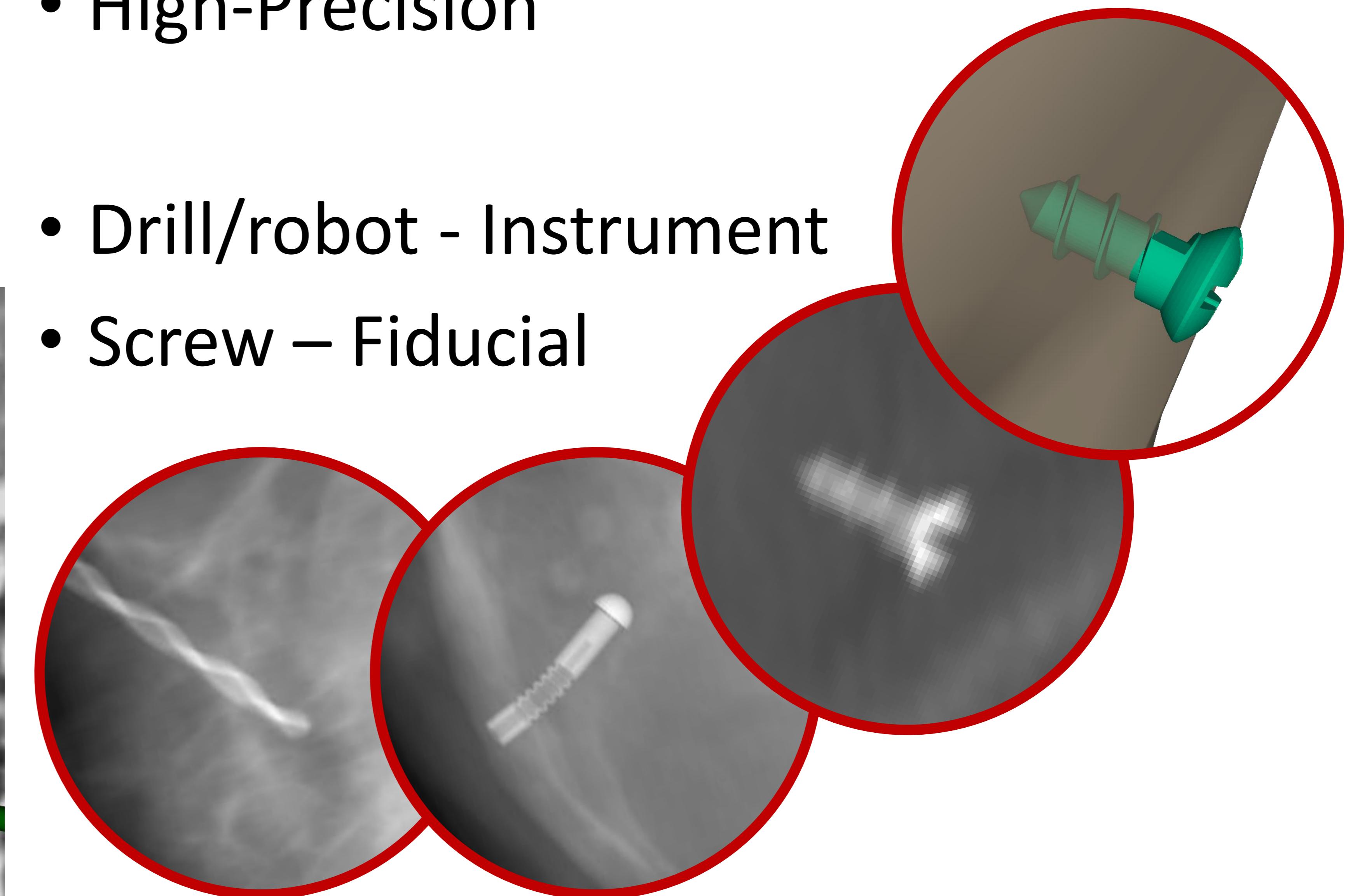
15PosNet, IPCAI2020



# Temporal bone surgery



- Minimally-Invasive
- High-Precision
- Drill/robot - Instrument
- Screw – Fiducial



