Deep DSA (DDSA)

Learning Mask-Free Digital Subtraction Angiography for Static and Dynamic Acquisition Protocols using a Deep Convolutional Neural Network

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DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Motivation

Digital subtraction angiography (DSA)

- Take series of x-ray images while injecting a contrast medium into the vessels
- Subtract a mask image (image acquired prior to contrast medium injection) from all subsequent frames
  → Enhances visibility of vessels

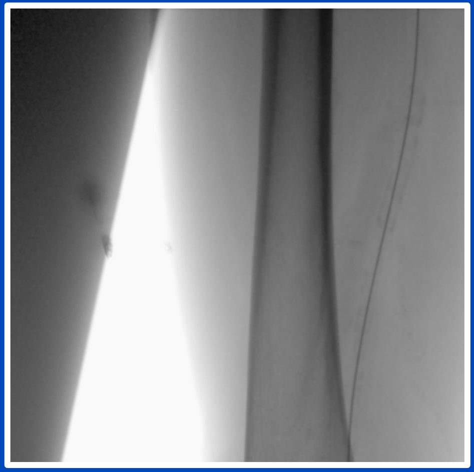
Drawbacks of DSA

- C-arm/table or organ motion leads to artifacts in the subtraction image → Limitation to static data
- Acquisition of mask image leads to increase of radiation dose

Deep DSA

→ Generate DSA-like images in real-time directly from contrast-enhanced fluoroscopic image without a mask image

Study of knee and distal femur



Bolus Chase Study of distal femur, knee and tibia

Methods

General principle

Conventional DSA

I_t

$-$

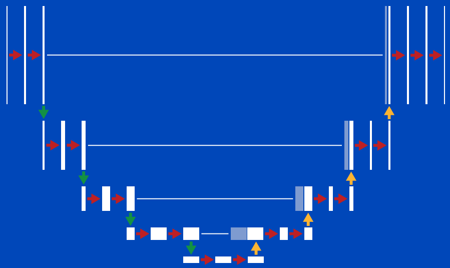
I_0

$=$

$\tilde{I}_t$

Deep DSA

I_t

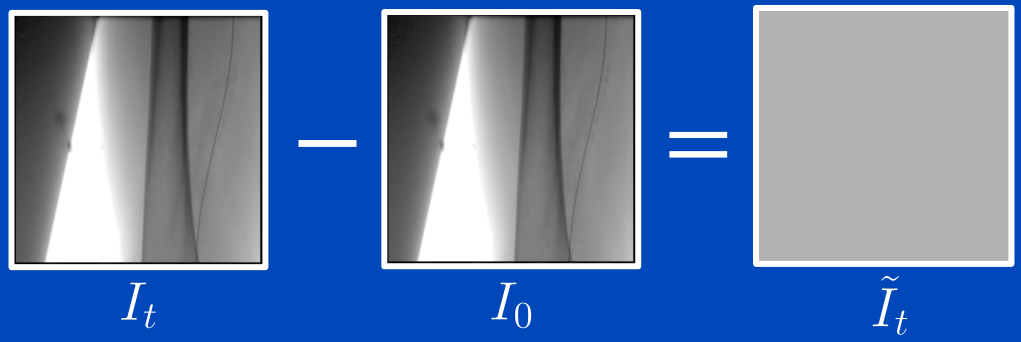


$\tilde{I}_t$

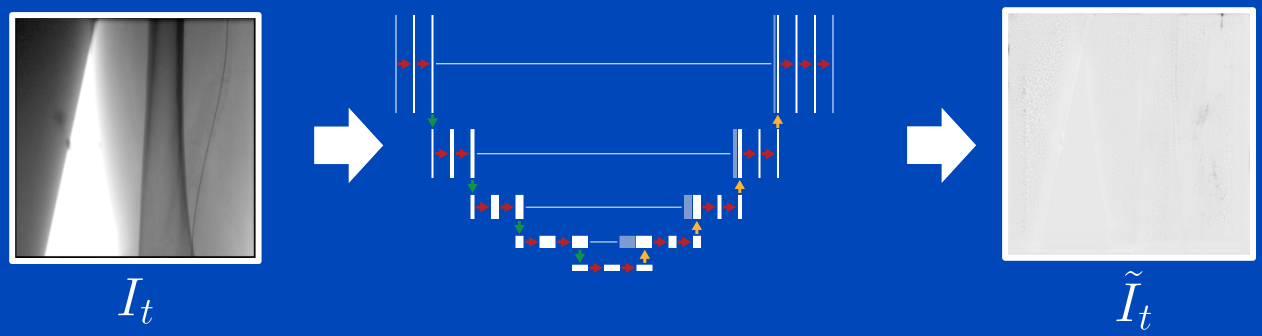
- **Train on static cases where ground truth is conventional DSA**

