Deep Inpainting for Photon-Counting Cone-Beam CT

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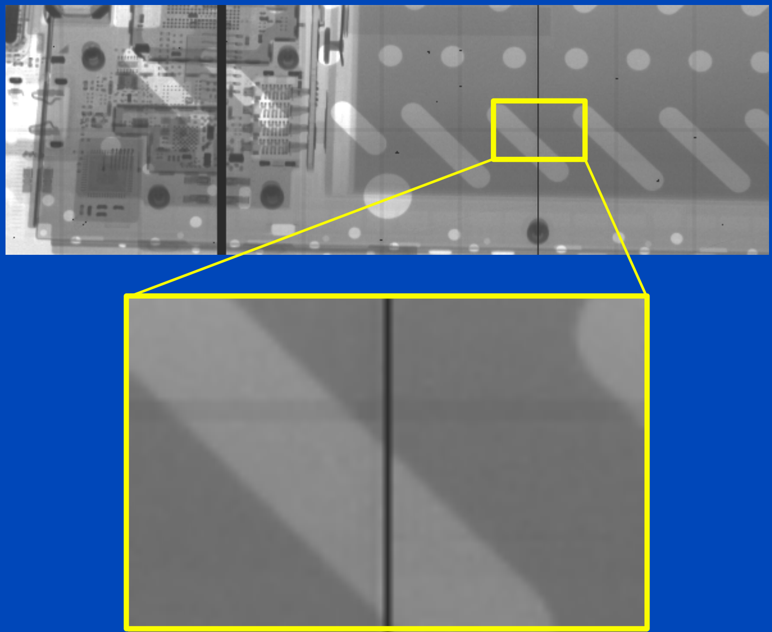
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Motivation

- **Photon counting detector technology has proven promising image quality for clinical CT[1].**
- **Likely that the same holds for CBCT**



Projection of smartphone from a Dectris Pilatus 3 photon counting sensor

- **ASIC modules are limited in size and thus need to be tiled in order to assemble larger flat detectors.**
- **Several-pixel wide gaps between the modules may occur.**
- **Need to be inpainted prior to reconstruction or examination of x-ray radiographs or fluoroscopy.**

[1] Pourmorteza, Amir, et al. "Abdominal imaging with contrast-enhanced photon-counting CT: first human experience." *Radiology* 279.1 (2016): 239-245.

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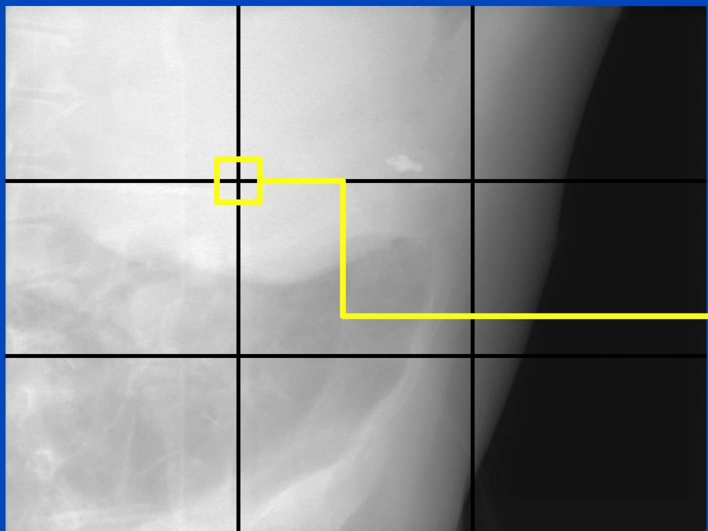
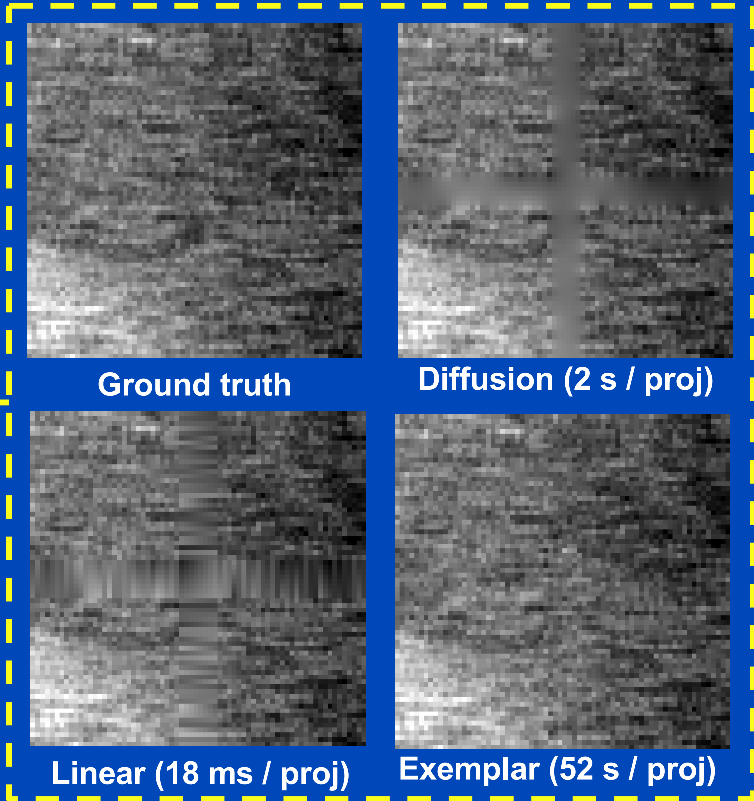
Prior Work

