Organ-Specific Context-Sensitive CT Image Reconstruction and Display

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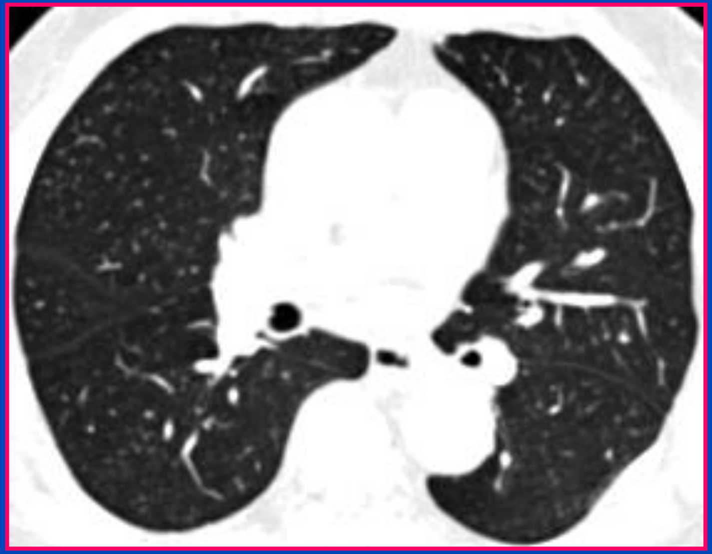
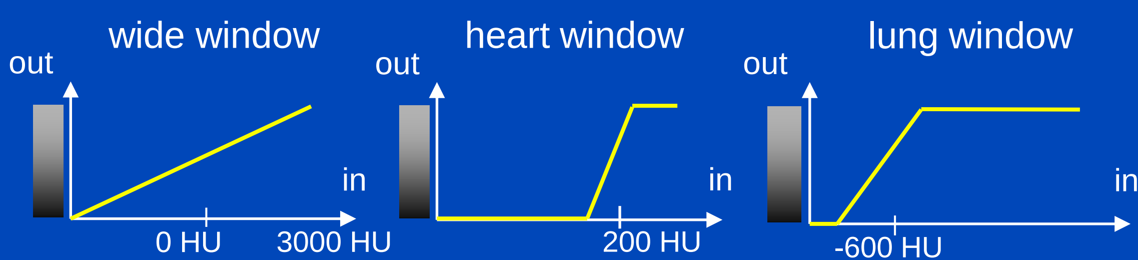
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

