Deep Learning-Aided CBCT Image Reconstruction of Interventional Material from Four X-Ray Projections

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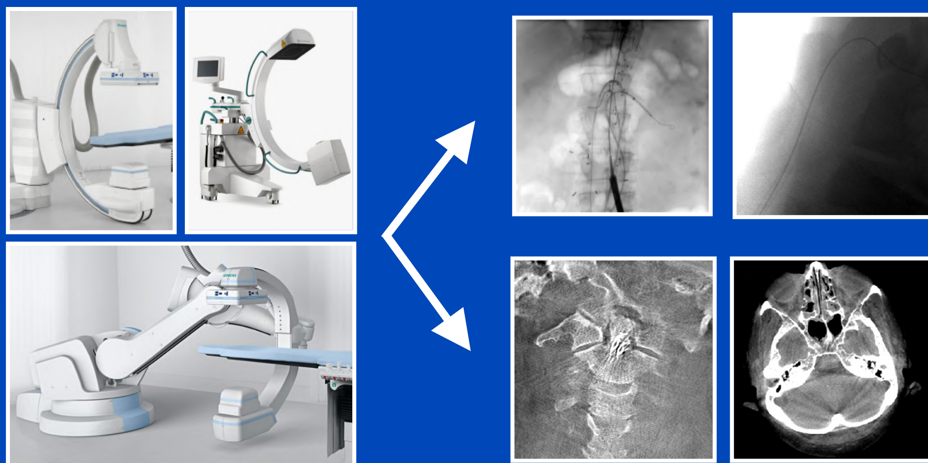
[3]Ziehm Imaging GmbH, Nürnberg, Germany

Stanford University

dkfz. DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Motivation & Prior Work

Today's Interventional guidance



C-arm systems

Fluoroscopy (2D + time)

- ➤ limited information about 3D structure of interventional tools (e.g. of stents)

Tomography (3D)

- ➤ no temporal information

Tomographic (4D) interventional guidance

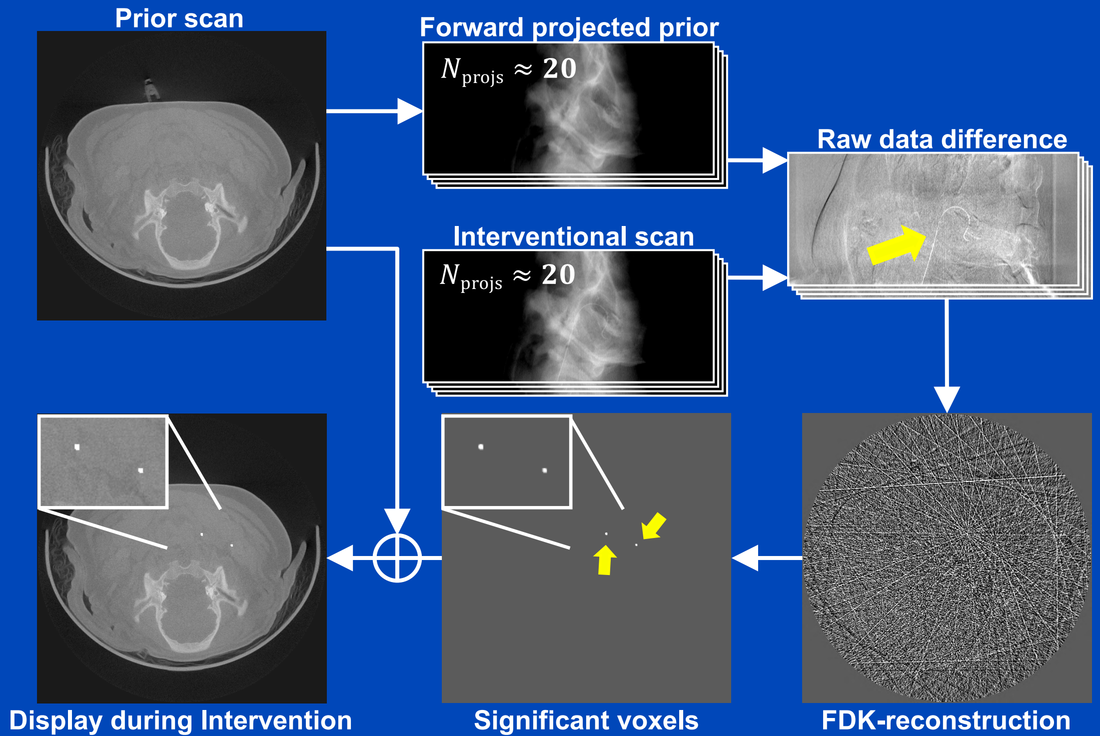
- could provide full spatiotemporal information about interventional tools
- could enable new minimally invasive radiological interventions

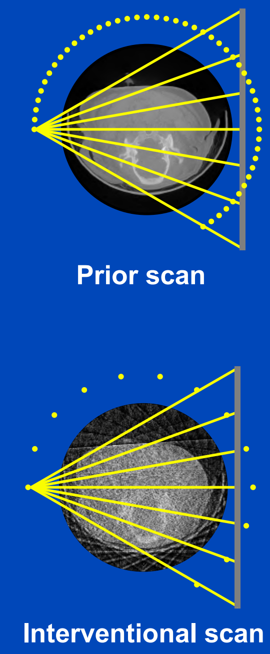
Currently, tomographic interventional guidance would result in excessively high dose due to the need for continuous CBCT scanning.

Motivation & Prior Work

PrIDICT[1] leverages the following characteristics of interventional imaging

- **Repetitive scanning of the same body region. Changes are sparse**
- **Interventional materials are fine structures (very few voxels) of high contrast**





Has been further improved to account for patient motion between the prior and the interventional acquisition via registration of the prior scan[2]

[1] J. Kuntz, M. Kachelrieß, et al., "Real-time x-ray-based 4D image guidance […]", Eur. Radiol., Jun. 2013.
[2] B. Flach, M. Kachelrieß, et al., "Low dose tomographic fluoroscopy: 4D intervention […].", Med. Phys., Oct 2013.