Existing methods either suffer from inferior quality or long computation times



Single projection (1024×768) from conventional CBCT with artificially induced 6-pixel wide gaps



Methods

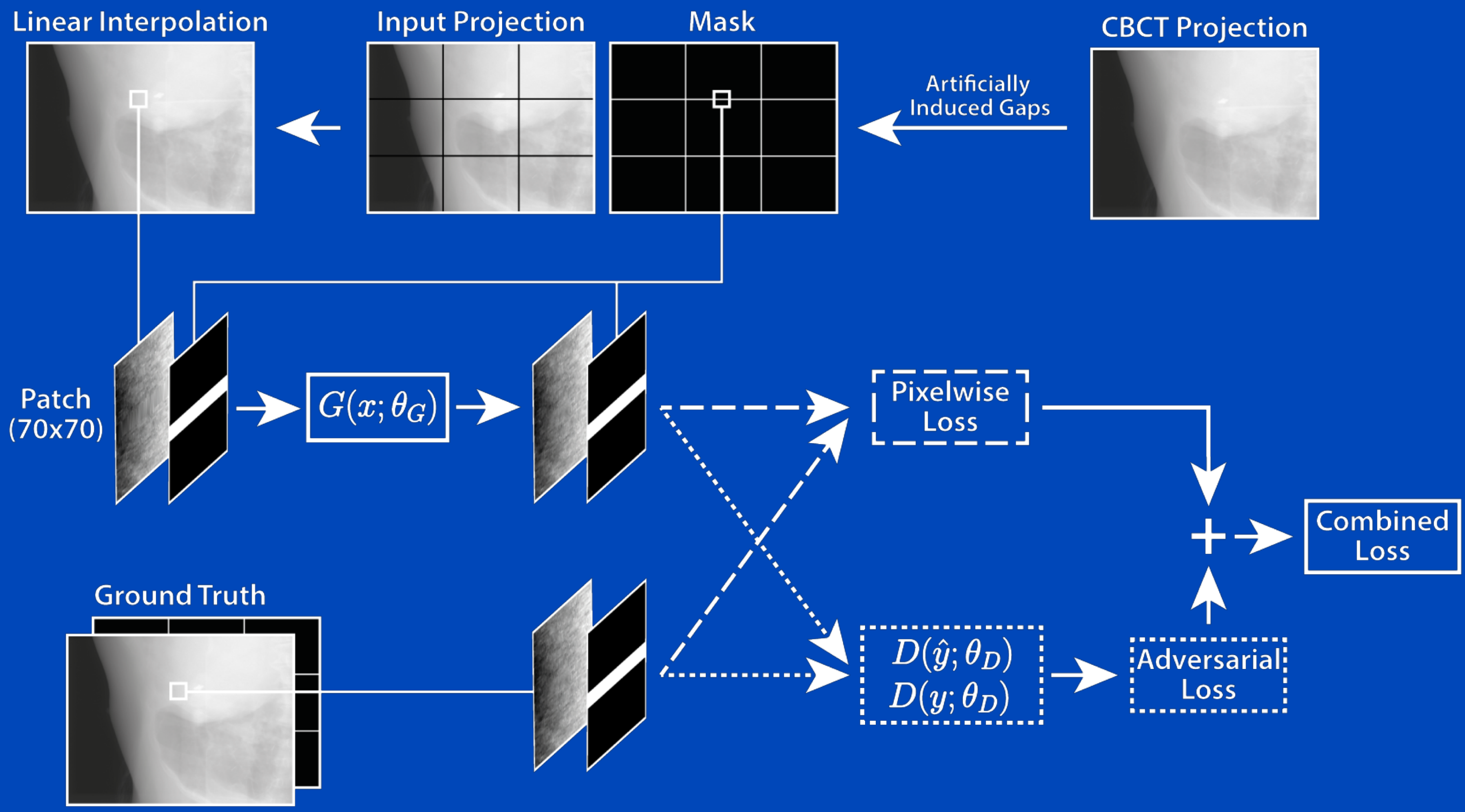
Adversarial Networks for Inpainting

Train adversarial network consisting of Generator G and Discriminator D to fill the dead pixels

Iizuka, S., Simo-Serra, E., & Ishikawa, H. (2017). Globally and locally consistent image completion. *ACM Transactions on Graphics (TOG)*, *36*(4), 107.