Methods
General principle

Conventional DSA



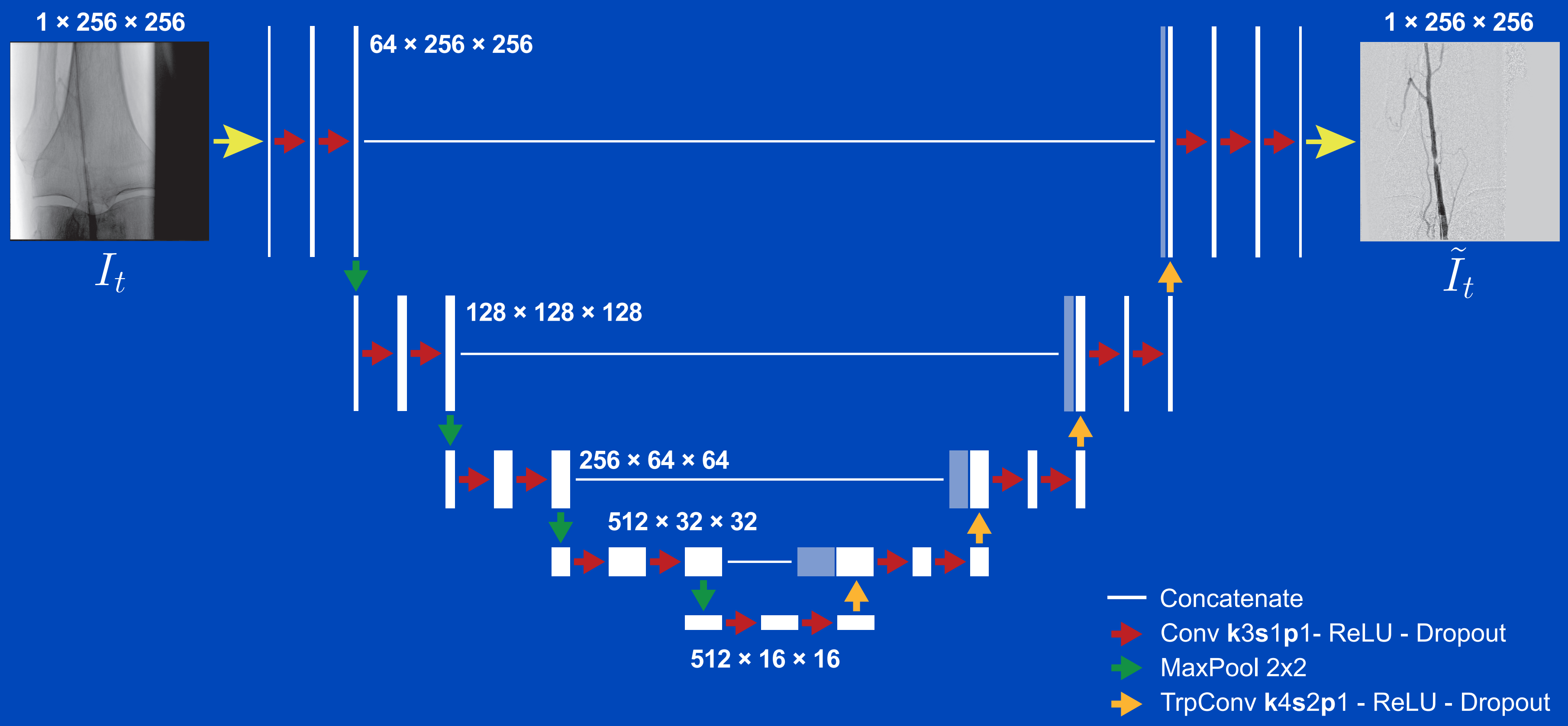
Deep DSA



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

Methods

Network structure adapted from U-Net[1]



[1]Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. ; 2015:234-241.