Motivation & Prior Work

Two main drawbacks of existing pipeline

- Further dose reduction by a factor of 5 to 10 is necessary
- Deformable volume-to-raw data (3D-2D) registration method[1] is too computing-intensive to realize the pipeline in real-time

➤ clinically impractical

Develop a novel deep learning-based pipeline

- Deep Tool Extraction (DTE)
  Eliminate the need for a patient prior or registration step by extracting the interventional tools in the projection domain

- Deep Tool Reconstruction (DTR)
  Reconstruct interventional tools from only four x-ray projections

[1]B. Flach, M. Kachelrieß, et al., "Low dose tomographic fluoroscopy: 4D intervention […].", Med. Phys., Oct 2013.

Deep Tool Extraction

Measurements

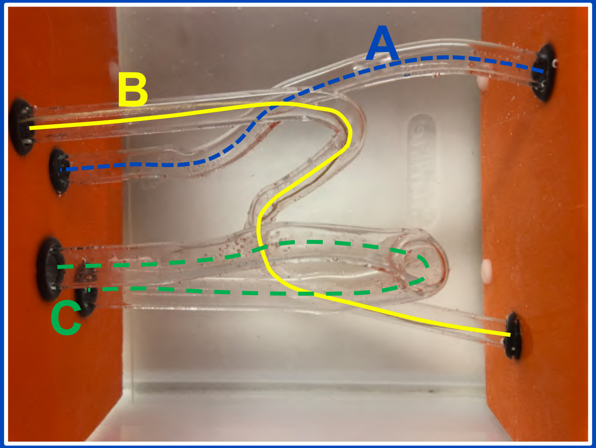
- Acquired data of guide wires and stents using custom built phantom for both training and testing of the CNN
- Measured 5 different stents (1-5) and 2 guide wires
  - in 3 different vessels (A-C)
  - in ~5 different positions each
- Use 3 stents for training/validation
- Use 2 stents and guide wires for testing

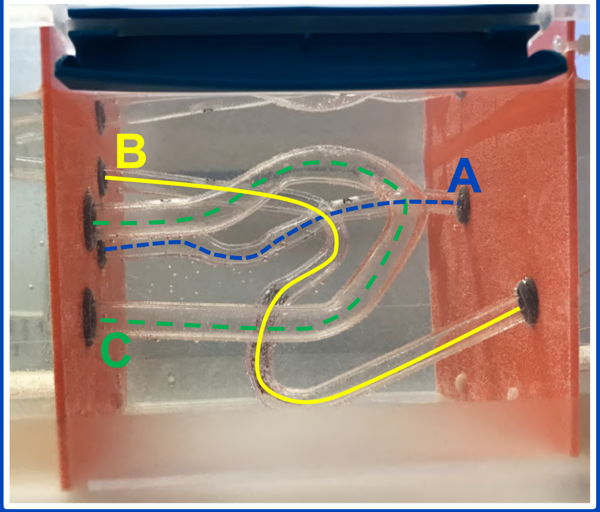
1 2 3

Stents for training

4 5

Stents for testing

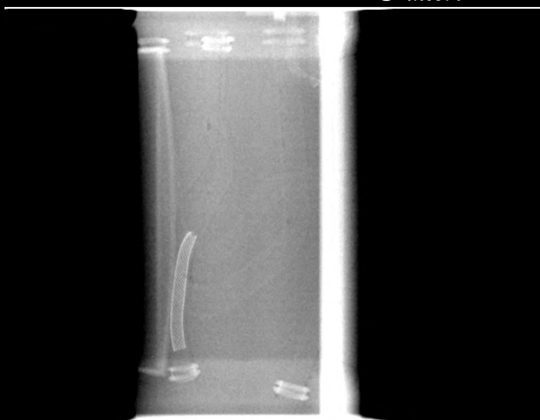




Deep Tool Extraction

Measurements

Interventional scan: $-\log I_{interv}$



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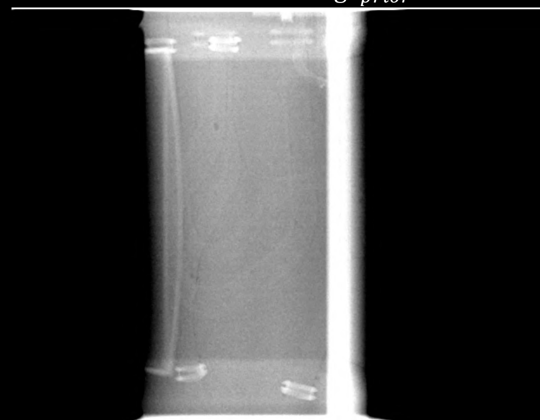
Prior scan: $-\log I_{prior}$



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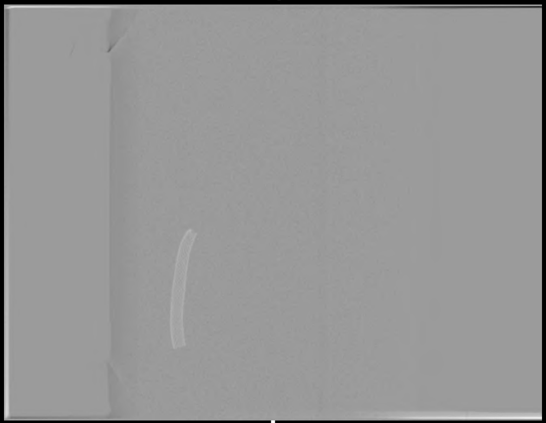
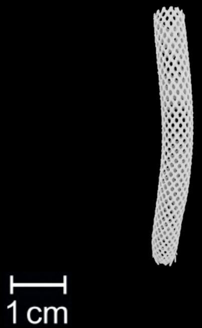
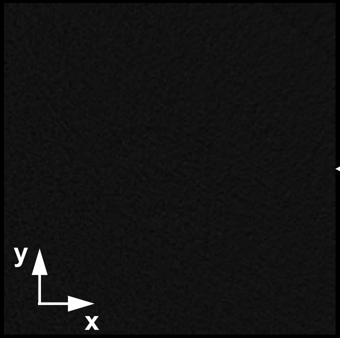
Difference: $\log I_{prior} - \log I_{interv}$