i3PosNet, IPCAI2020

# AI-readiness of CAI

Application/ Domain

Learning

Bedside Application

Dataset  
 $(x, y)$

Mathematical Model  
 $f$ : Model function

Parameters & Training  
 $\omega$

Surgical Outcome

Clinical Implementation

Surgeon Interaction

Annotation

Augmentation

Architecture

Optimization

Images

Problem Design

Regularization

Hyperparameter

Evaluation

# Generating a CAI Dataset

Images/Annotation - Augmentation - Problem Design

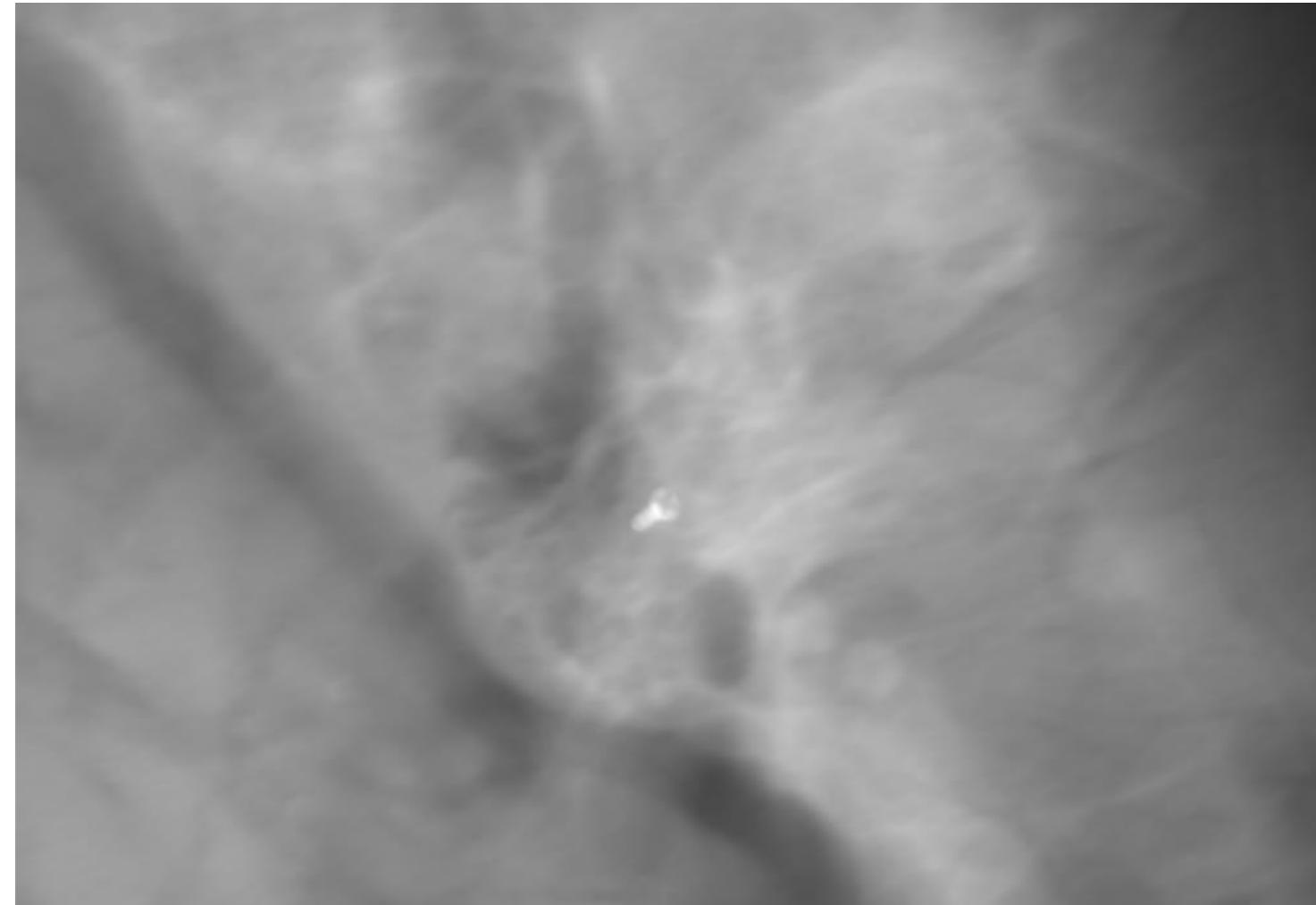
# Dataset

<https://i3posnet.david-kuegler.de/>

## Synthetic Images (DRR)

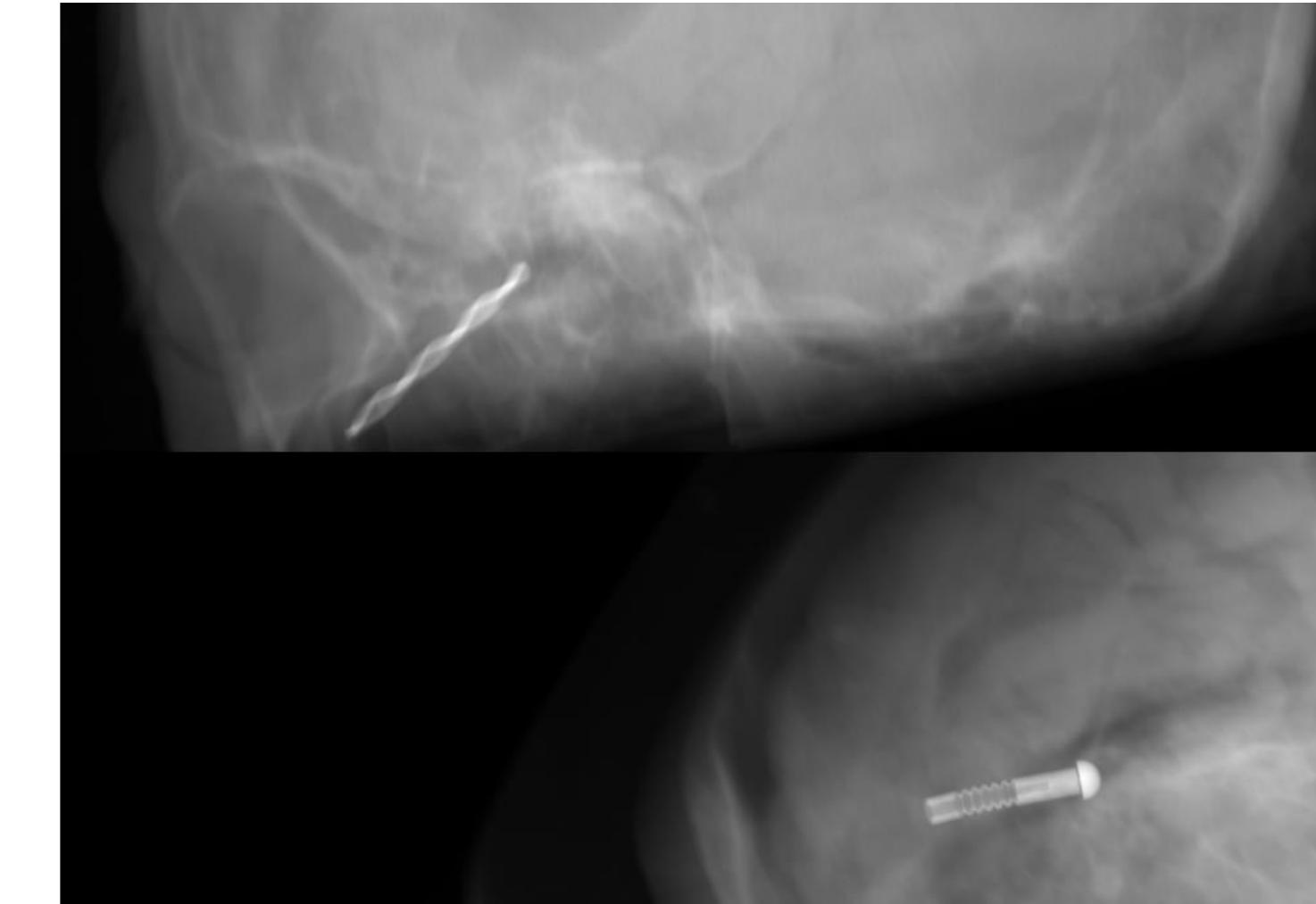
### Dataset A

- Screw
- Geometric annotation
- 18k images



### Dataset B

- Robot and drill
- 2x 18k images



## Real X-ray

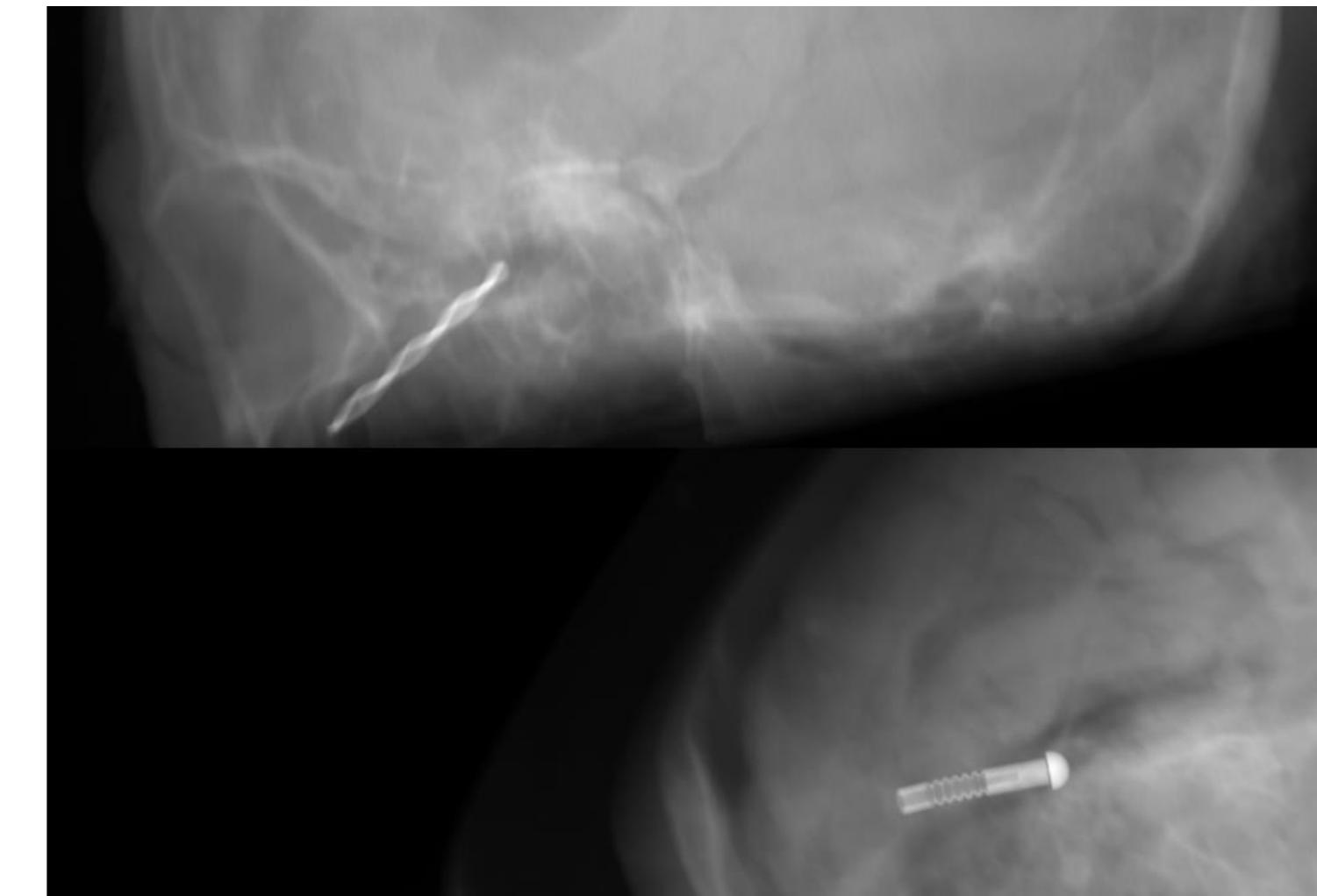
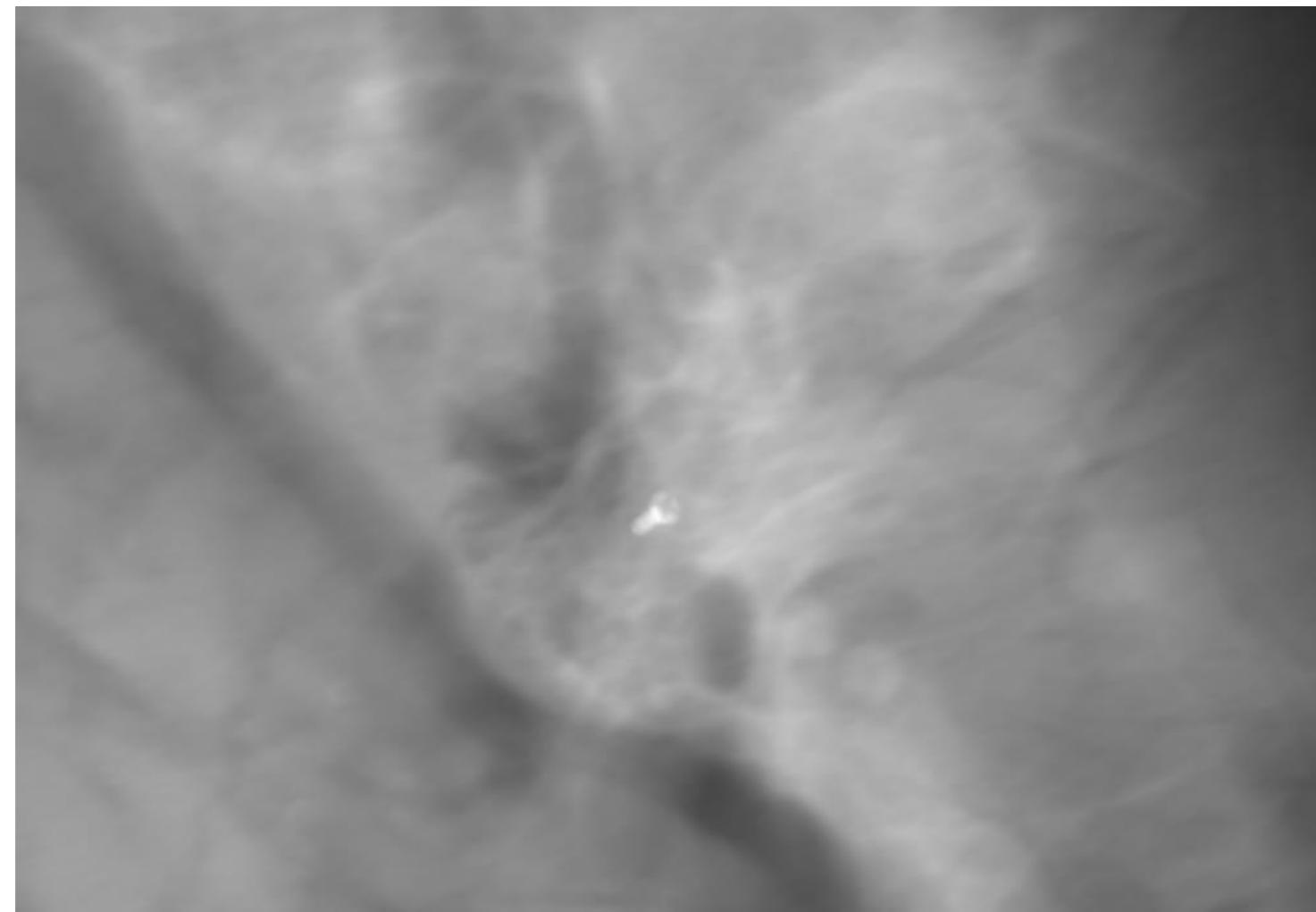
### Dataset C