smooth kernel reconstruction



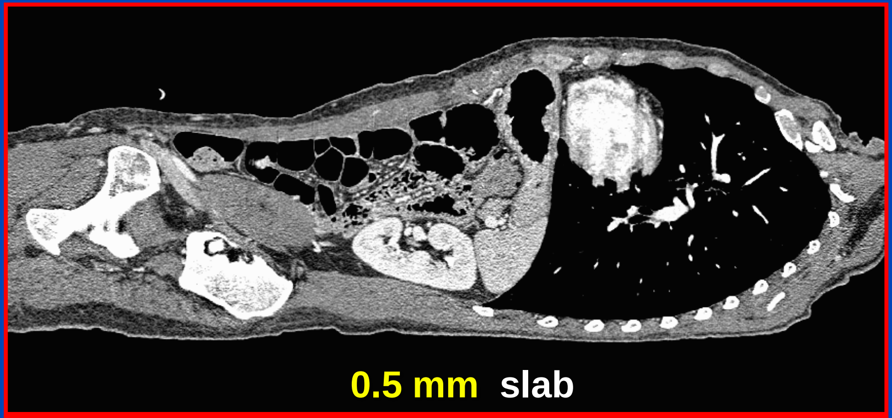
sharp kernel reconstruction

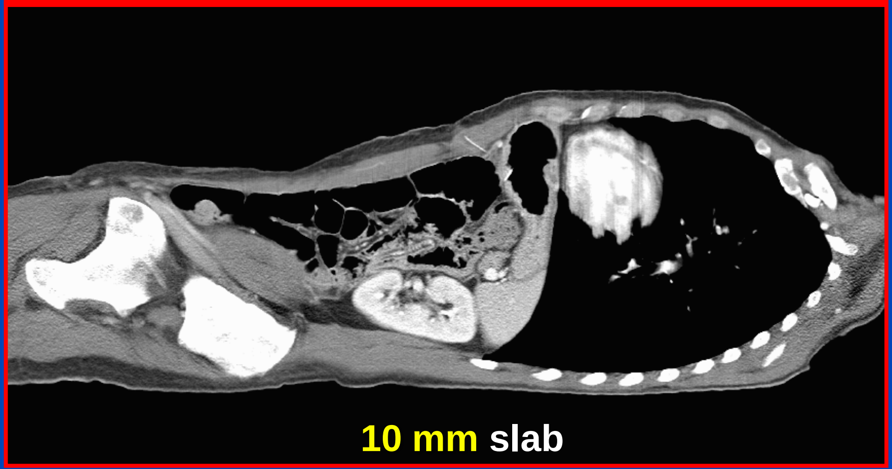
	Center	Width
pelvis	35 HU	350 HU
soft tissue	60 HU	400 HU
abdomen	40 HU	300 HU
liver	40 HU	200 HU
lung	-600 HU	1200 HU
heart	200 HU	600 HU
bone	450 HU	1500 HU
spine	40 HU	350 HU
mediastinum	40 HU	400 HU
angiography	80 HU	700 HU



sliding thin slab (STS) display with
maximum intensity projection (MIP)

sliding thin slab (STS) display with
mean intensity projection (mean-IP)





Aim

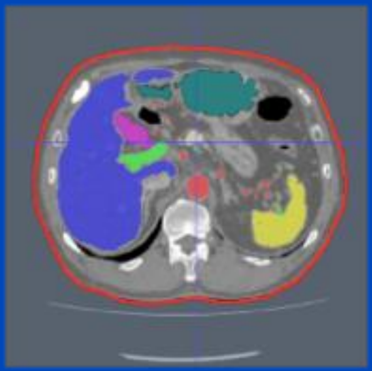
To combine mutually exclusive CT image properties into a single organ-specific image reconstruction and display using prior anatomical information.

Methods

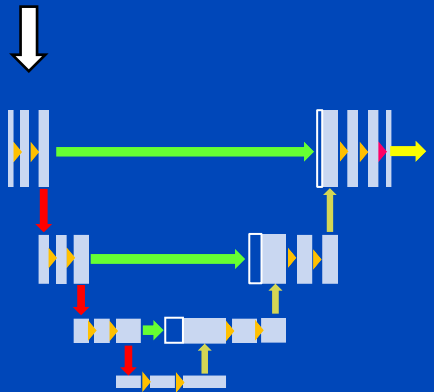
- **Prior anatomical knowledge is gained from an automatic multi-organ segmentation**
- **Hirarchical 3D fully convolutional neural network consisting of two consecutive stages[1]**
  - **Coarse-to-fine segmentation based on 3D U-Net**
    1. **Detection of abdominal cavity**