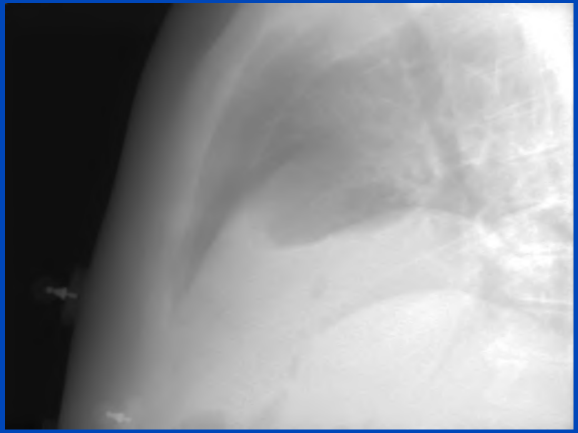
3D Rendering



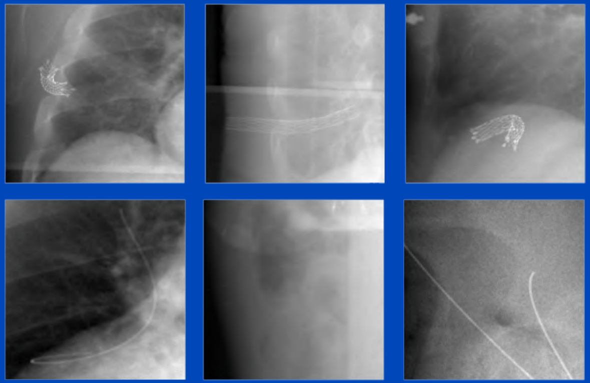
Reconstruction from $N_{\mathrm{projs}} = 496$

Deep Tool Extraction
Simulations

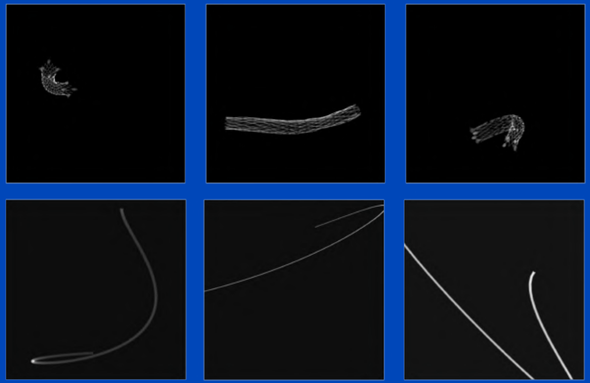
- **Forward-project STLs of stents and simulated guide wires**
- **During training, randomly crop patches of patient scans (thorax) and add projections of interventional tools**
- **Patient scans were acquired with a shifted detector**
  ➤ reject patches p where $\mathrm{median}(p) \leq 1\ \mathrm{cm}^{-1}$



Patient scan



Sample inputs



Respective targets

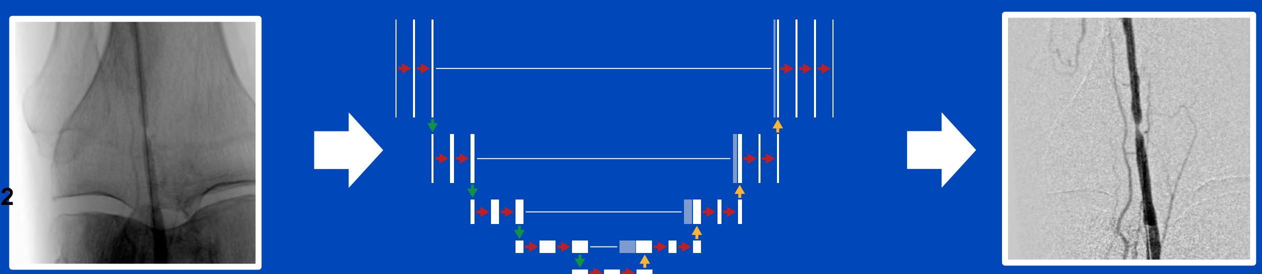
Deep DSA

General principle

Conventional DSA

$I_t - I_0 = \tilde{I}_t$

Deep DSA[1,2]



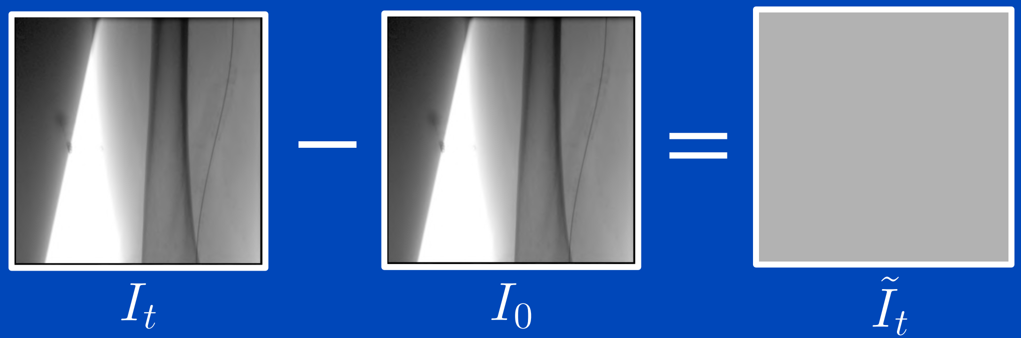
$I_t \Rightarrow \tilde{I}_t$

- **Train on static cases where ground truth is conventional DSA**

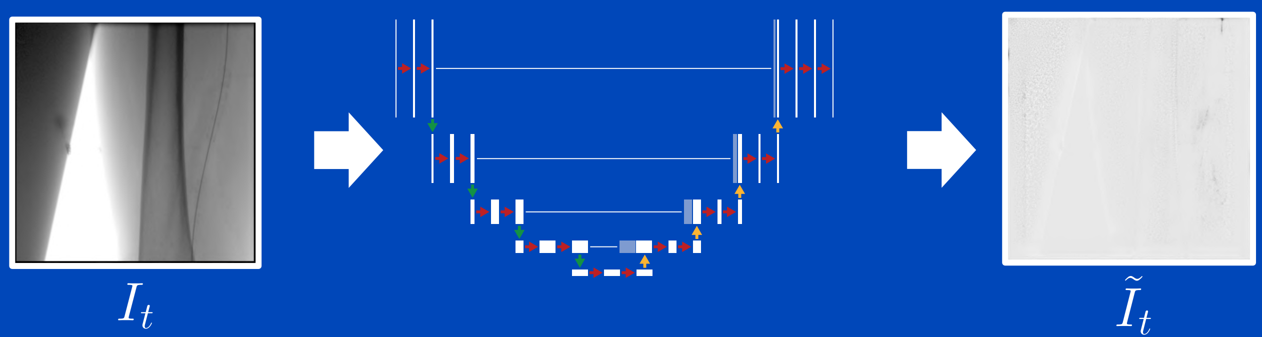
[1] E. Eulig, M. Kachelrieß et al., "Learned Digital Subtraction Angiography (Deep DSA) […]", Fully 3D, Jun. 2019.
[2] E. Eulig, M. Kachelrieß et al., "Deep DSA: Learning Mask-Free Digital Subtraction Angiography […] ", ECR, Feb. 2019.