Methods
Training details

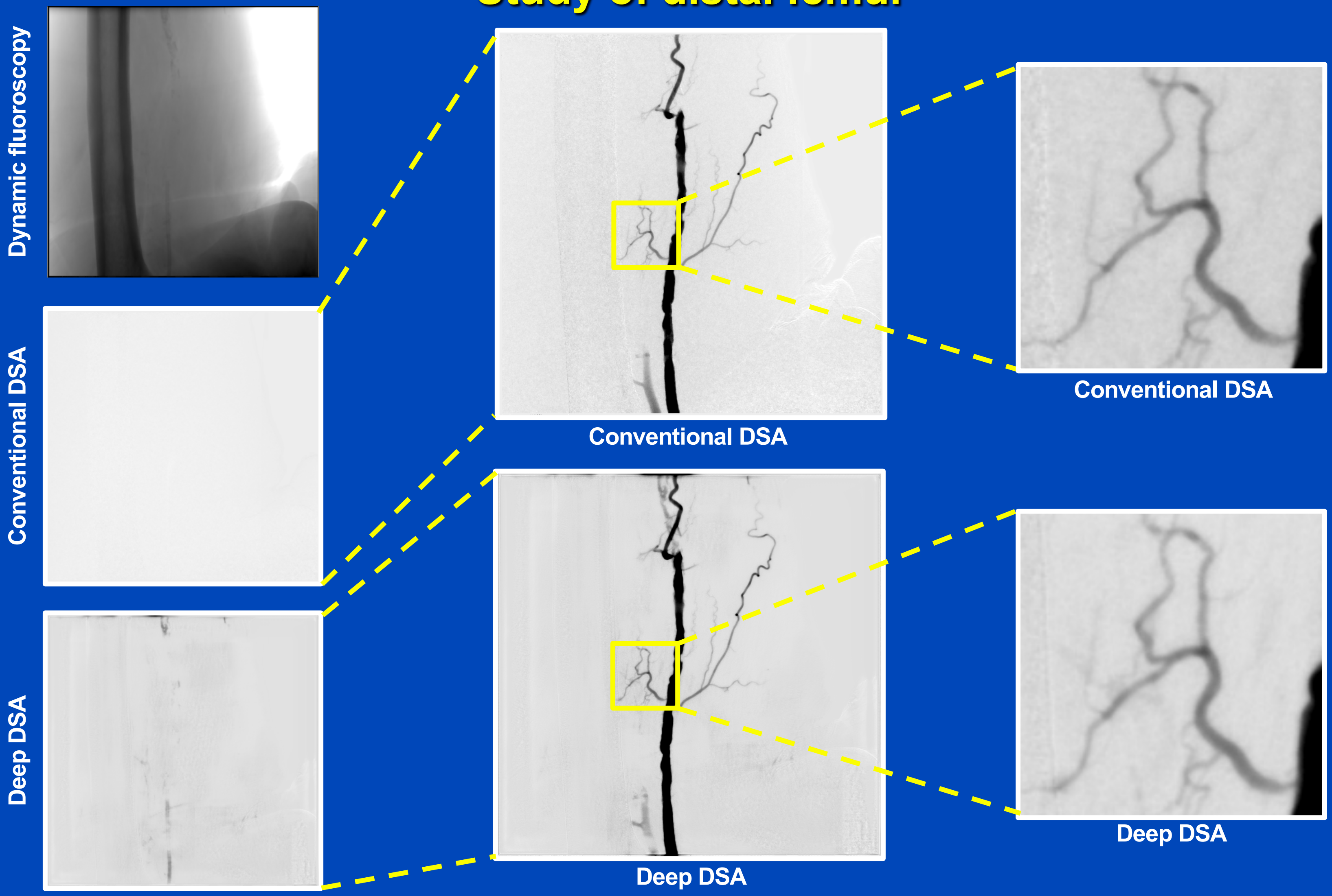
- Trained on randomly sampled image patches (256 × 256 px) from 48 exams (3054 images) acquired using a commercial C-arm system
- Validated on randomly sampled patches from 12 exams (570 images)
- Trained using Adam[1] optimizer and minimizing L_1
- All weights were initialized using He initialization[2]
- Data were normalized to unit mean, zero variance
- Data augmentation
  - Flips
  - Rotations
  - Shearing
  - Average blur
  - Piecewise affine transformations
  - Scaling