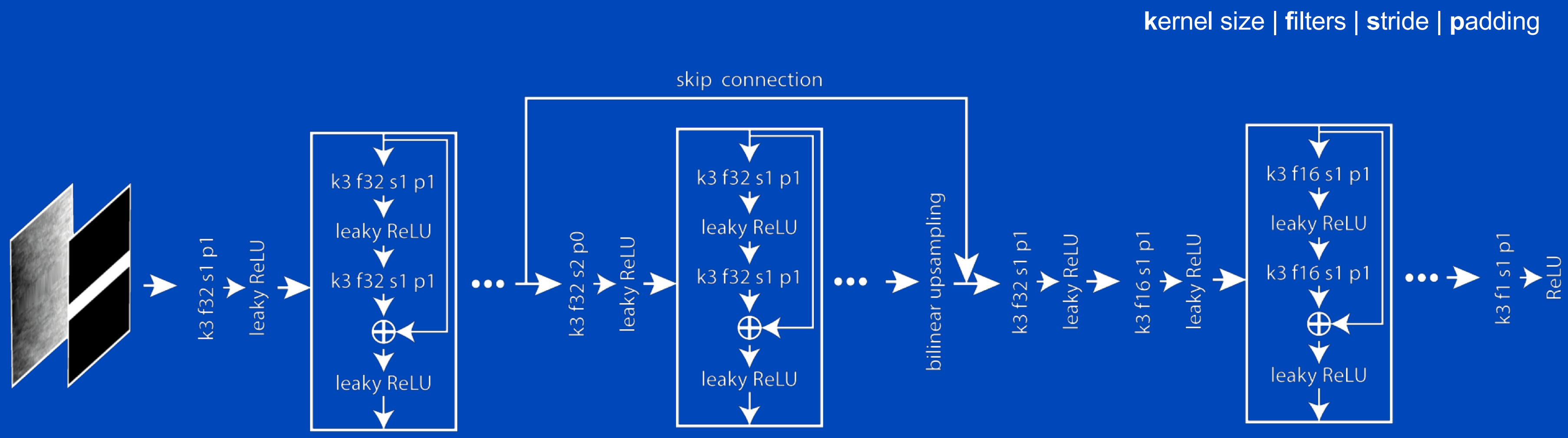
Methods

Training Procedure



Methods

Generator Structure



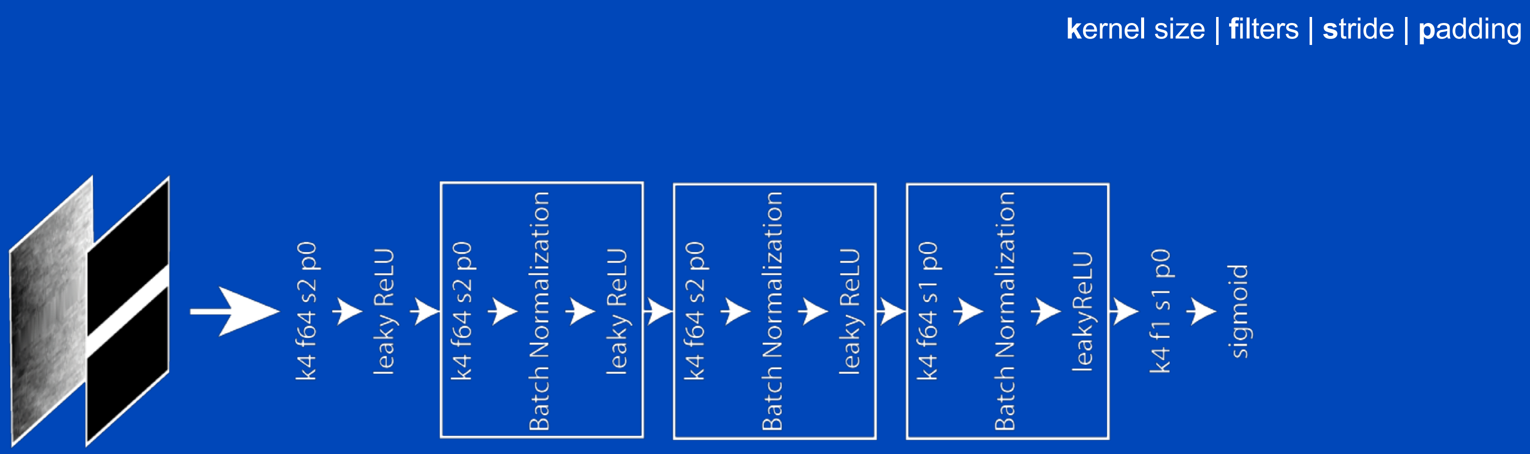
- **Receives patch and mask as input**
- **Fully convolutional**

- **Leaky ReLUs as nonlinearities to further training stability**
- **Consists of several residual blocks[1]**
- **One downsampling with skip connection to upsampled image to increase the receptive field.**

[1] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

Methods

Discriminator Structure



- **Receives patch and mask as input**
- **Fully convolutional**

- **Leaky ReLUs as nonlinearities to further training stability**
- **Final nonlinearity is sigmoid to give rating between 0 and 1 whether seen patch originates from ground truth distribution or was generated.**

Methods

Dataset Details

- Training
  1 abdomen, 4 thorax CBCT datasets, yielding 3286 projections
- Validation
  1 abdomen, 1 thorax CBCT datasets, yielding 1314 projections
- Tube voltage: 125 kV
- Scanner: Varian TrueBeam®
- Detector: Varian 4030 flat detector (40×30 cm)