Stage 1

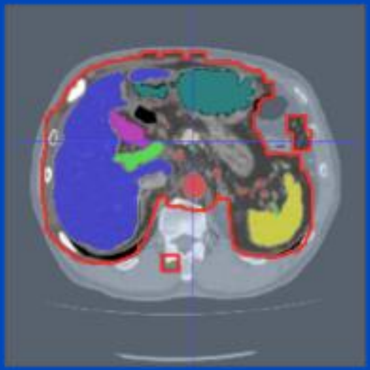
mask



$$f_{\mathrm{label}}, f_{\mathrm{mix}}, f_{\mathrm{mask}}$$



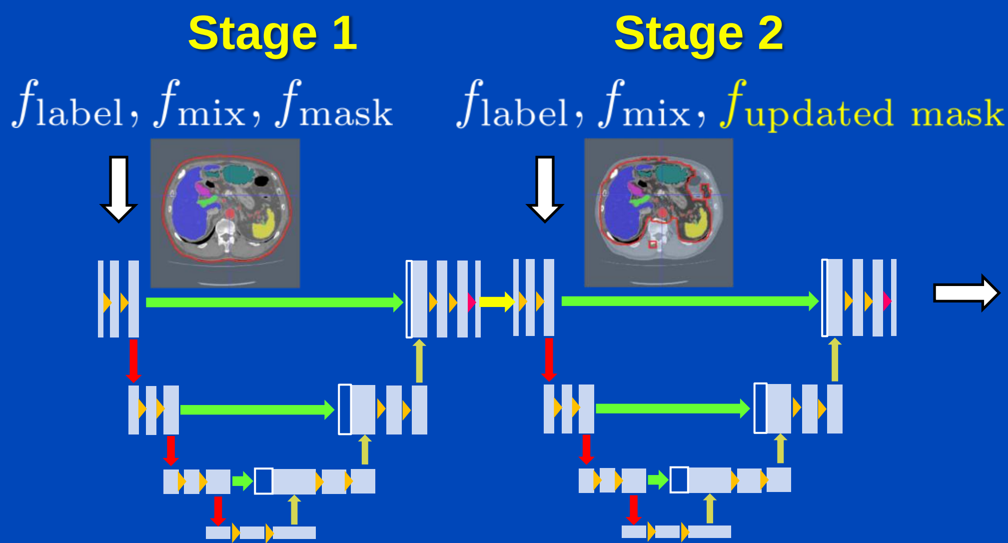
updated mask

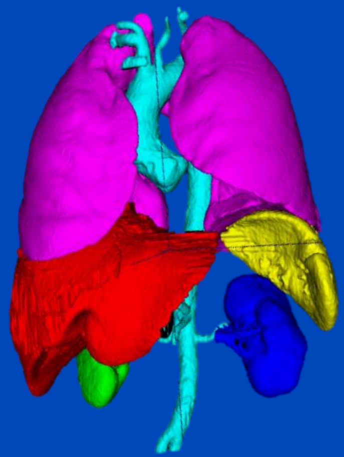


[1] S. Chen, H. Roth, S. Dorn, M. May, A. Cavallaro, M. Lell, M. Kachelrieß, H. Oda, K. Mori, and A. Maier. Towards Automatic Abdominal Multi-Organ Segmentation in Dual Energy CT using Cascaded 3D Fully Convolutional Network. *CoRR*, 2017

Methods

- **Prior anatomical knowledge is gained from an automatic multi-organ segmentation**
- **Hirarchical 3D fully convolutional neural network consisting of two consecutive stages[1]**
  - **Coarse-to-fine segmentation based on 3D U-Net**
    1. **Detection of abdominal cavity**
    2. **Detection of target organ boundaries**





detection of multiple organs

[1] S. Chen, H. Roth, S. Dorn, M. May, A. Cavallaro, M. Lell, M. Kachelrieß, H. Oda, K. Mori, and A. Maier. Towards Automatic Abdominal Multi-Organ Segmentation in Dual Energy CT using Cascaded 3D Fully Convolutional Network. *CoRR*, 2017

Methods

Open-source implementation of two stages cascaded network[2]
→ fine-tuning of pre-trained network to fit to our data

- **42 contrast-enhanced clinical torso DECT datasets**
  - **30 for training, 6 for validation, 6 for test**

- **NVIDIA GeForce GTX 1080 Ti**
- **Training: ~ 3 days per stage**
- **Segmentation: several minutes**

[2] H. Roth, H. Oda, Y. Hayashi, M. Oda, N. Shimizu, M. Fujiwara, K. Misawa and K. Mori. Hierarchical 3D fully convolutional networks for multi-organ segmentation. *arXiv preprint arXiv:1704.06382*, 2017

Methods

- Automatic segmentation: **liver, kidneys, spleen, lung, aorta**.
- Thresholding remaining voxels into the following tissue types: **muscles, fat, bone, vasculature**.
- Currently, manual corrections are necessary (until today).