Deep DSA
General principle

Conventional DSA



Deep DSA

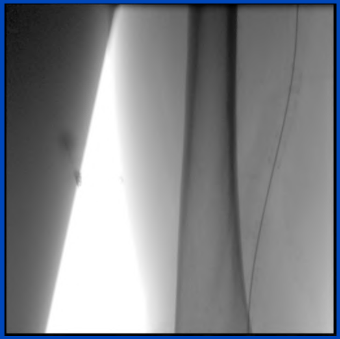


- **Train on static cases where ground truth is conventional DSA**
- **During inference CNN can be applied to both static and dynamic cases**

Deep DSA

Bolus chase study

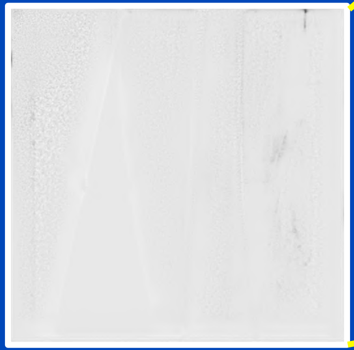
Dynamic fluoroscopy



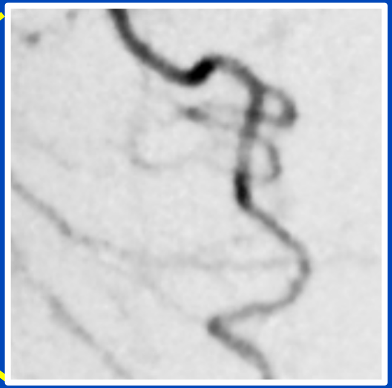
Conventional DSA

Conventional DSA infeasible due to C-arm motion

Deep DSA



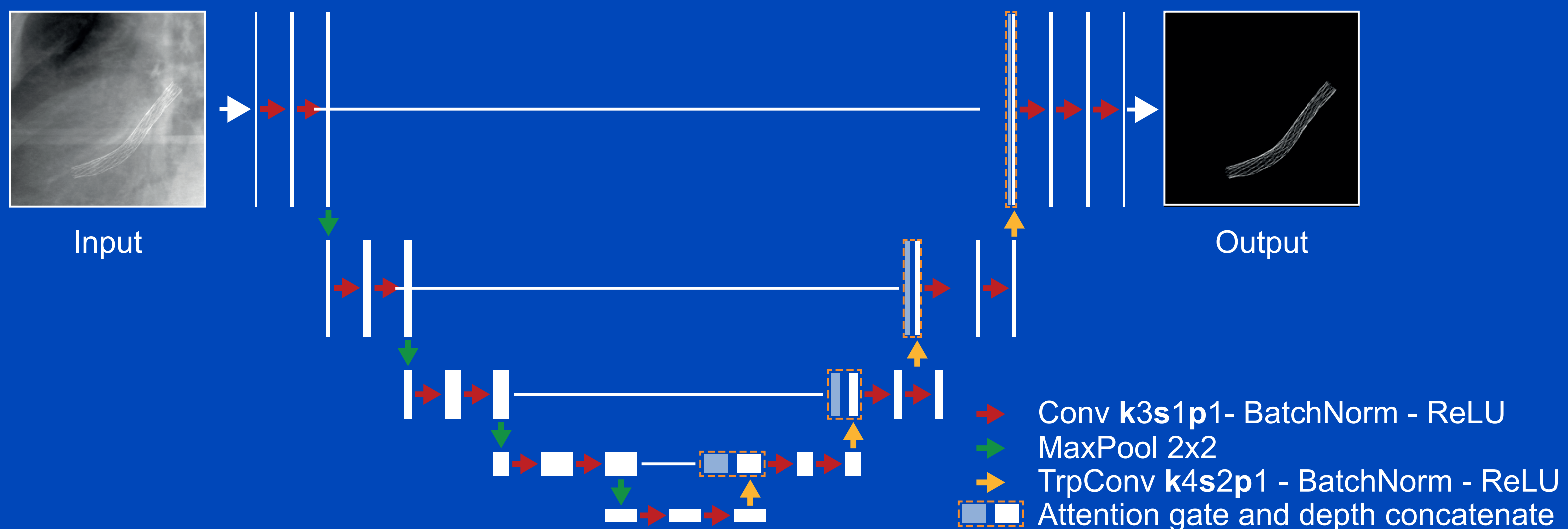
Deep DSA at $\mathrm{t} = t_a$



Deep DSA at $\mathrm{t} = t_a$

Deep Tool Extraction
Training Details

- **Network structure: 2D attention U-Net[1] with projections of tools + patient as input ➤ Predict projection values of tool only**



- **Optimize L_1 loss using Adam[2]**

$$\mathcal{L}_1 = \frac{1}{N}\sum_{x=1}^{N} |y_x - \hat{y}_x|$$

Stanford

[1]Oktay, O. et al., "Attention U-net: Learning where to look [...]," Medical Imaging with Deep Learning, 2018.
[2]Kingma, D. P. & Ba, J., "Adam: A method for stochastic optimization," ICLR (2015).