- Screw
- Manual annotation
- 540 images



# Dataset limitations

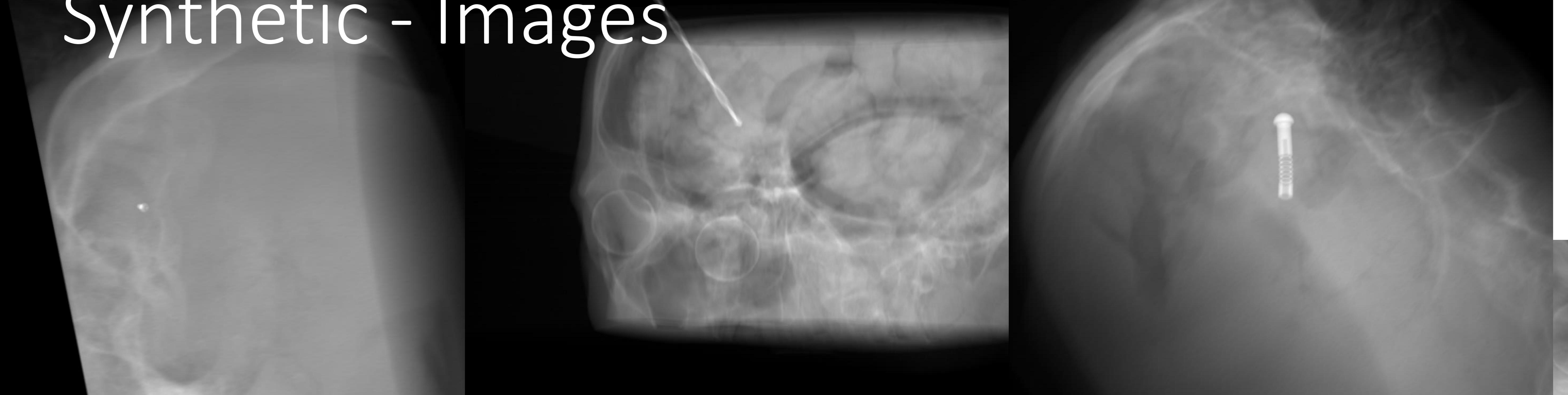
Generation	Image Realism	Annotation Quality	Cost / size
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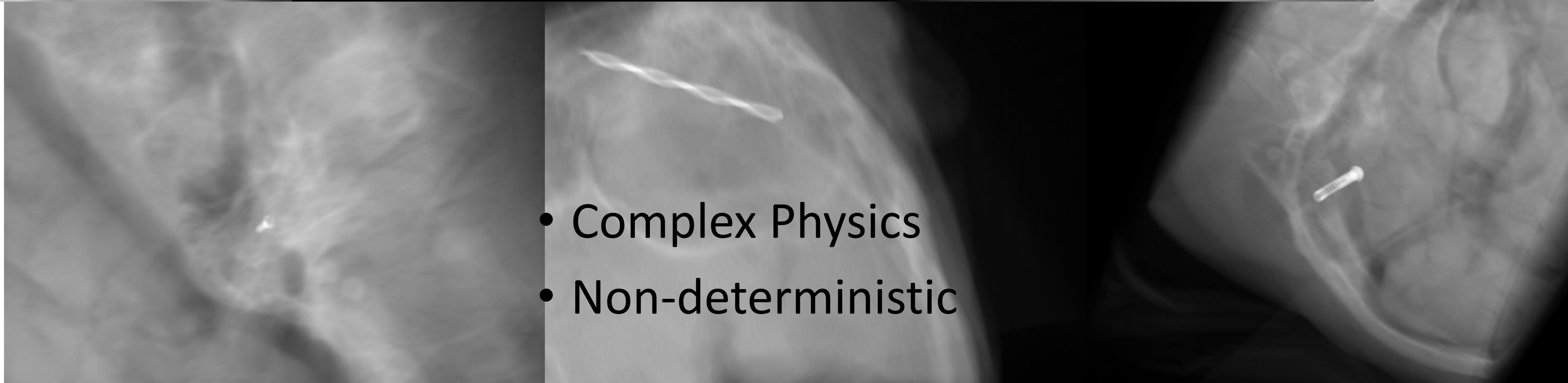
# Real x-ray - images

- Phantom and manufacturing differences → only proxy
- Ethics → no actual humans
- Non-destructive

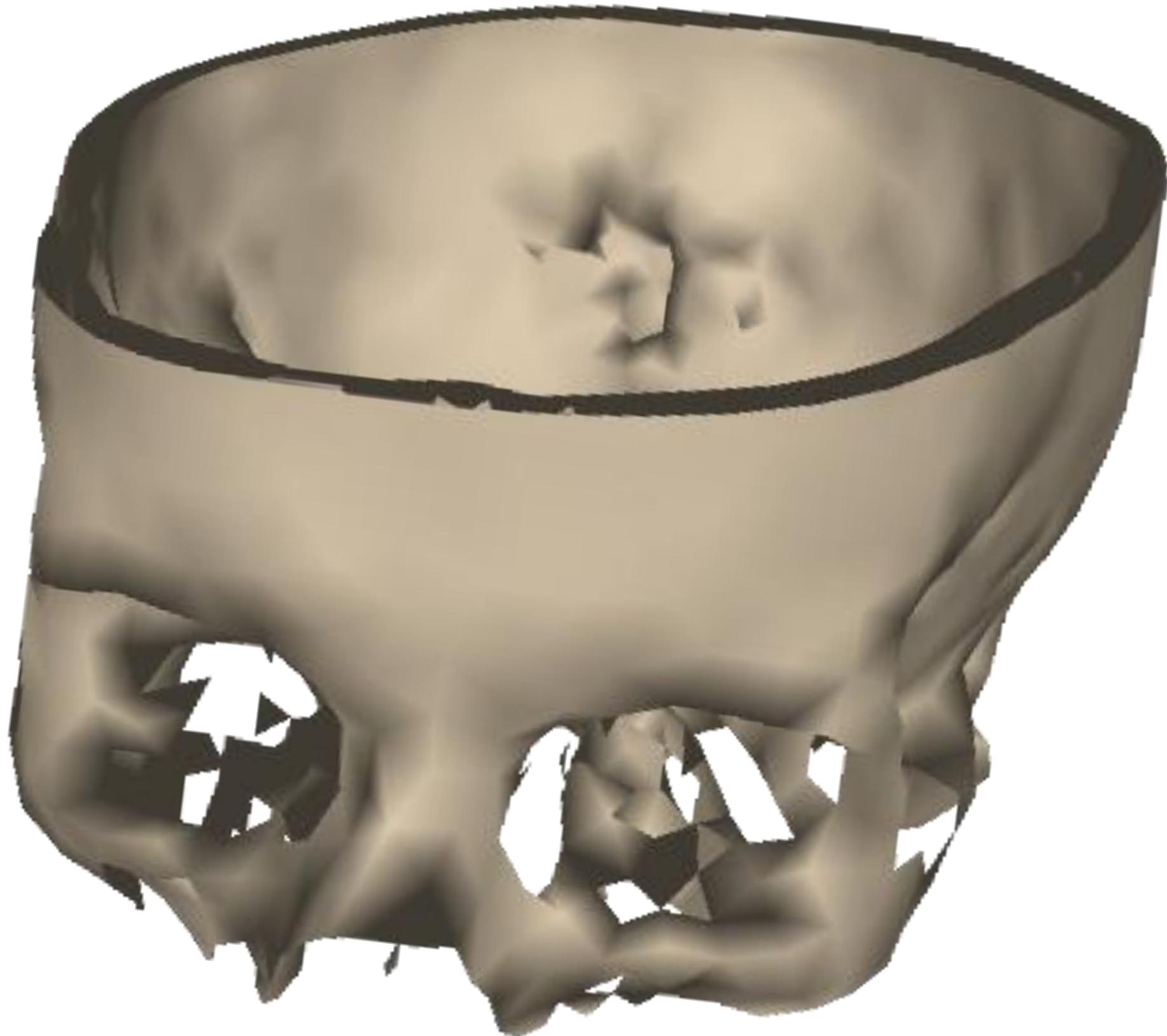
# Synthetic - Images



- Complex Physics
- Non-deterministic



# Generation of a Dataset



## Stochastic Sampling of

- Projection and
- Pose Parameters

---

### Algorithm 1: Generation of DRRs for training and testing

**Input:** Distributions  $\mathcal{P}(\vec{x}_{instr})$ ,  $\mathcal{P}(\vec{n}_{instr})$  and  $\mathcal{P}(P)$ ,  
Polygons  $\vec{x}_{poly,i}$  for  $i \in \{lower, upper\}$ , CTVolumeData,  
InstrumentMesh

**Output:** Image, pose  $\theta$

```

1: repeat
2:    $\vec{x}_{instr} \leftarrow \text{draw\_position}(\mathcal{P}(\vec{x}_{instr}))$ 
3:    $\vec{n}_{instr} \leftarrow \text{draw\_orientation}(\mathcal{P}(\vec{n}_{instr}))$ 
4:   repeat
5:      $P \leftarrow \text{draw\_projection}(\mathcal{P}(P))$ 
6:      $\theta \leftarrow \text{project\_point}(P, \vec{x}_{instr})$        $\triangleright$  Output pose
7:      $\theta_{poly,i} \leftarrow \text{project\_point}(P, \vec{x}_{poly,i})$ 
8:     valid  $\leftarrow \text{not any}(\text{inside\_polygon}(\vec{x}_{instr}, \theta_{poly,i}))$ 
9:   until valid           $\triangleright$  Fail after a defined number of
10:  until valid          $\triangleright$  unsuccessful iterations.
11:  Anatomy  $\leftarrow \text{interpolate}(\text{CTVolumeData})$ 
12:  Mesh  $\leftarrow \text{transform}((\vec{x}_{instr}, \vec{n}_{instr}), \text{InstrumentMesh})$ 
13:  Instrument  $\leftarrow \text{rasterize\_mesh}(\text{Mesh})$ 
14:  Volume  $\leftarrow \text{combine}(\text{Anatomy}, \text{Instrument})$ 
15:  Image  $\leftarrow \text{project}(P, \text{Volume})$ 

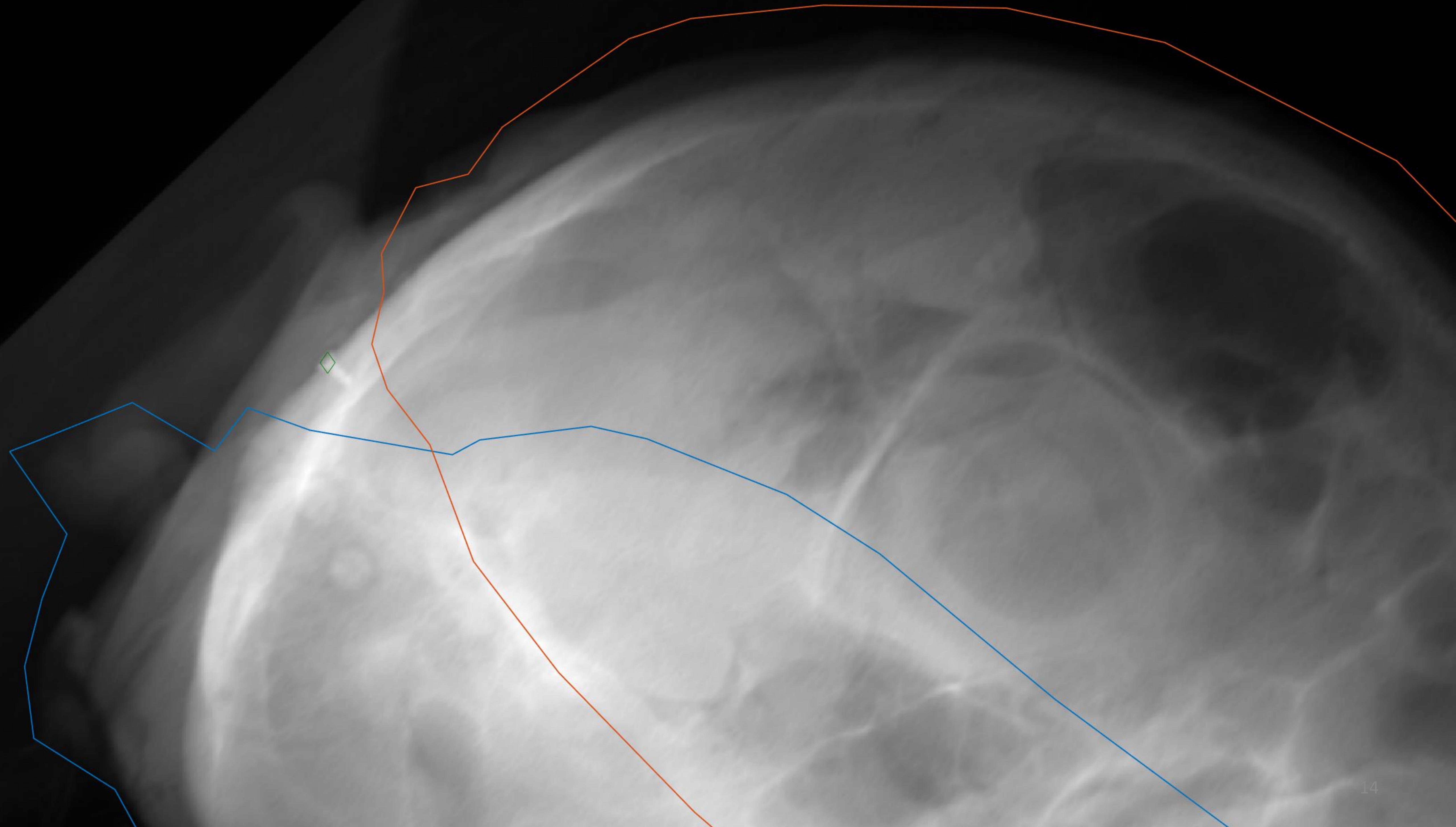
```