→ Segmentation delivers a binary mask $m_l(\mathbf{r})$ for each tissue label

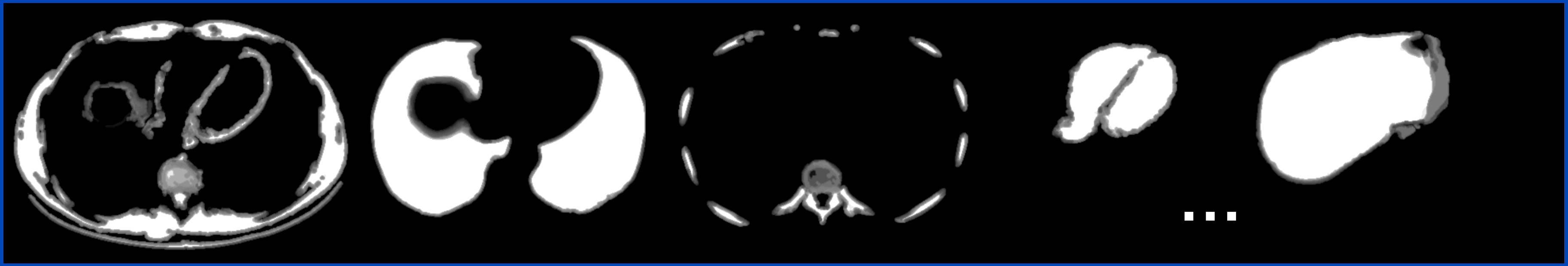
Methods

- Smoothing of the binary masks $m_l(\mathbf{r})$ to cope with the boundaries of adjacent anatomical structures.

$$\bar{w}_l(\mathbf{r}) = m_l(\mathbf{r}) * G(\mathbf{r}) \qquad G(\mathbf{r}) = \frac{1}{\sigma\sqrt{2\pi}} \exp^{-\frac{\mathbf{r}^2}{2\sigma}}$$

$$w_l(\mathbf{r}) = \frac{\bar{w}_l(\mathbf{r})}{\sum_l^L \bar{w}_l(\mathbf{r})} \qquad \sum_l^L w_l(\mathbf{r}) = 1$$

- Zero-mean Gauss, σ determines width of overlap in mm.
- Weighting masks $w_l(\mathrm{r})$ allow for individual settings for each organ.



Context-sensitive (CS) = organ-dependent parameter adaptation

Context-Sensitive (CS) Reconstruction

- Reconstruct *B* basis $f_b(\mathbf{r})$ emphasizing certain image properties
  - f_1 = smooth reconstruction (for e.g. soft tissue, liver, etc.)
  - f_2 = sharp reconstruction (for e.g. lung, bone, etc.)

- The CSR image is defined as

$$f_{\mathrm{CSR}}(\mathbf{r}) = \sum_{l=1}^{L} \sum_{b=1}^{B} w_l(\mathbf{r}) \cdot \Gamma(l,b) \cdot f_l(\mathbf{r})$$

$$\Gamma(l,b) = \begin{cases} 1 & \text{, if basis image } b \text{ is assigned to label } l \\ 0 & \text{, otherwise.} \end{cases}$$