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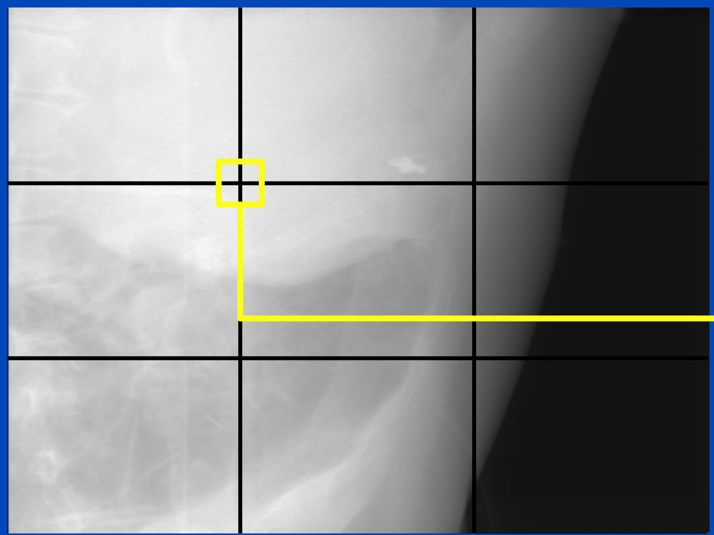
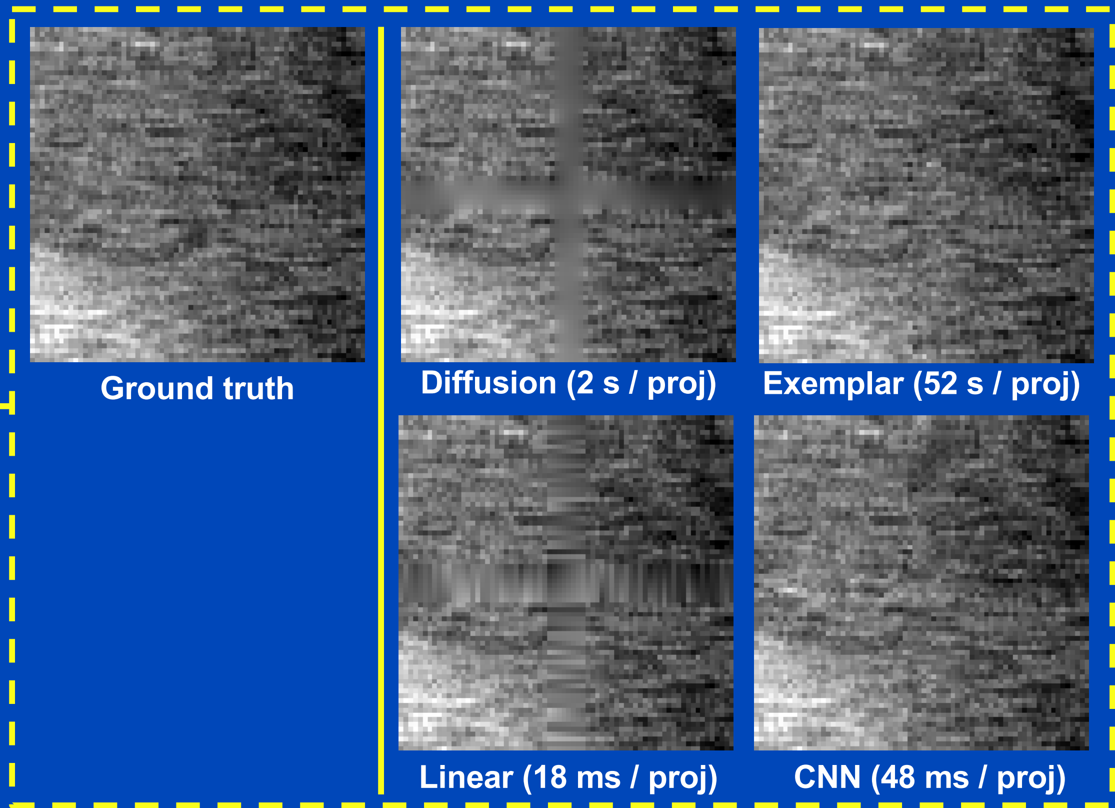
Results