---

Parameter	Training	Evaluation
Position	$\mathcal{N}(0, (5 \text{ mm})^2)^3$	$\mathcal{N}(0, (1 \text{ mm})^2)^3$
Orientation (Rotations)	$\mathcal{U}(0^\circ, 360^\circ) \times \mathcal{N}(0, (30^\circ)^2)^2$	$\mathcal{U}(0^\circ, 360^\circ) \times \mathcal{N}(0, (15^\circ)^2)^2$
Projection	$\mathcal{P}(P)$	
• Source-Object-Distance	$\mathcal{P}(d_{SOD})$	$\mathcal{U}(362.8 \text{ mm}, 725.61 \text{ mm})$
• Object Offset	$\mathcal{P}((r, \varphi))$	$\mathcal{U}(0 \text{ mm}, 100 \text{ mm}) \times \mathcal{U}(0^\circ, 360^\circ)$
• Rotations	$\mathcal{P}(P_{Rot})$	$\mathcal{U}(0^\circ, 360^\circ) \times \mathcal{U}(-60^\circ, 60^\circ) \times \mathcal{U}(0^\circ, 360^\circ)$

TABLE I

PARAMETERS OF THE DRR GENERATION WITH  $\mathcal{N}(\mu, \sigma^2)$  FOR NORMAL AND  $\mathcal{U}(\text{MIN}, \text{MAX})$  FOR UNIFORM DISTRIBUTIONS