- L #labels
- B #basis images
- $w_l(\mathbf{r})$ prior organ-specific weight for each voxel $\mathbf{r}$

$$L \geq B$$

Context-Sensitive (CS) Display

- The CS center and width for each voxel is given by

$$C_{\mathrm{CS}}(\mathbf{r}) = \sum_{l=1}^{L} w_l(\mathbf{r}) \cdot C_l,$$

$$W_{\mathrm{CS}}(\mathbf{r}) = \sum_{l=1}^{L} w_l(\mathbf{r}) \cdot W_l.$$

- C_l, W_l predefined center/width for label *l*

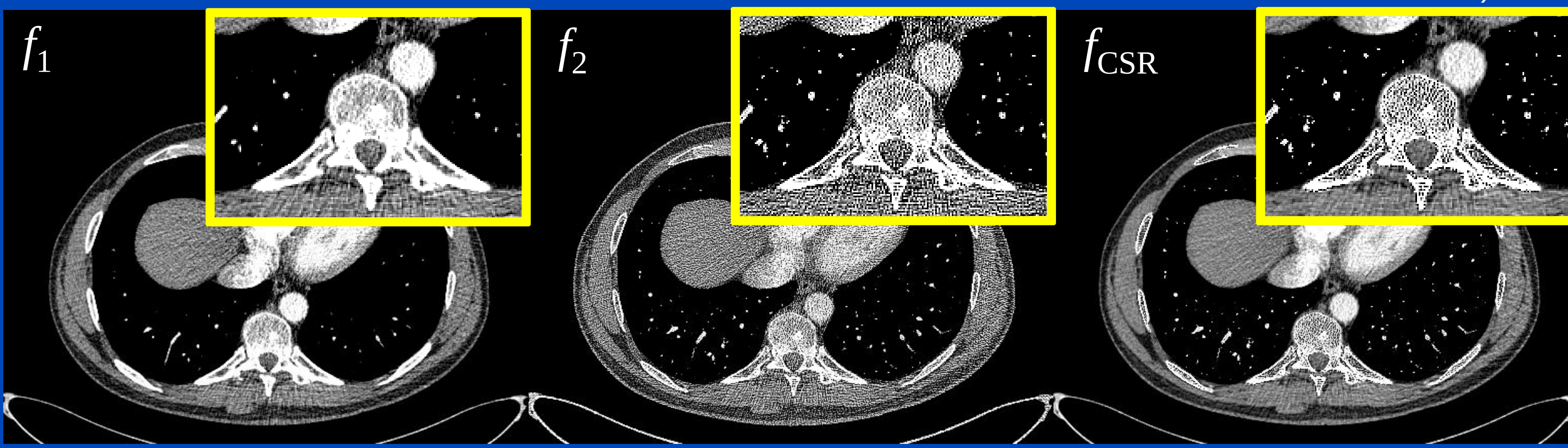
- Images are viewed with an adaptive sliding thin slab (STS) technique.
  - STS mean intensity projection in e.g. soft tissue
  - STS maximum intensity projection (MIP) in e.g. lung

CS Reconstruction

standard low resolution image (smooth kernel D30f)

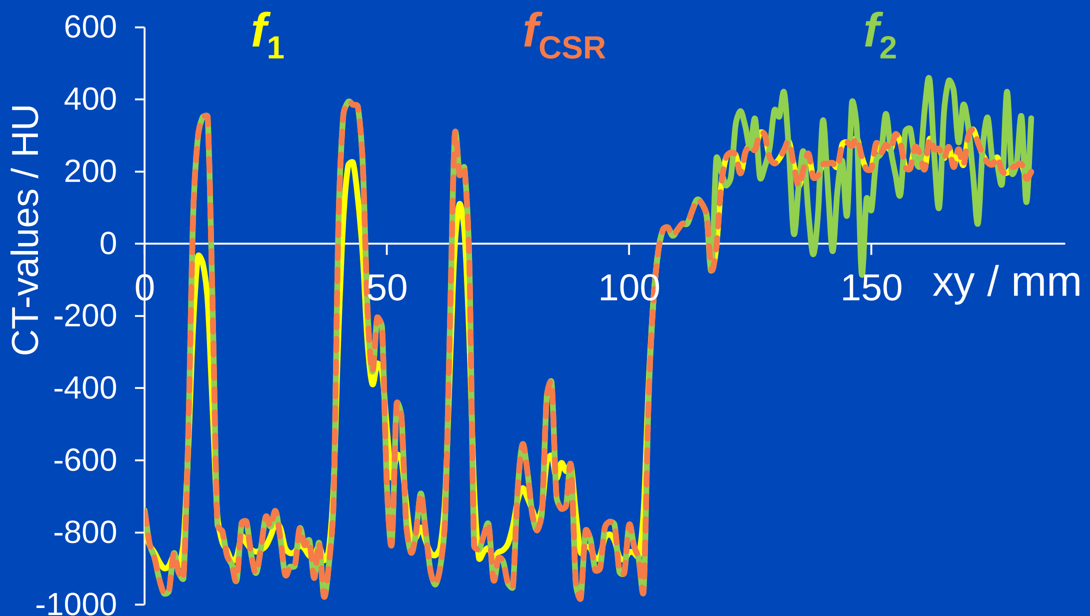
standard high resolution image (sharp kernel B70f)