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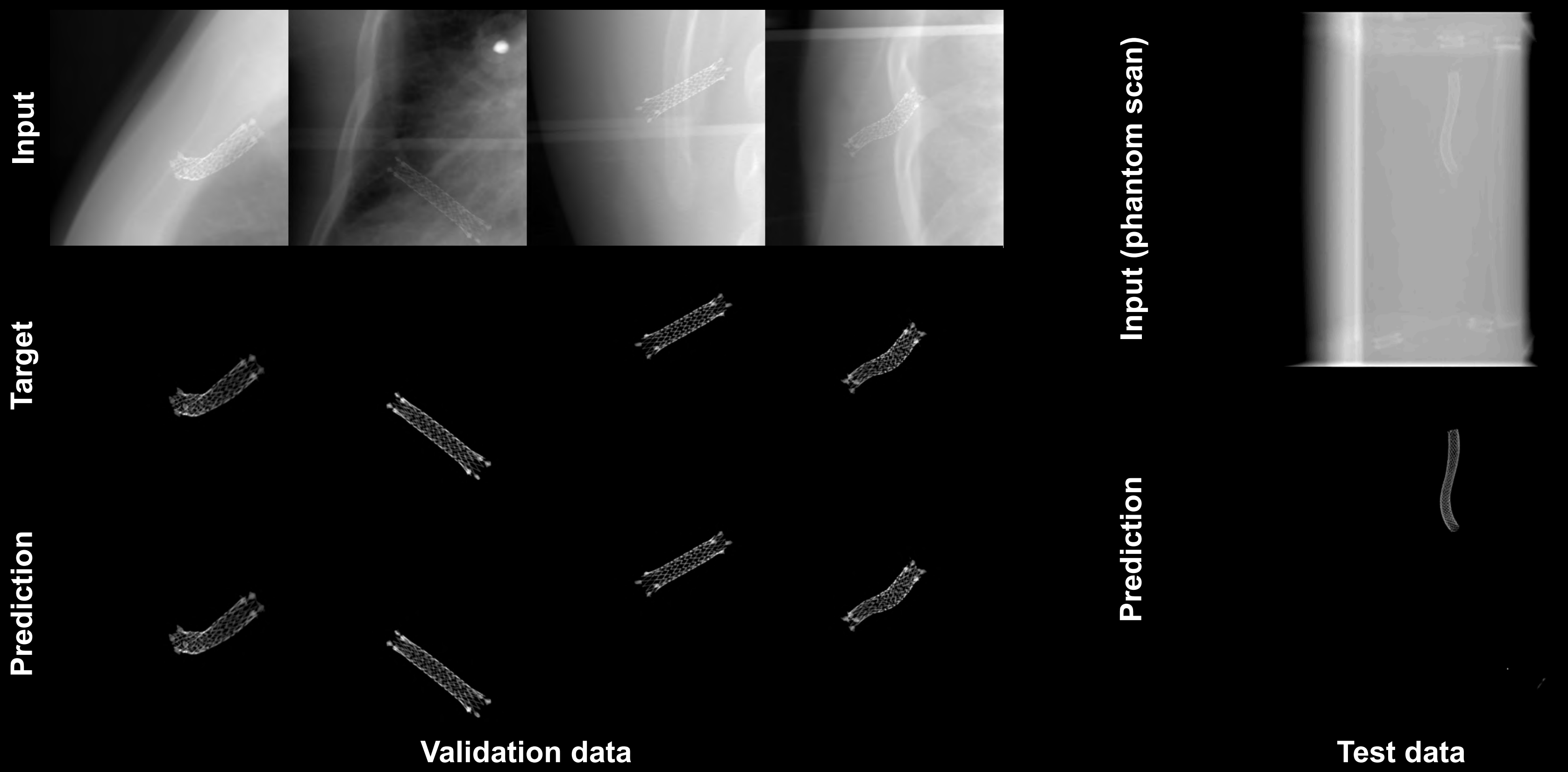
Deep Tool Extraction

Results



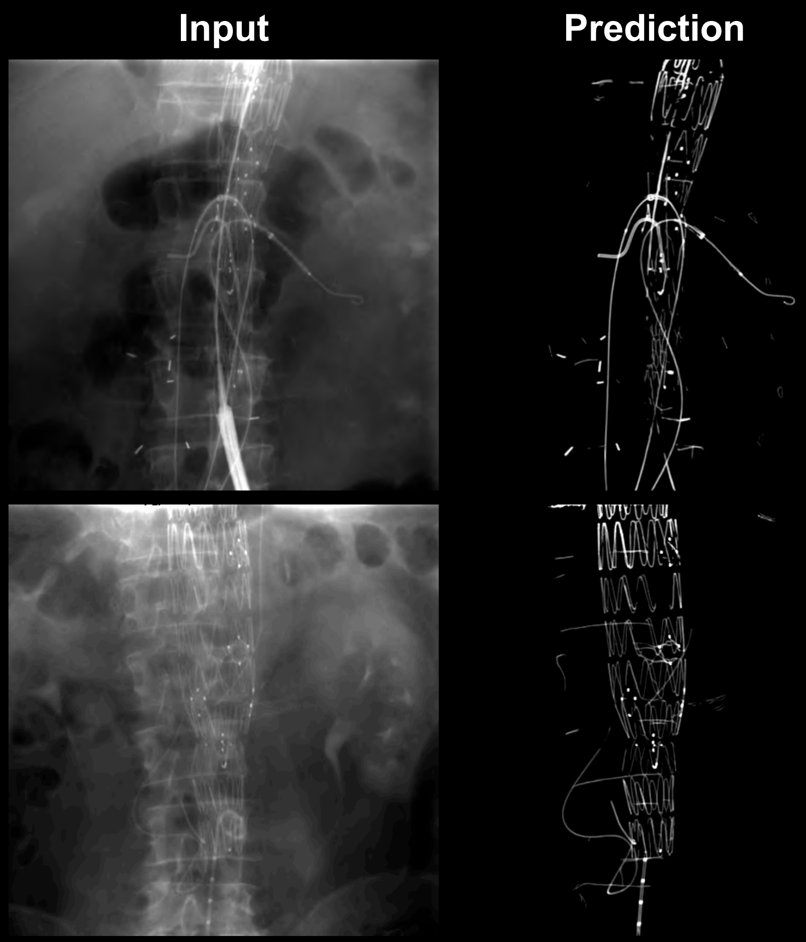
Good results for both simulated patient data and phantom measurements
➤ indicator how well the network generalizes

Deep Tool Extraction

Results

We applied DTE to fluoroscopy data of interventions to test it on non-simulated patient data

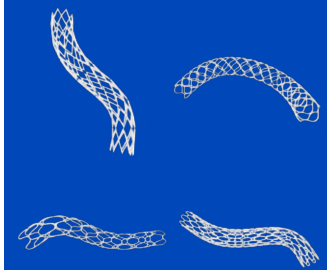
➤ generalized well to unseen structures of interventional tools and background (i.e. contrast media)