# Meaningful Annotation

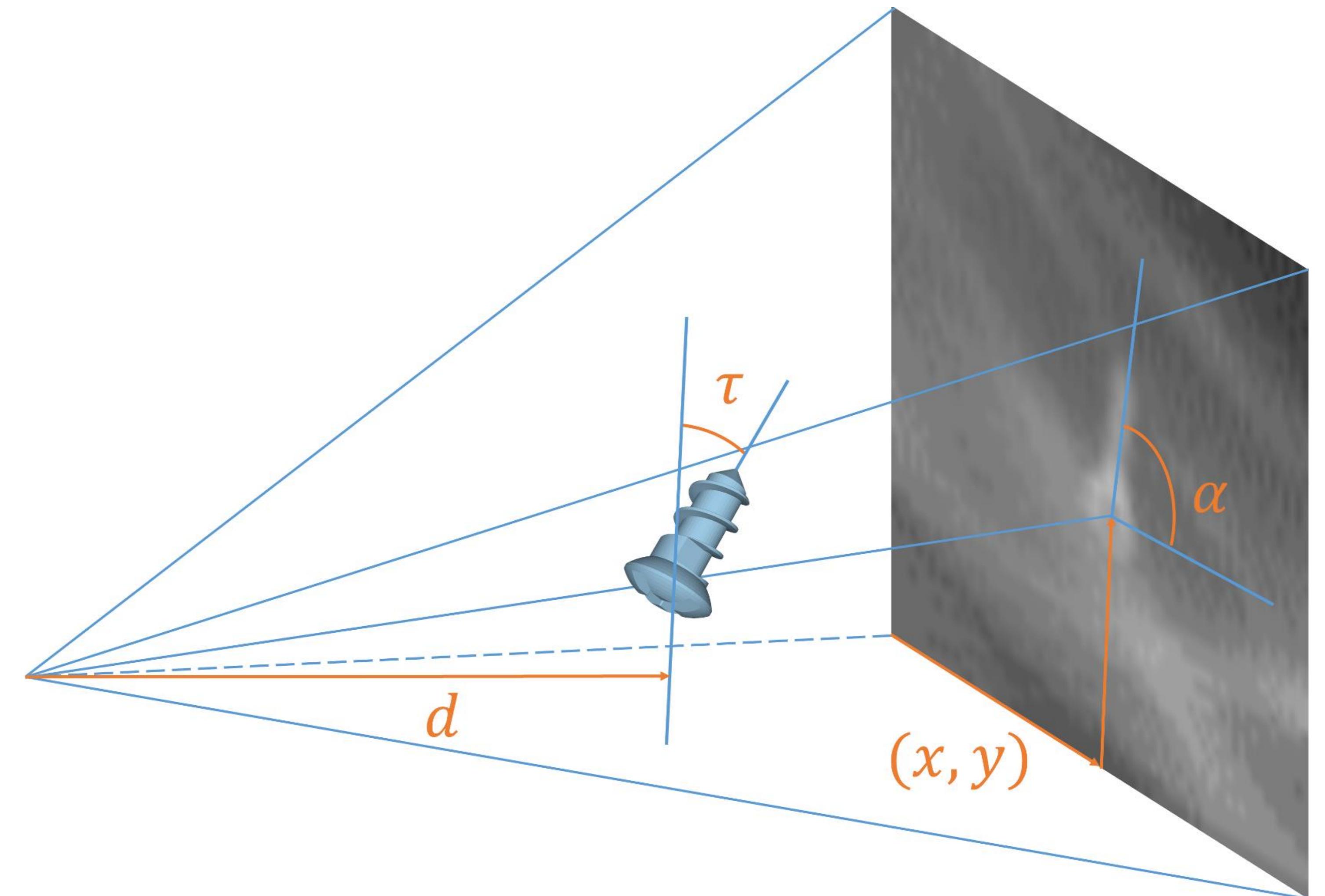
- In projection space

## Synthetic annotation

- Perfect knowledge

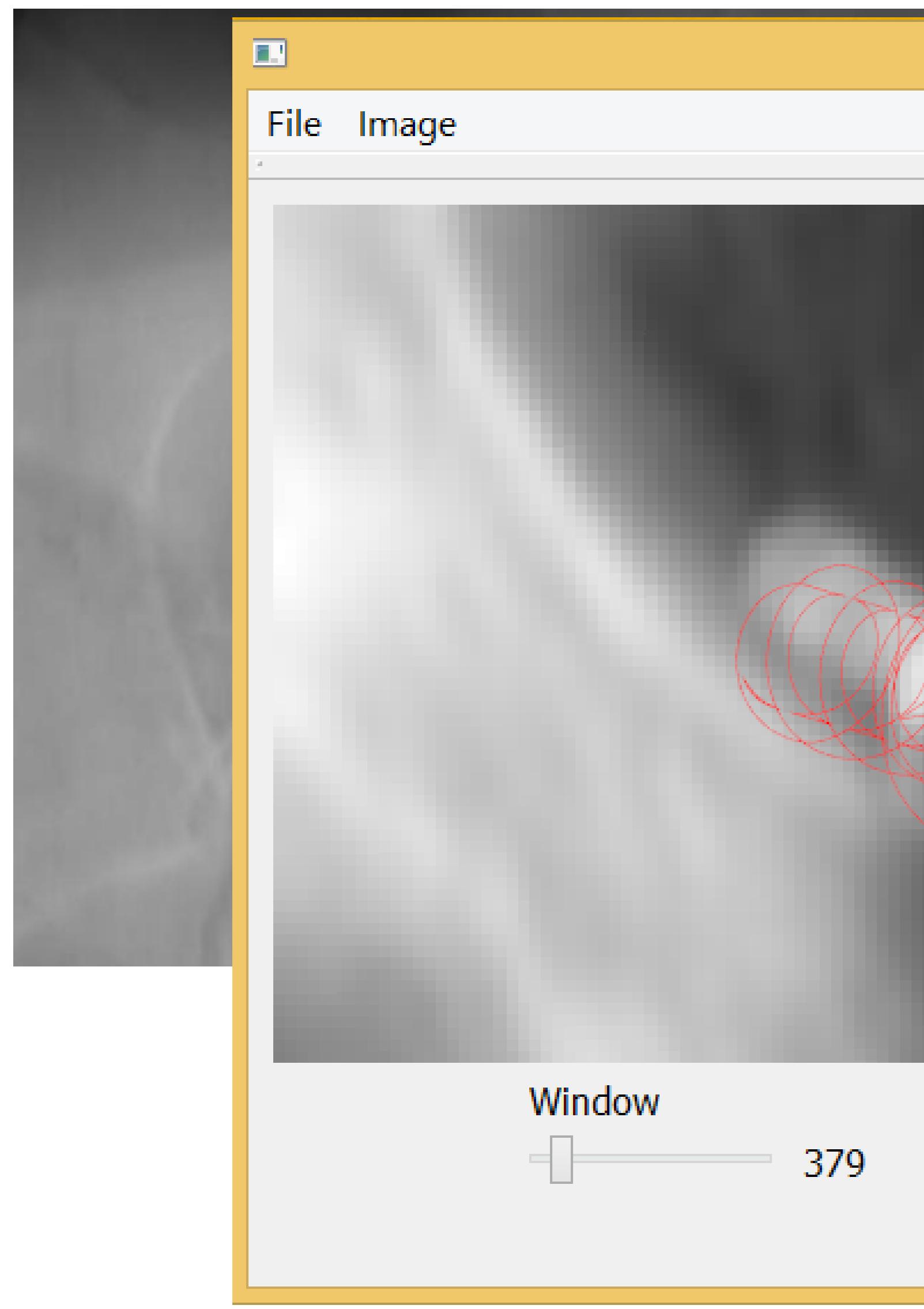
## Real x-ray

- Reference method (Registration)
- Manual
- Calibration

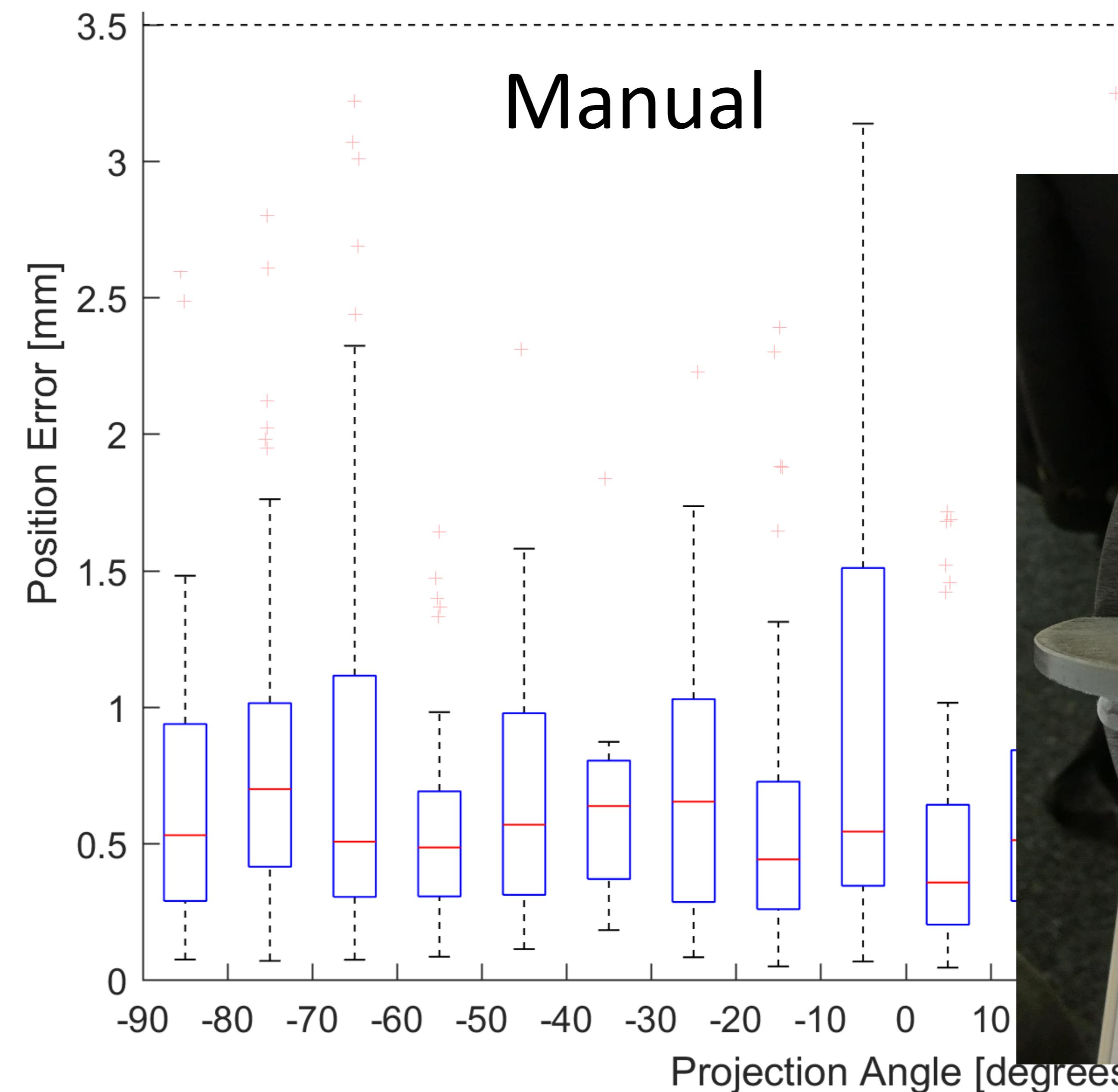


# Real x-ray - Annotation

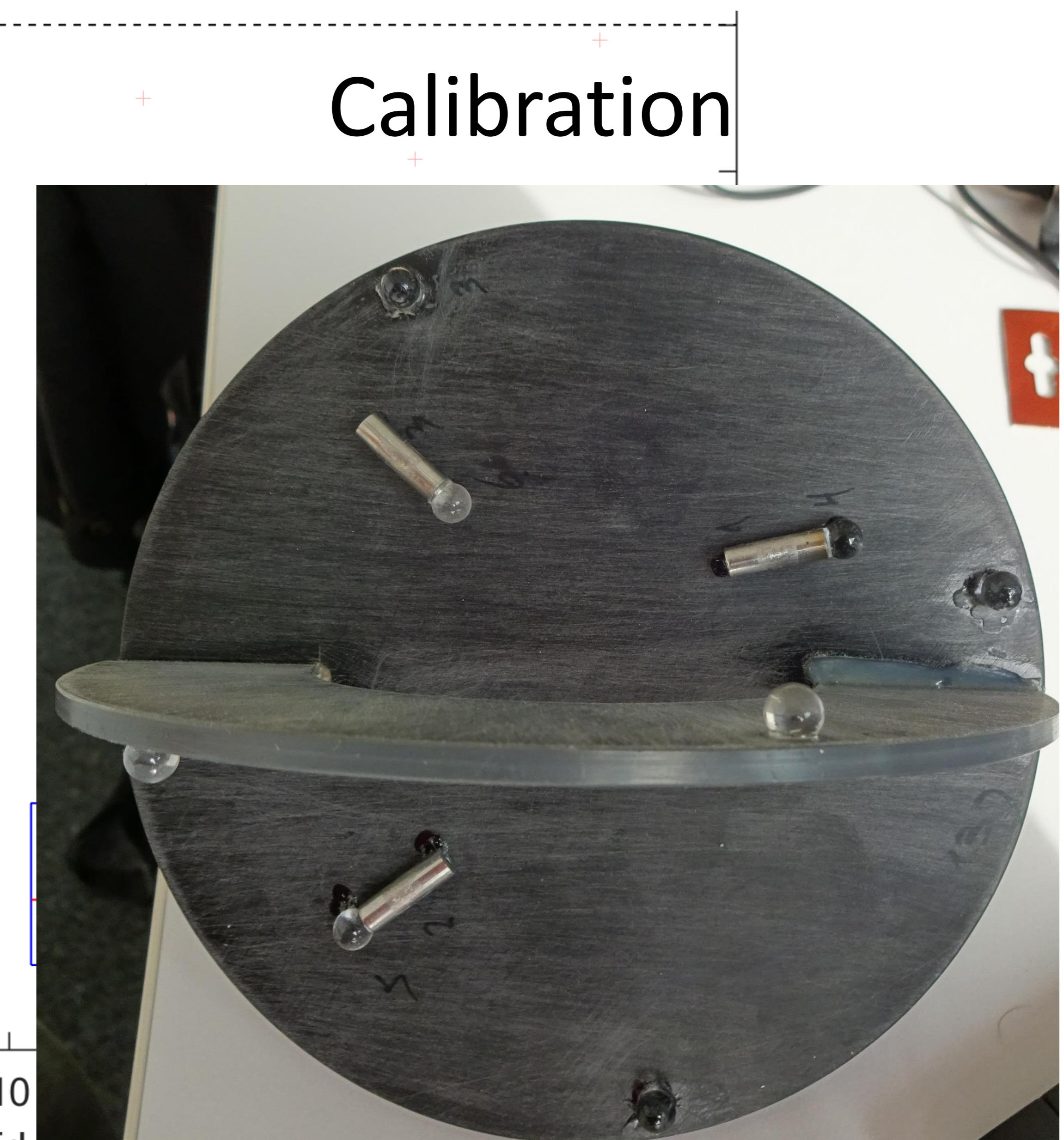
Registration



Manual



Calibration



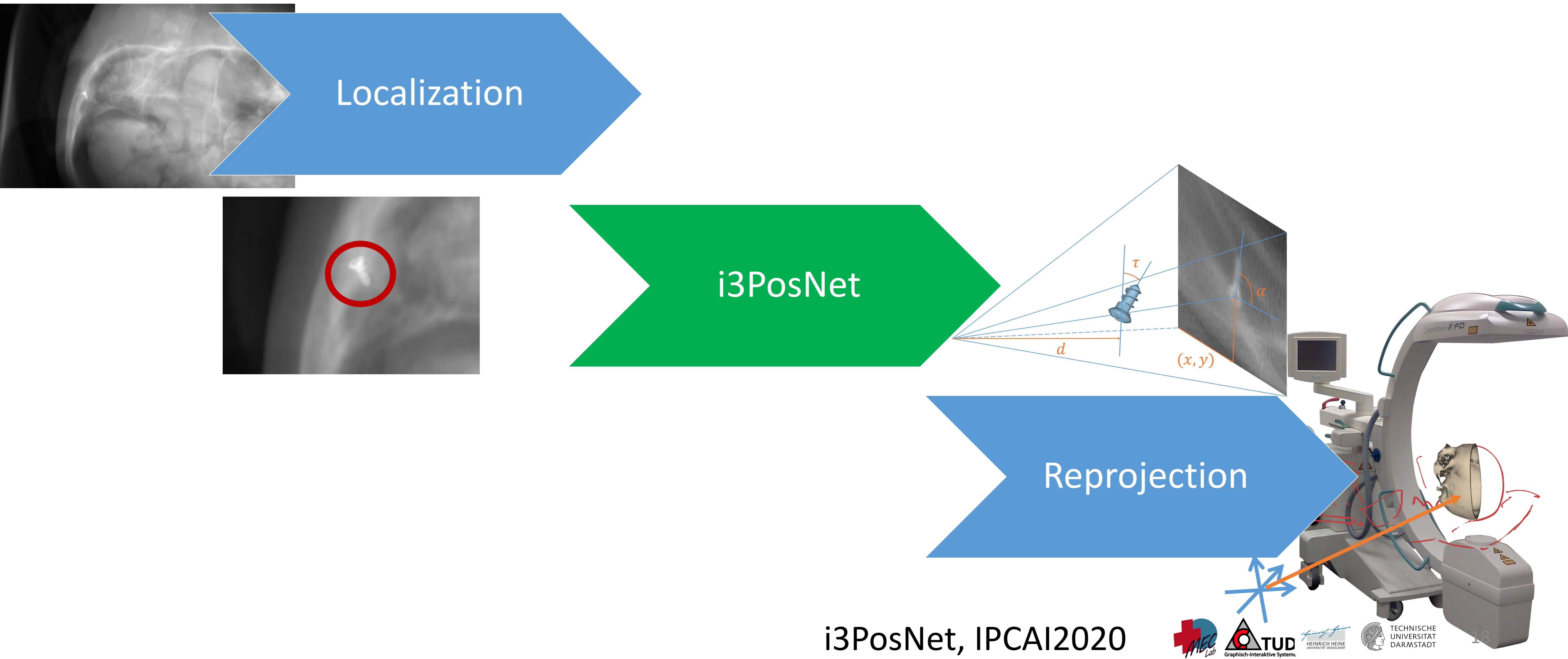
[Krumb et al., IJCARS 2020]