  and random cropping were performed online

[1]Kingma DP , Lei Ba J. Adam: A Method for Stochastic Optimization.; 2014.
[2]He K, Zhang X, Ren S, Sun J. Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification.; 2015

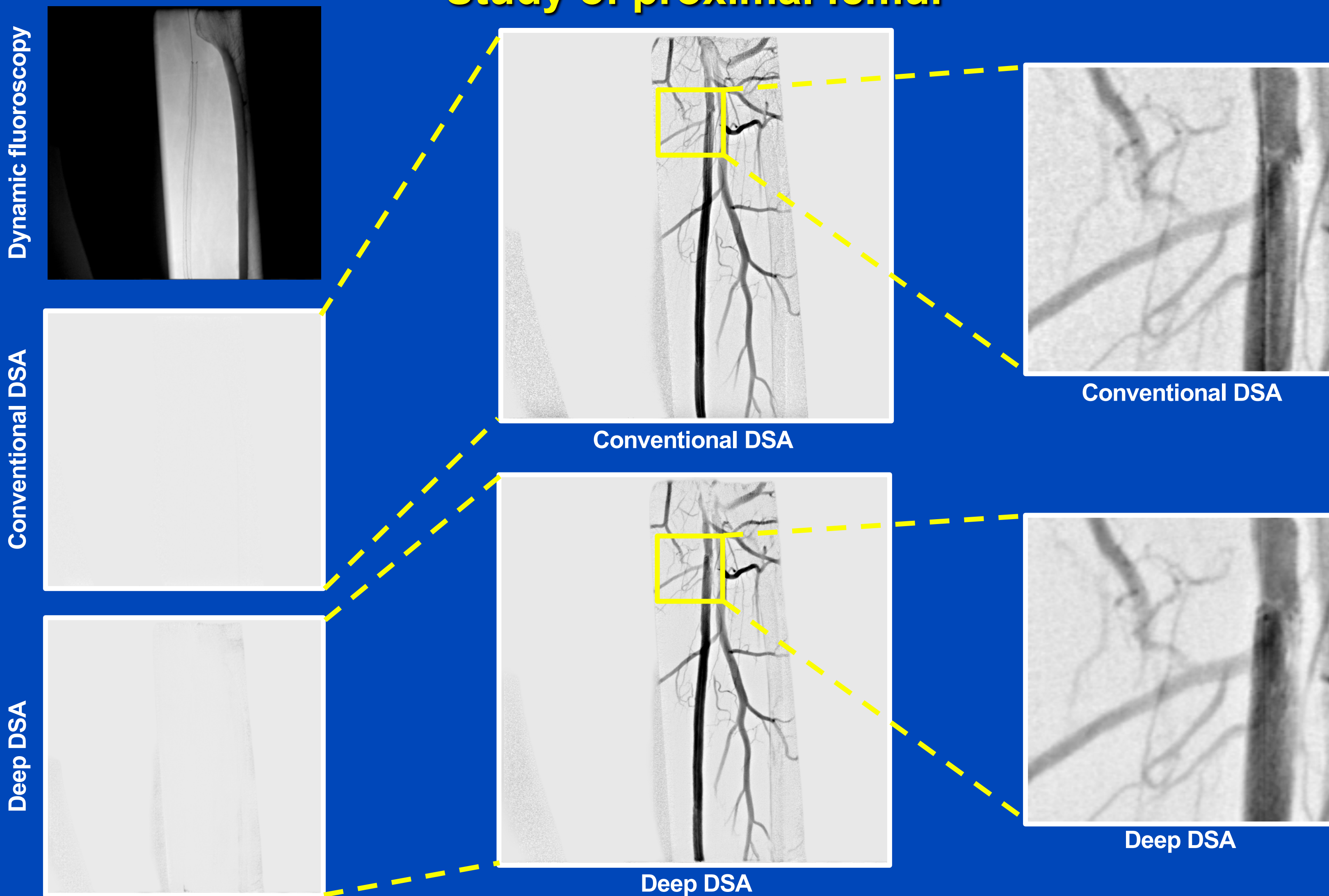
Results

Study of distal femur



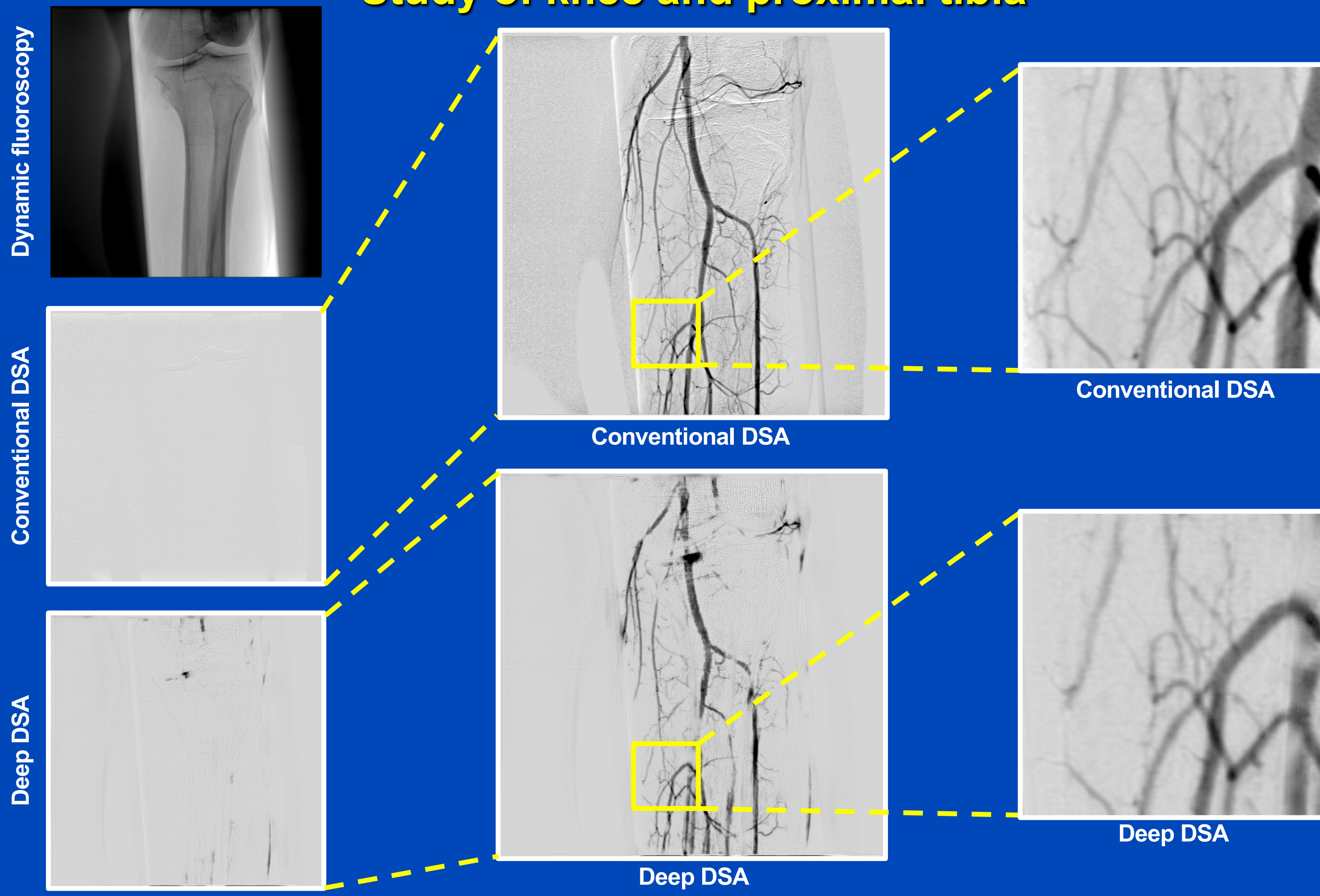
Results

Study of proximal femur



Results

Study of knee and proximal tibia



Results

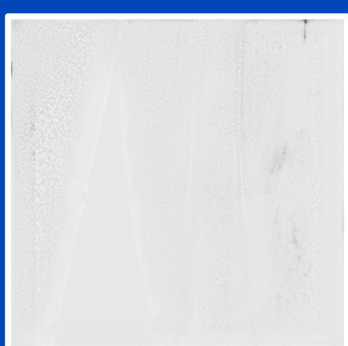
Bolus chase study

Dynamic fluoroscopy

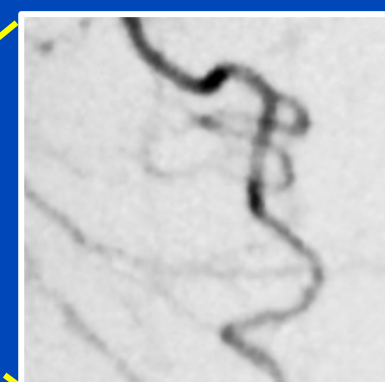