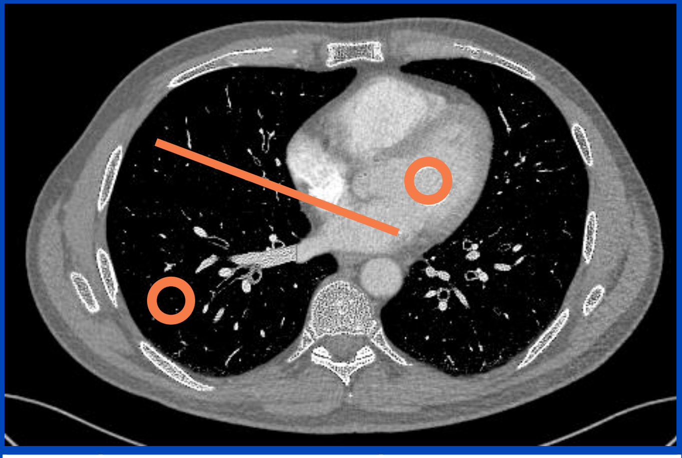
resolution-mixed image (high resolution in lung and bone, low noise in soft tissue)



C / W = 60 / 400 HU

CS Reconstruction





	ROI_1 lung $\mu \pm \sigma$	ROI_2 heart $\mu \pm \sigma$
f_1	-820 ± 58 HU	240 ± 48 HU
f_2	-814 ± 152 HU	233 ± 121 HU
f_{CSR}	-814 ± 152 HU	240 ± 48 HU

- ✓ **Increased spatial resolution in bone and lung**
- ✓ **Decreased noise level in soft tissue**