Deep Tool Reconstruction

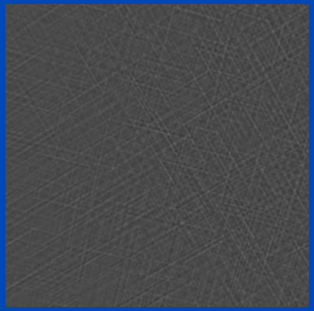
Simulations

Simulate CBCT data according to Zeego geometry with perfect prior

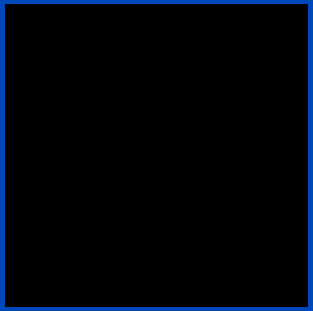


STL files

forward projected STL with Poisson noise



FDK[1] reconstruction



GT segmentation

Guide wire dataset

- Center slices (512 × 512 px) of reconstructions of 1-16 guide wires
- Randomly positioned and randomly rotated

Stent dataset

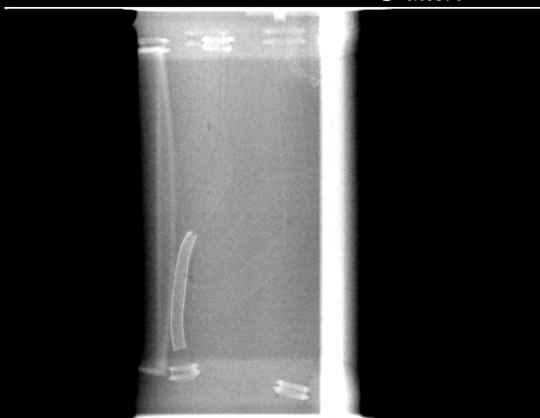
- 20 reconstructions (512 × 512 × 768 px) of 6 different stents each
- Variable strut thickness and stent diameter
- Randomly deformed, positioned and rotated

[1]L. Feldkamp, et al., “Practical cone–beam algorithm”, Journal of the Optical Society of America, 1984.

Deep Tool Reconstruction

Measurements

Interventional scan: $-\log I_{interv}$



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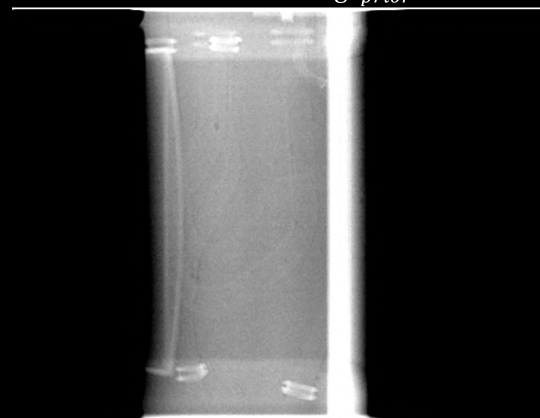
Prior scan: $-\log I_{prior}$



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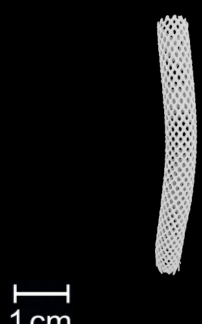
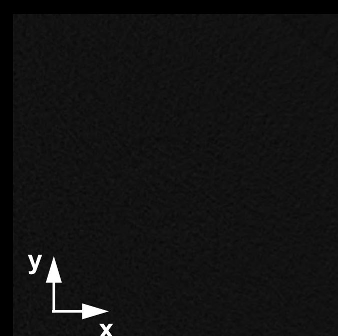
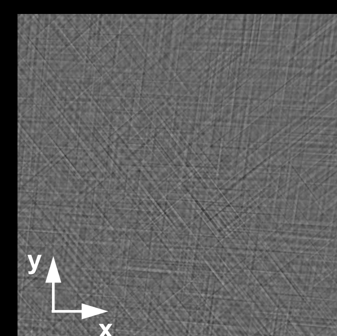
Difference: $\log I_{prior} - \log I_{interv}$



3D Rendering



Reconstruction from $N_{\text{projs}} = 496$

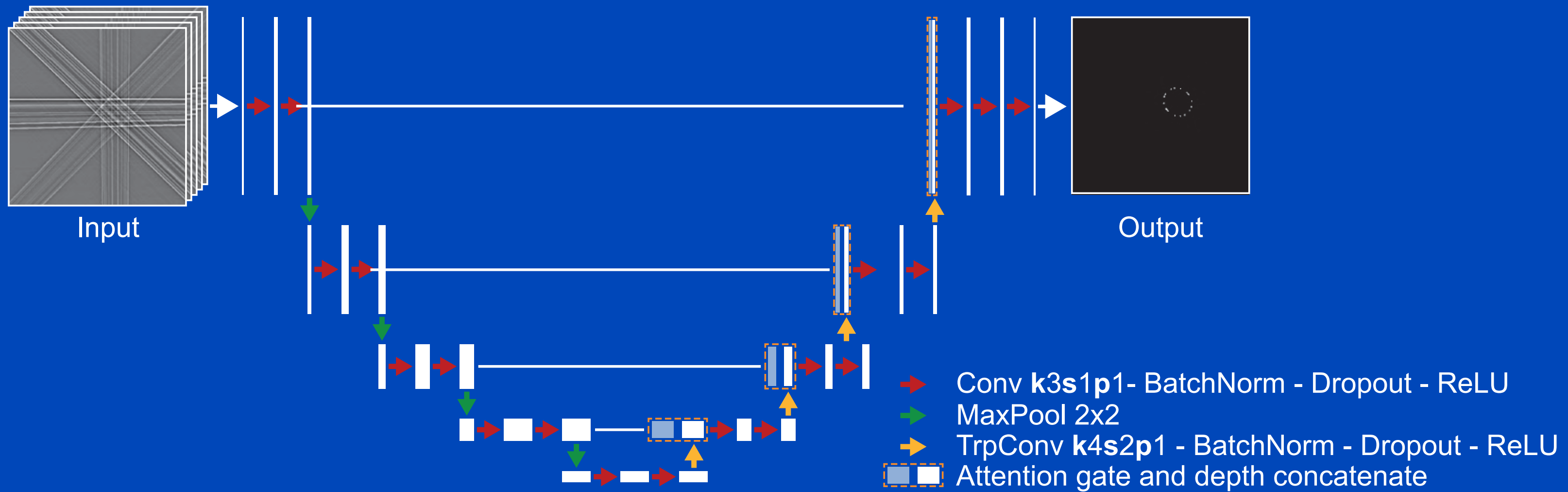


Reconstruction from $N_{\text{projs}} = 4$

Deep Tool Reconstruction

Training Details

- **Network structure: 2D Attention U-Net[1] with 13 slices of reconstruction as channel inputs ➤ Predict segmentation of center slice**