[Kügler et al., WBIR 2018] i3PosNet, IPCAI2020

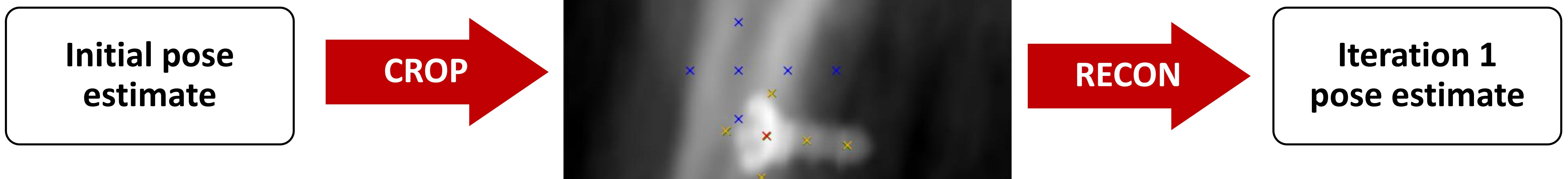
# Appearance Normalization

Images/Annotation - Augmentation - Problem Design

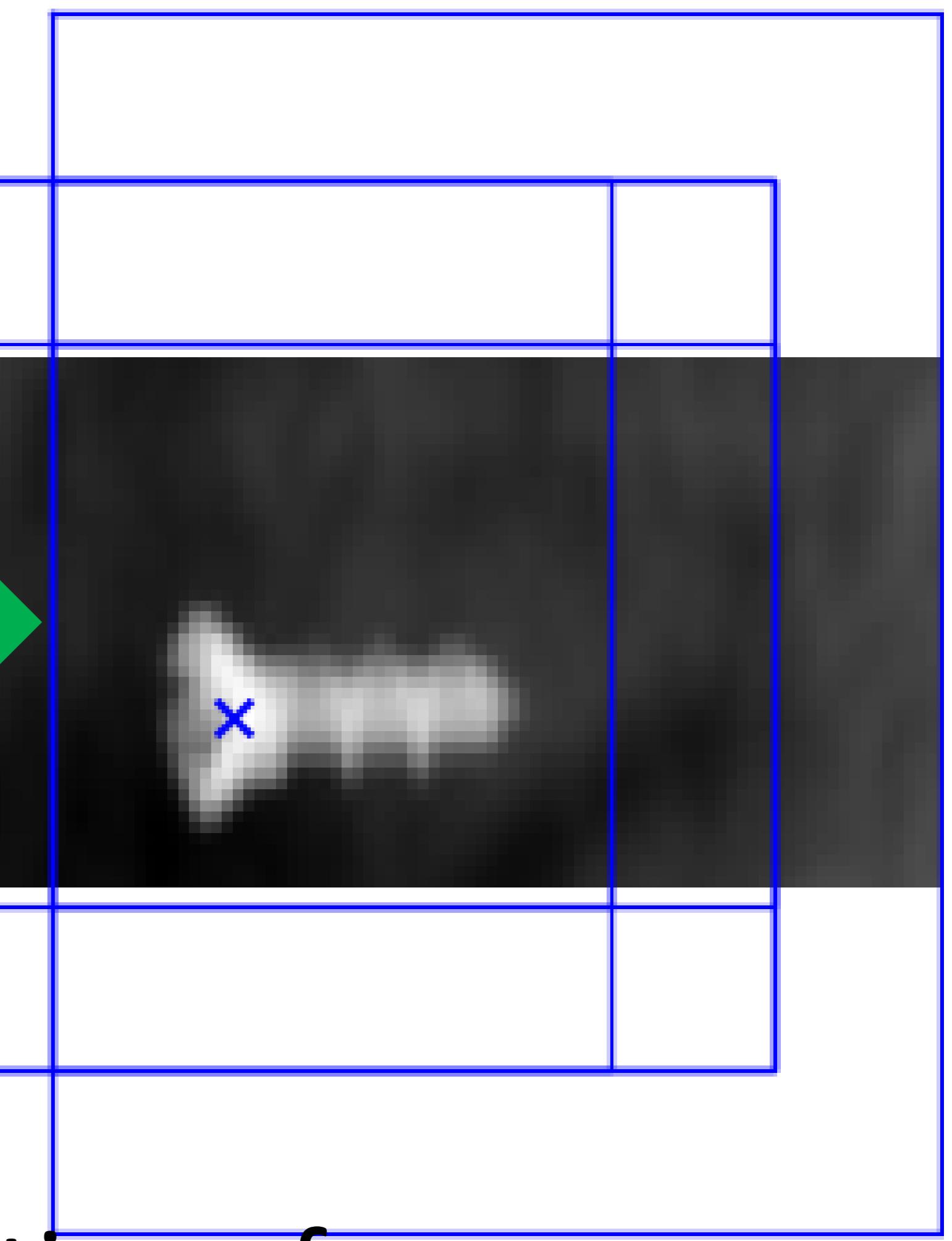
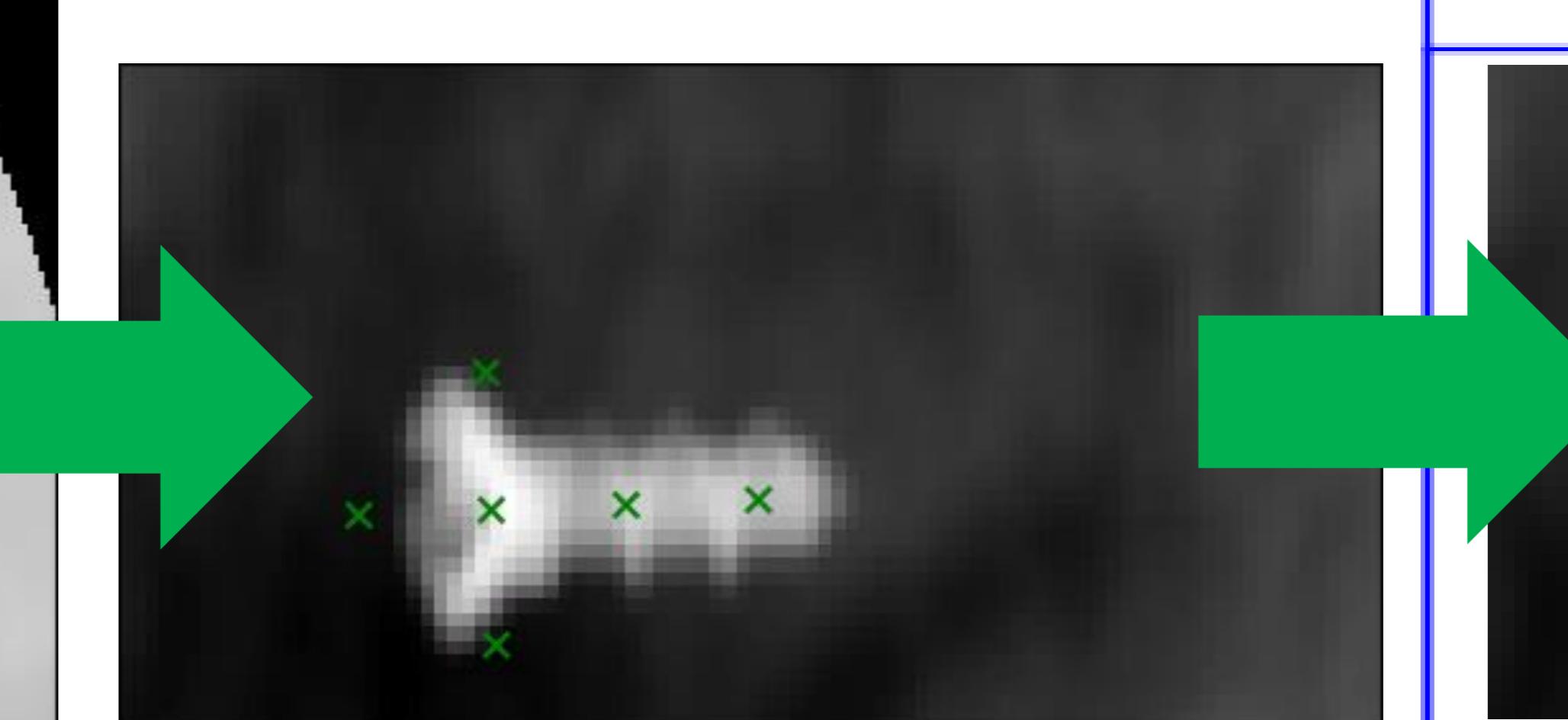
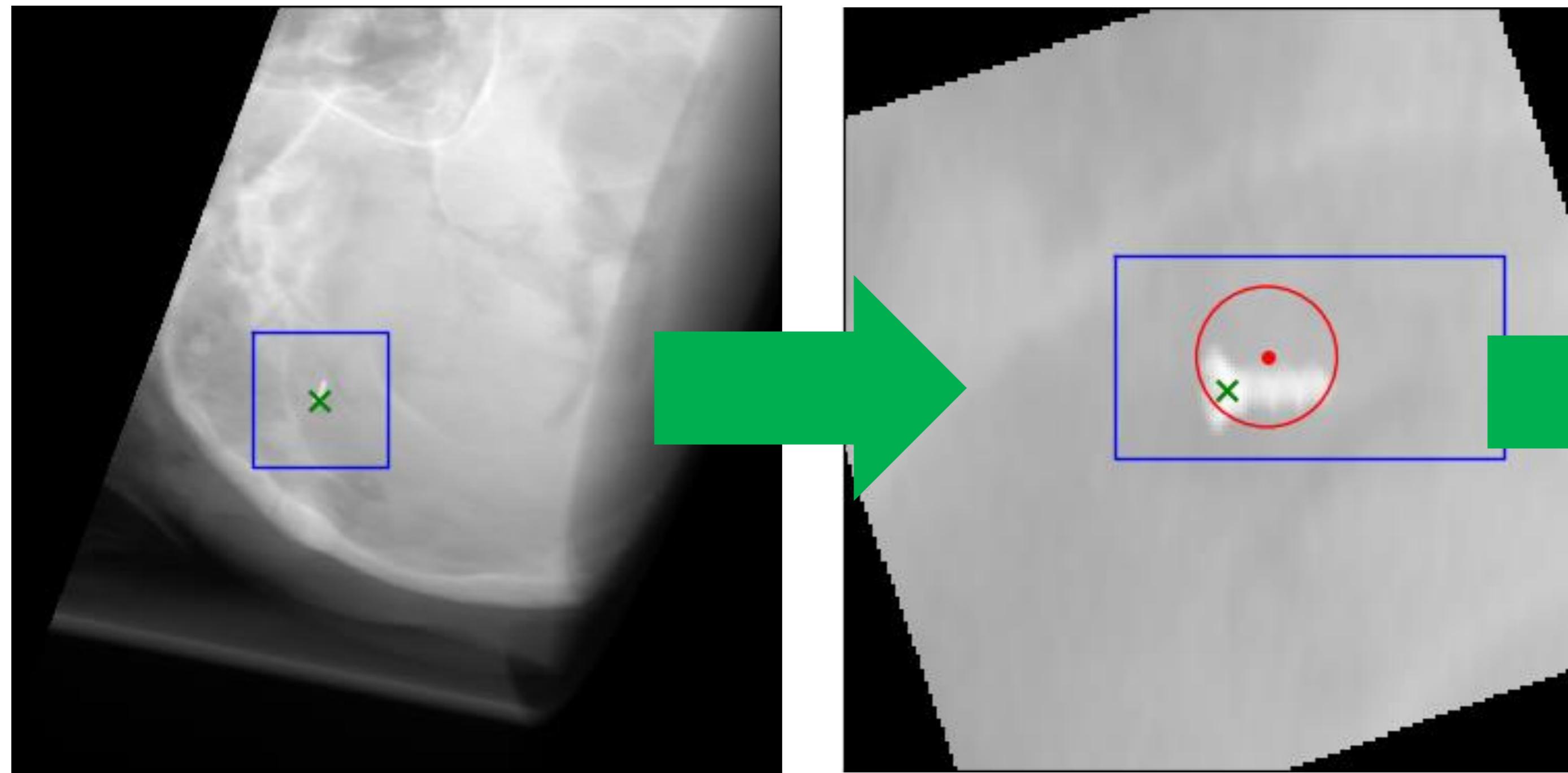
# Fluoroscopy-Guided Tracking