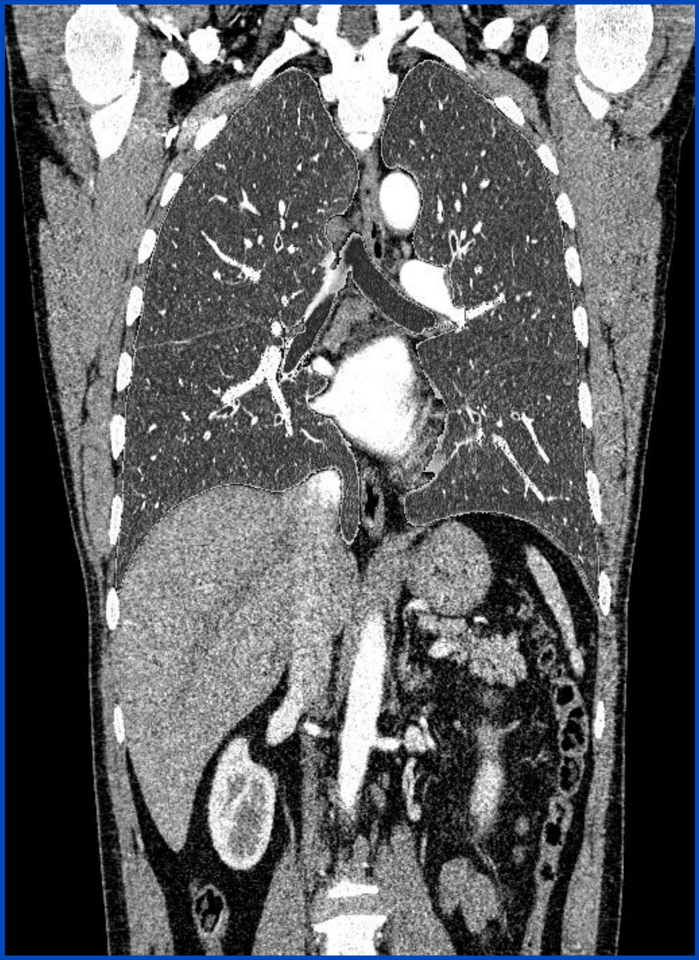
CS Reconstruction

abdomen window	lung window	bone window
C/W = 40 / 300 HU	C/W = -600/1200 HU	C/W = 450/1500 HU

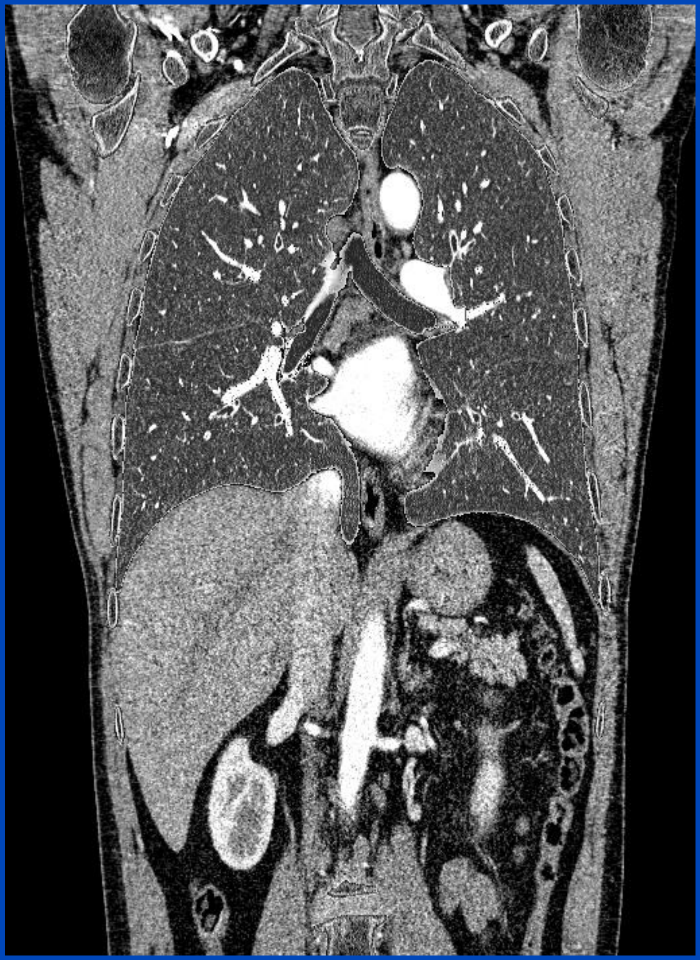
→ Need of a context-sensitive display approach!