Conventional DSA

Conventional DSA infeasible due to C-arm motion

Deep DSA



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

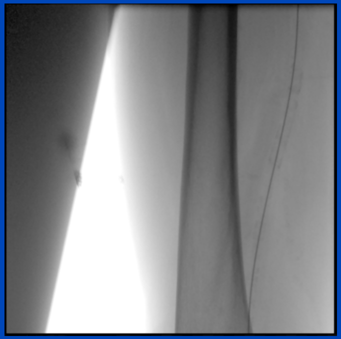


Deep DSA at $\mathrm{t} = t_a$

Results

Bolus chase study

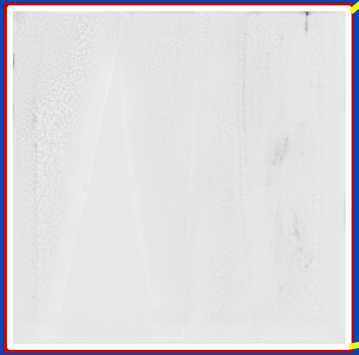
Dynamic fluoroscopy

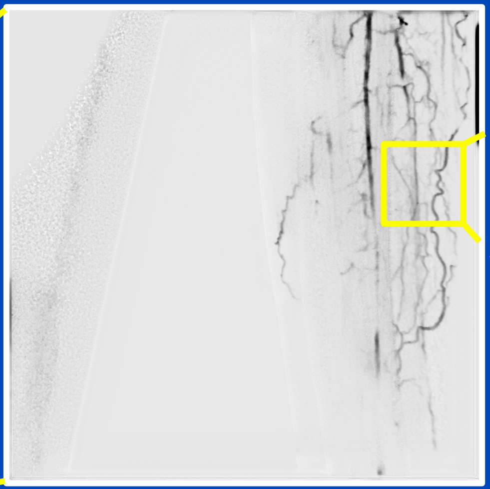


Conventional DSA

Conventional DSA infeasible due to C-arm motion

Deep DSA





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

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

Conclusion & Outlook

Deep DSA has the potential to

- expand conventional DSA to dynamic acquisitions such as bolus chase studies
- reduce dose compared to conventional DSA

Drawbacks of current Deep DSA framework

i. Missing ground truth leads to challenges for exams which are subject to organ motion
ii. Temporal information in fluoroscopy is not leveraged

Outlook

i. Train Deep DSA unsupervised (e.g. using cGANs) or using autoencoders
ii. Train recurrent Deep DSA pipeline

Study of abdomen/pelvis

Thank You!

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.