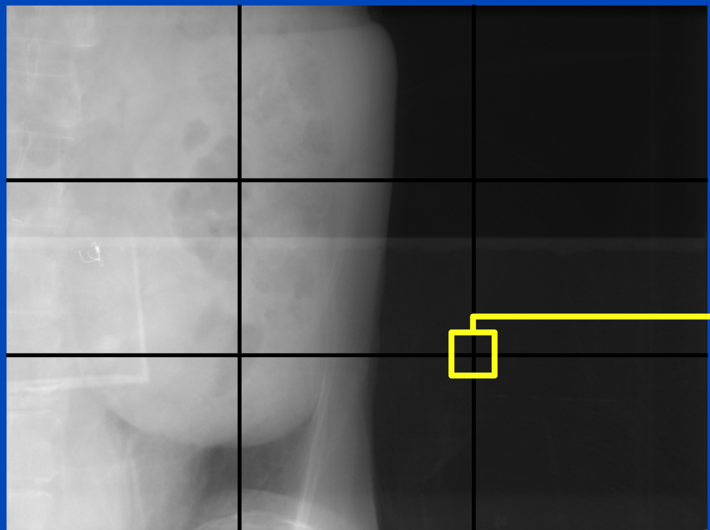


Single projection (1024×768) from conventional CBCT with artificially induced 6-pixel wide gaps