- **Pretrain on guide wire data**
- **Fine-tune on stent data (measured or simulated)**
- **Optimize soft Dice loss with Laplace smoothing using Adam[2]**

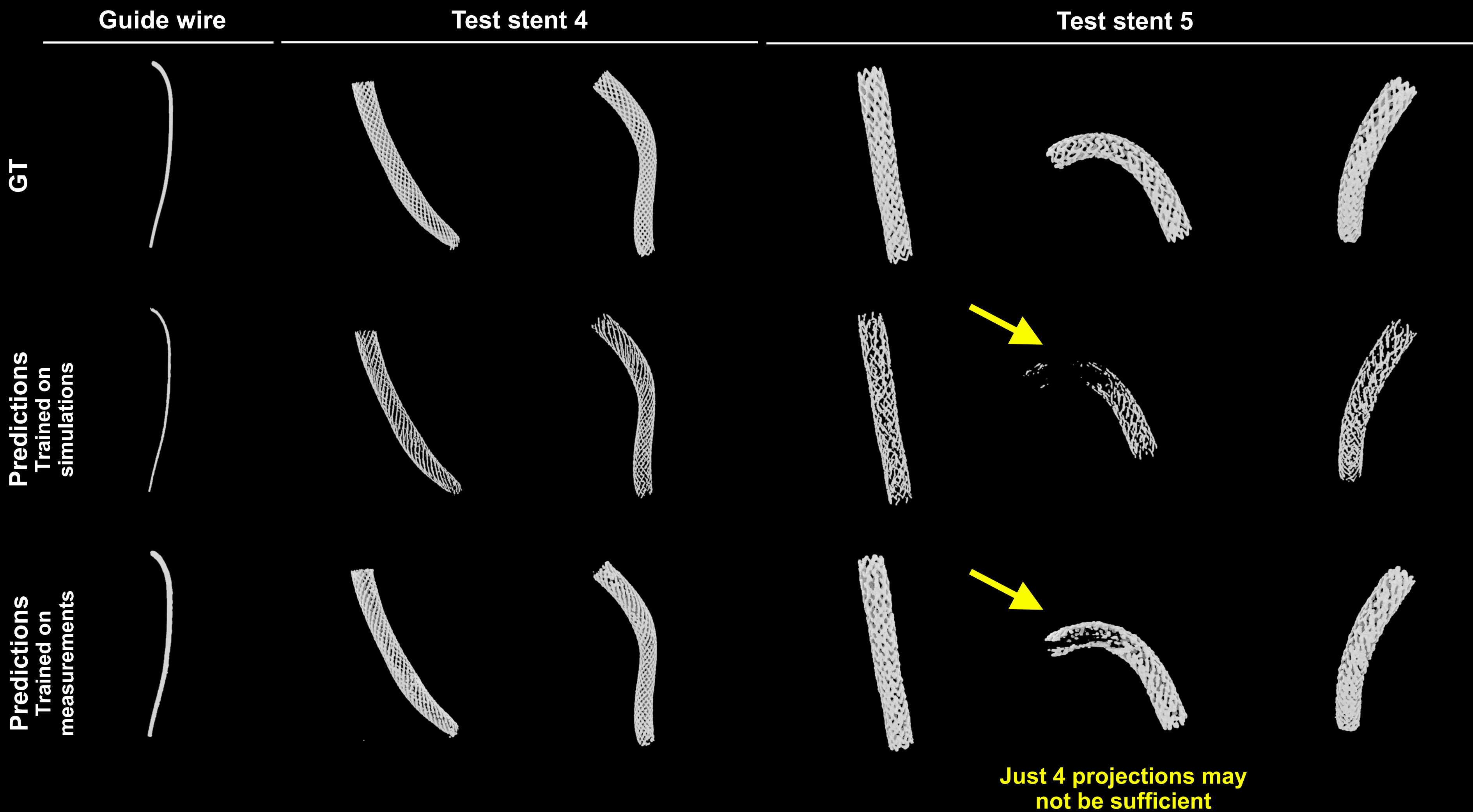
$$\mathcal{L}_{\text{Dice}} = 1 - \frac{2\sum_x y_x \hat{y}_x + 1}{\sum_x y_x + \sum_x \hat{y}_x + 1}$$

- **During inference threshold with $\theta = 0.5$**

[1]Oktay, O. et al., "Attention U-net: Learning where to look [...]," Medical Imaging with Deep Learning, 2018.
[2]Kingma, D. P. & Ba, J., "Adam: A method for stochastic optimization," ICLR (2015).