# Method



# Appearance Normalization Pipeline



Normalization of

- Intensity
- Annotation

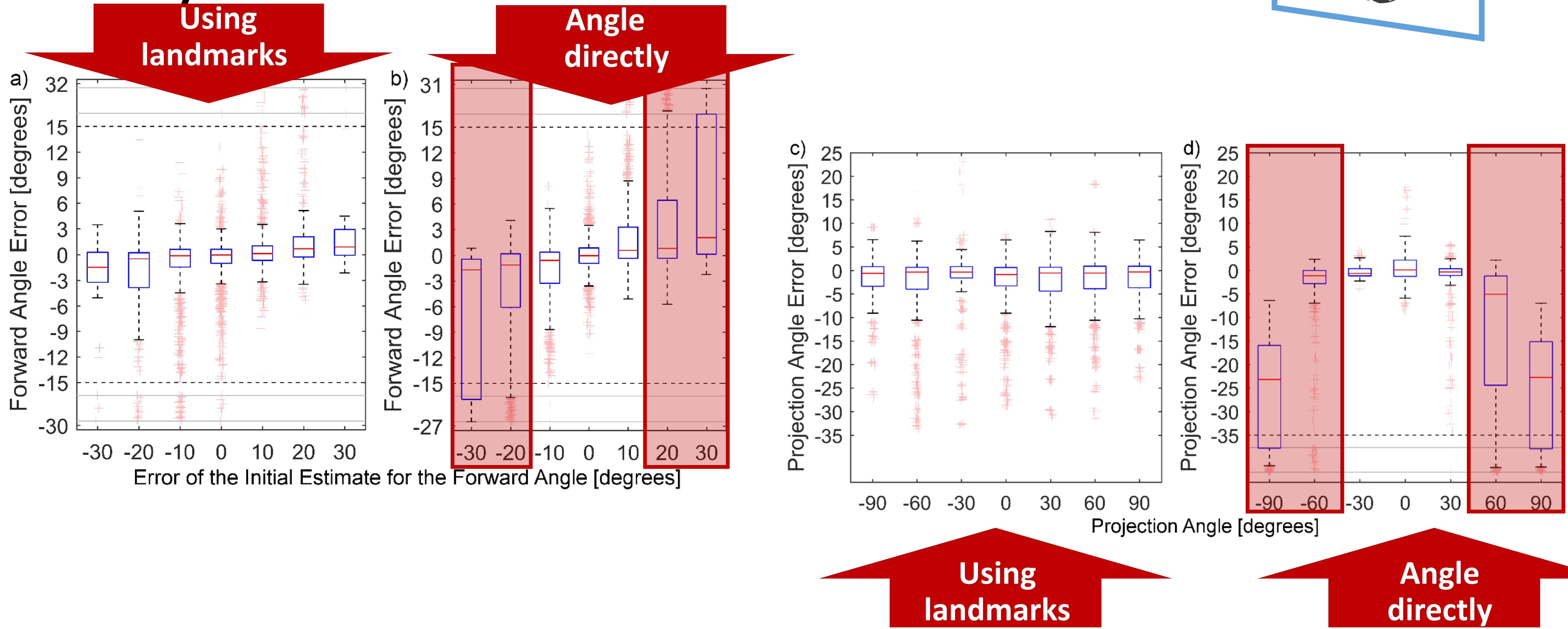
Distribution of

- Annotation

# Not learning end-to-end

Images/Annotation - Augmentation - Problem Design

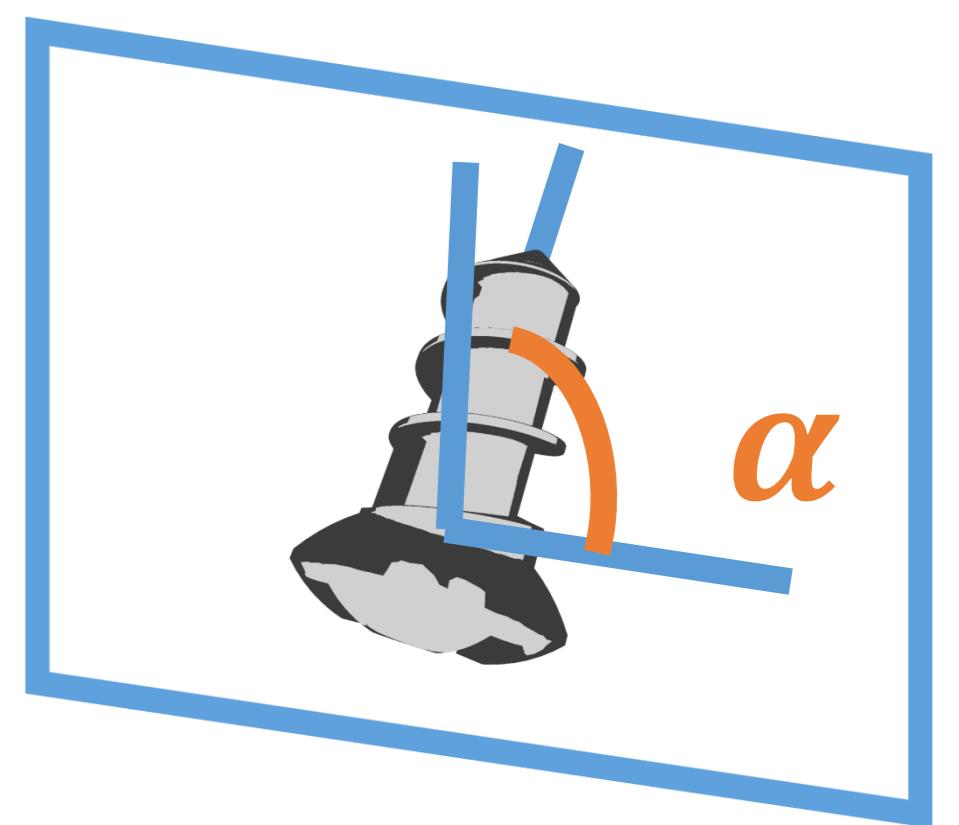
# Why landmarks?