→ CNN is factor 1000 faster than exemplar-based inpainting

Results



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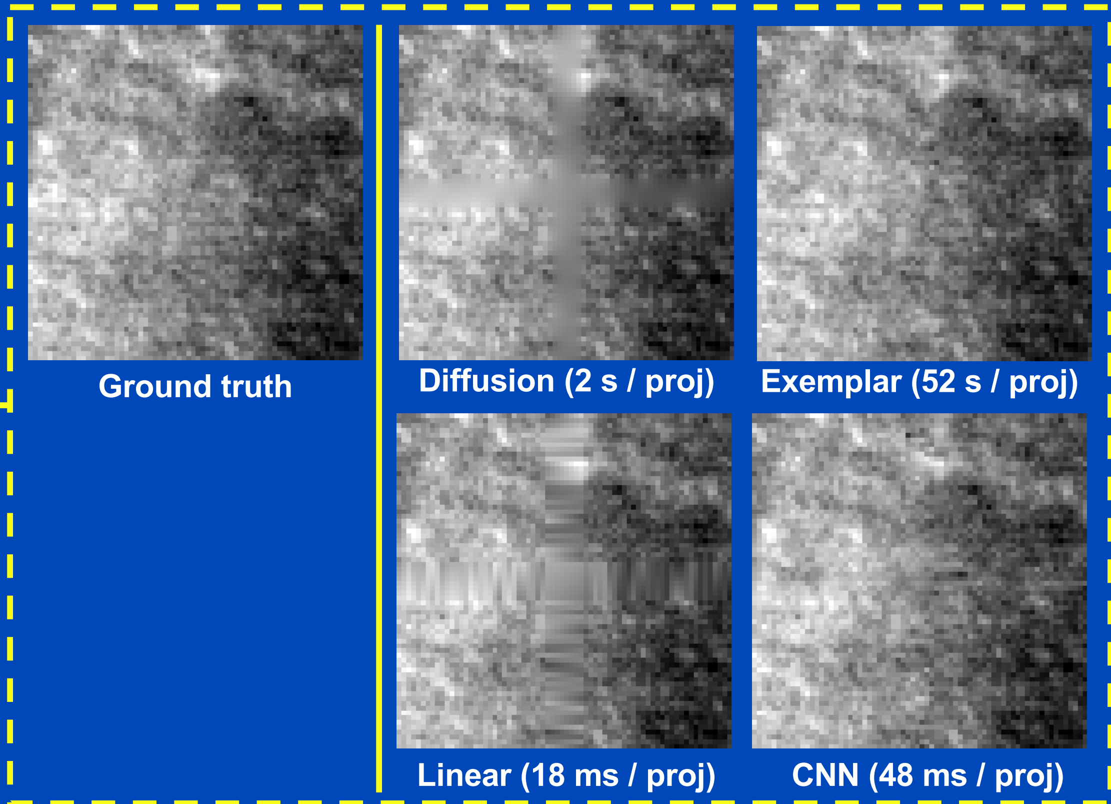

→ CNN is factor 1000 faster than exemplar-based inpainting

Computation times refer to mean values over all 1314 projections of the validation set

Conclusion & Outlook

- Deep inpainting can remove gaps between detector modules as good as exemplar-based inpainting while reducing the computation time by a factor of 1000.
- Proof of principle on data from conventional CBCT
- Deep inpating does not need gapless data for training. It is rather trained using the data with pixel gaps and dead pixels.
- Brings photon counting detector technology for CBCT one step closer to clinical routine.

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Thank You!

The 6th International Conference on

Image Formation in X-Ray Computed Tomography

Conference Chair: **Marc Kachelrieß**, German Cancer Research Center (DKFZ), Heidelberg, Germany

This presentation will soon be available at www.dkfz.de/ct.
Job opportunities through DKFZ's international Fellowship programs (marc.kachelriess@dkfz.de).
Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.