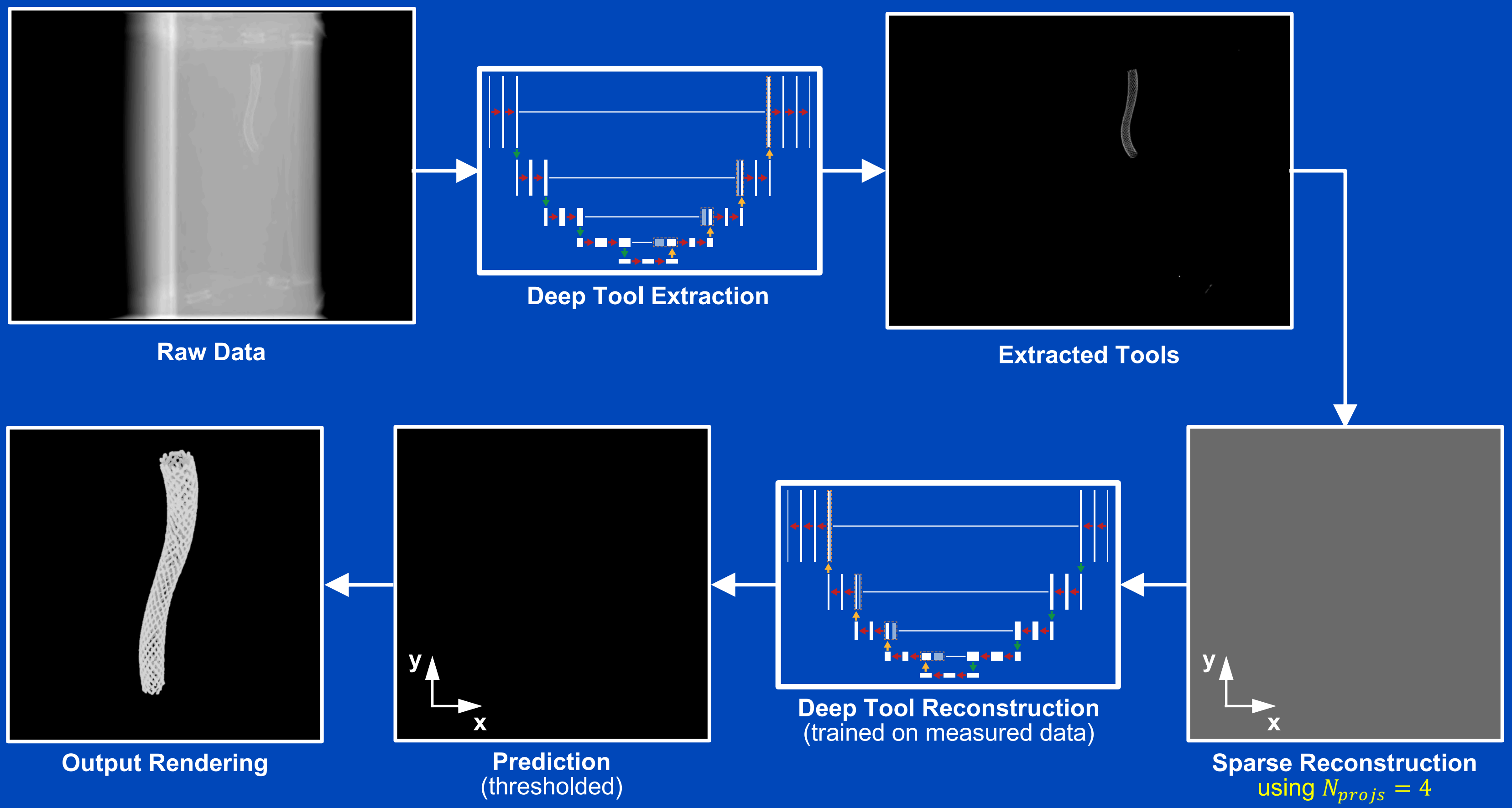
Deep Tool Reconstruction

Results



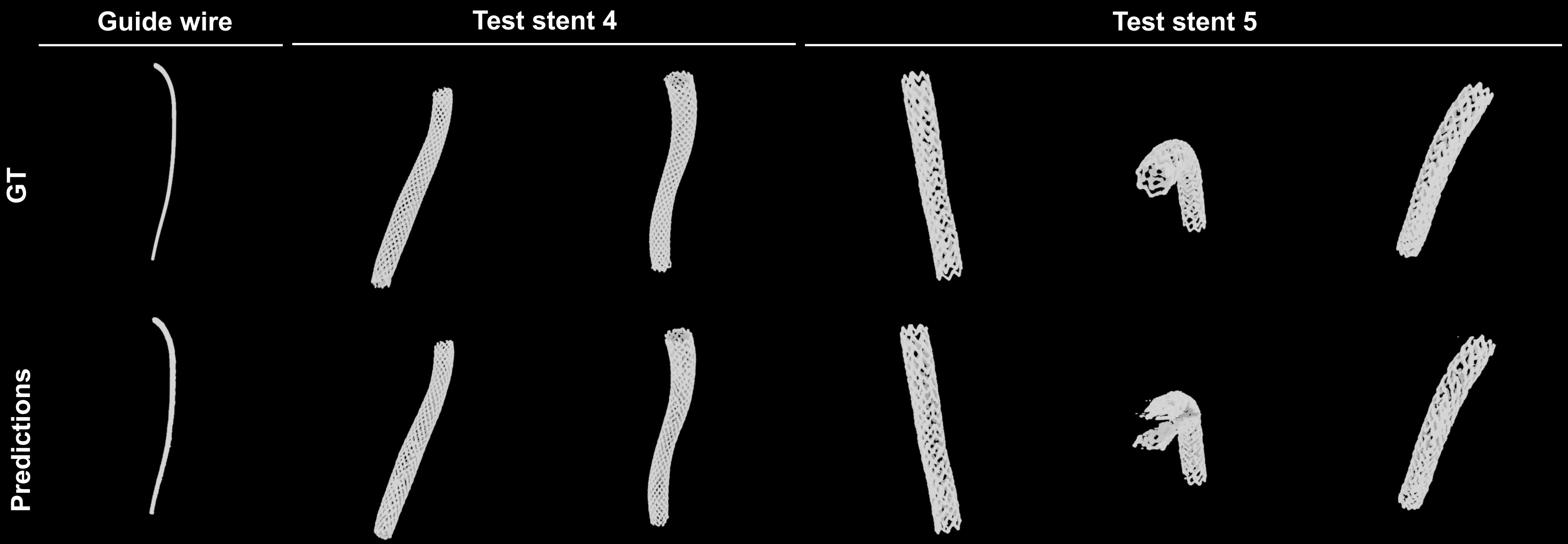
Combined Pipeline

Overview



Combined Pipeline

Results



Conclusion & Outlook

Deep Tool Extraction

- eliminates the need for a prior scan and registration step
  - ➤ This eases clinical workflow
  - ➤ No problems with patient motion
  - ➤ Complete pipeline is applicable in real time

Deep Tool Reconstruction

- can reconstruct interventional tools (here with focus on stents and guide wires) from only 4 x-ray projections with high accuracy
- is currently limited to the case where no motion of the tools occurs between the acquisition of the individual projections

Future work comprises

- investigating performance for other interventional tools such as catheters and coils
- testing our pipeline on clinical CBCT scans
- training the pipeline end-to-end

Thank You!

This presentation will soon be available at www.dkfz.de/ct.
We are hiring for this and similar topics! Contact: marc.kachelriess@dkfz.de.
Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.