Using  
landmarks

Angle  
directly

# Exploration on a toy dataset

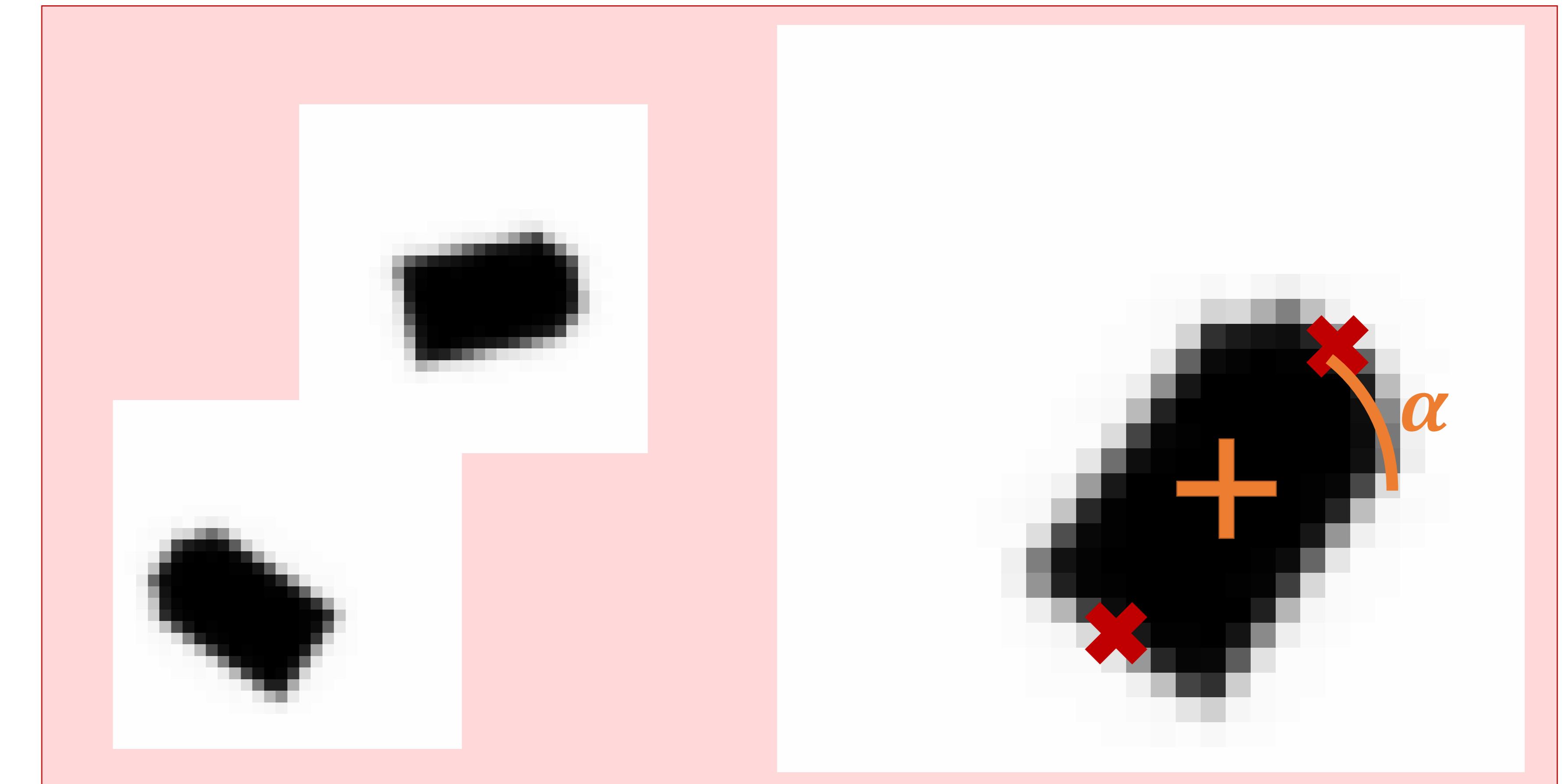


## Toy Dataset

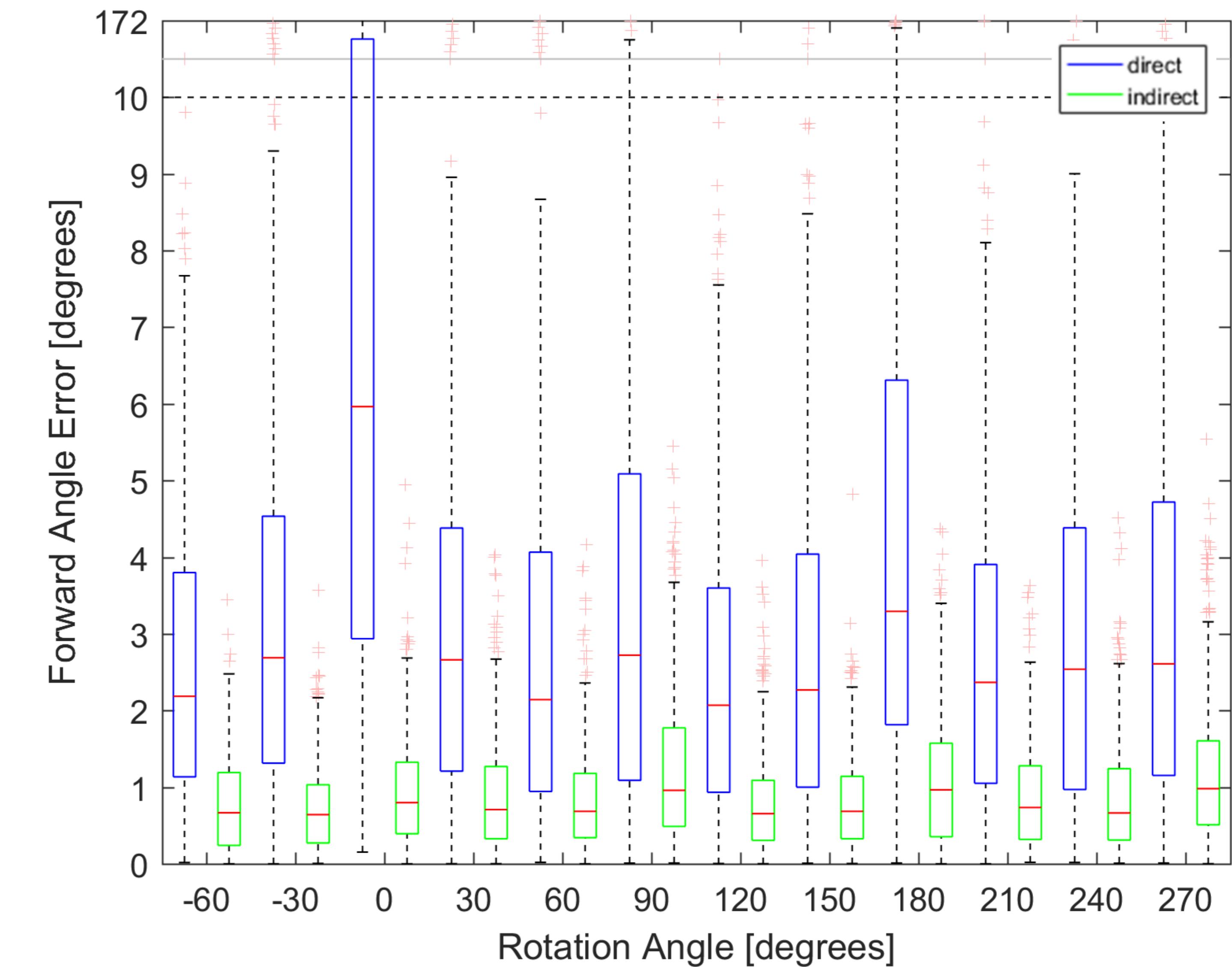
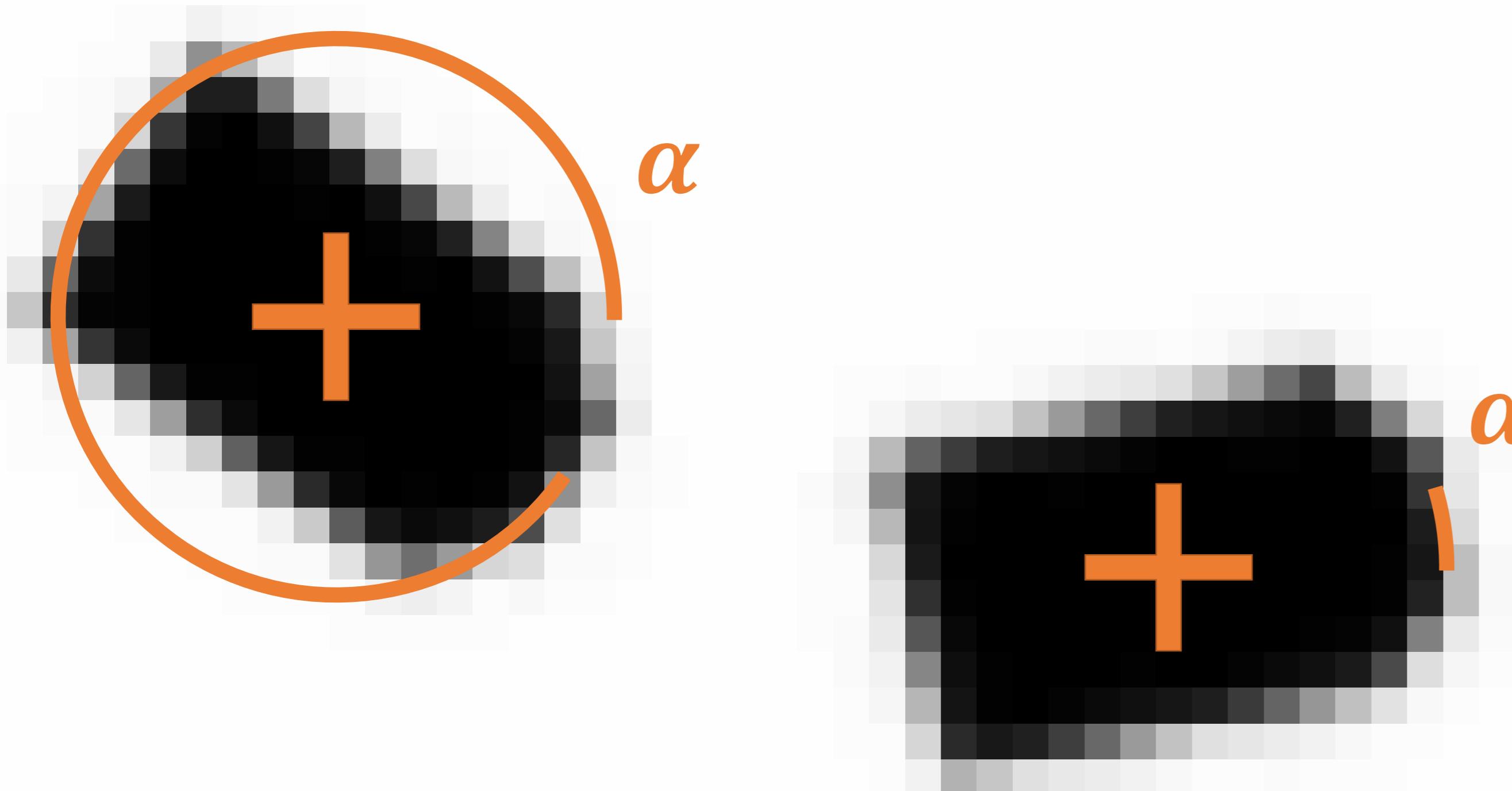
- Rectangle  
(one side rounded corners)
- Random position
- Random „forward angle“  $\alpha$

**Task:** Predict  $\alpha$

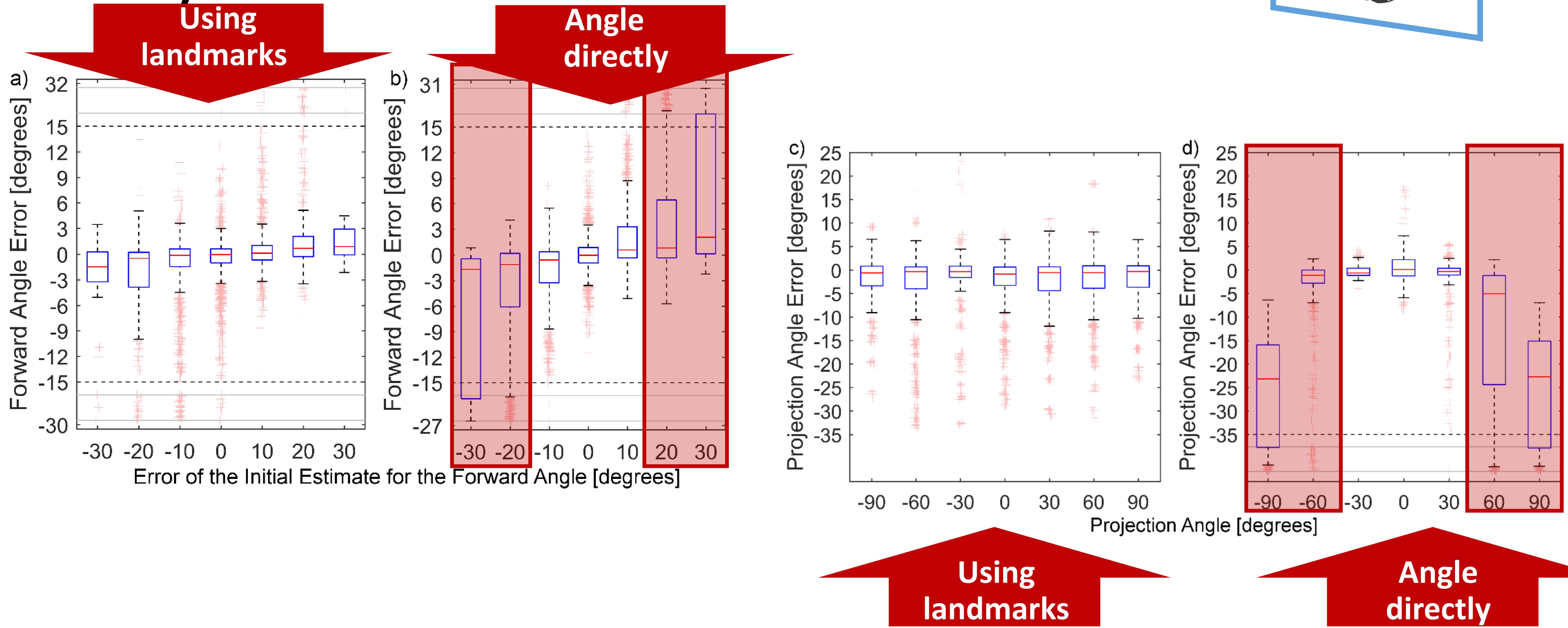
landmarks vs. angle (indirect vs. direct)



# Exploration on a toy dataset



# Why landmarks?



Using  
landmarks

Angle  
directly

# AI-readiness of CAI

Application/ Domain

Learning

Bedside Application

Dataset  
 $(x, y)$

Mathematical Model  
 $f$ : Model function

Parameters & Training  
 $\omega$

Surgical Outcome

Annotation

Architecture

Optimization

Clinical Implementation

Augmentation

Regularization

Surgeon Interaction

Images

Loss

Hyperparameter

Evaluation

Problem Design

# Summary



@kueglerd @anirbanakash

## AI-readiness of Instrument pose estimation

- Images/Augmentation
- Augmentation
- Problem Design

## Limitations

- Projection angle
- Transfer from synthetic to real x-rays

## Future Work

- Improved deep learning
- Multi-instrument

<https://i3posnet.david-kuegler.de>