CS Display
Adaptive Windowing

CS Display
Adaptive Windowing

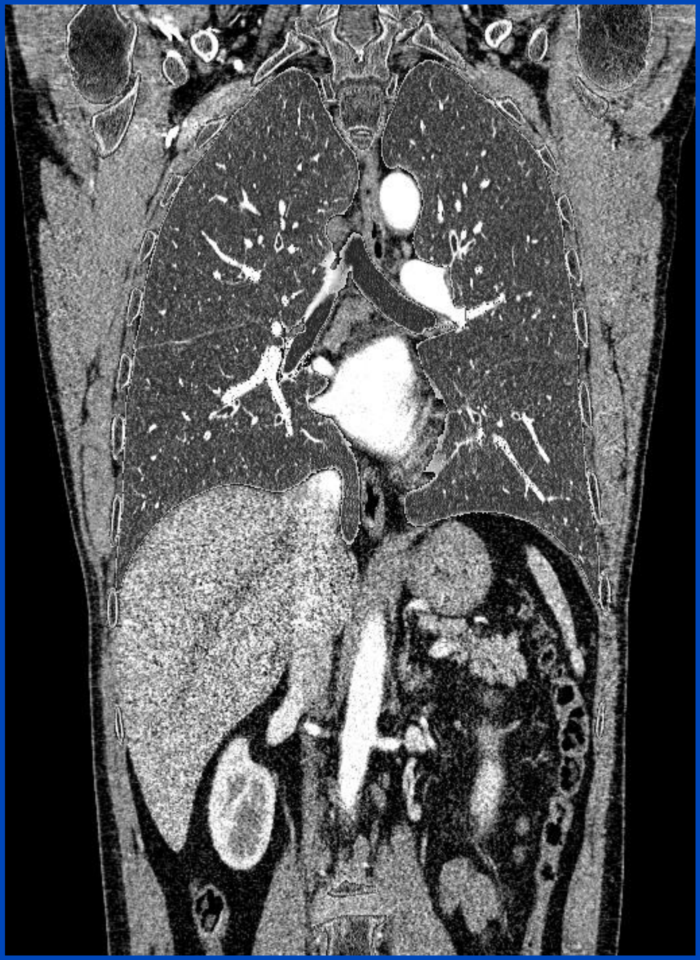


CS Display
Adaptive Windowing



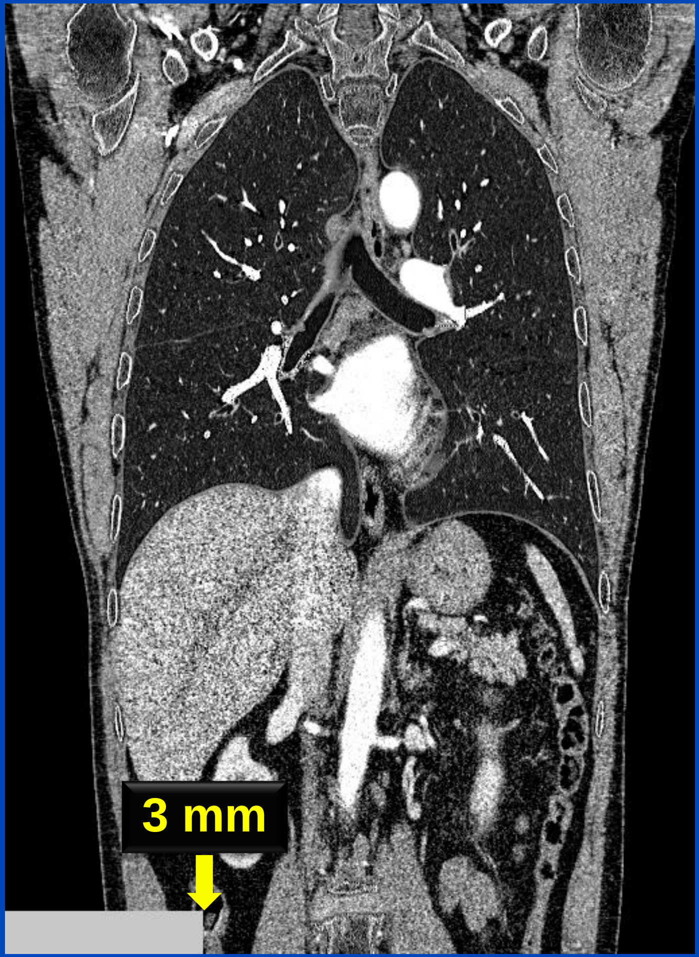
dkfz.

CS Display
Adaptive Windowing



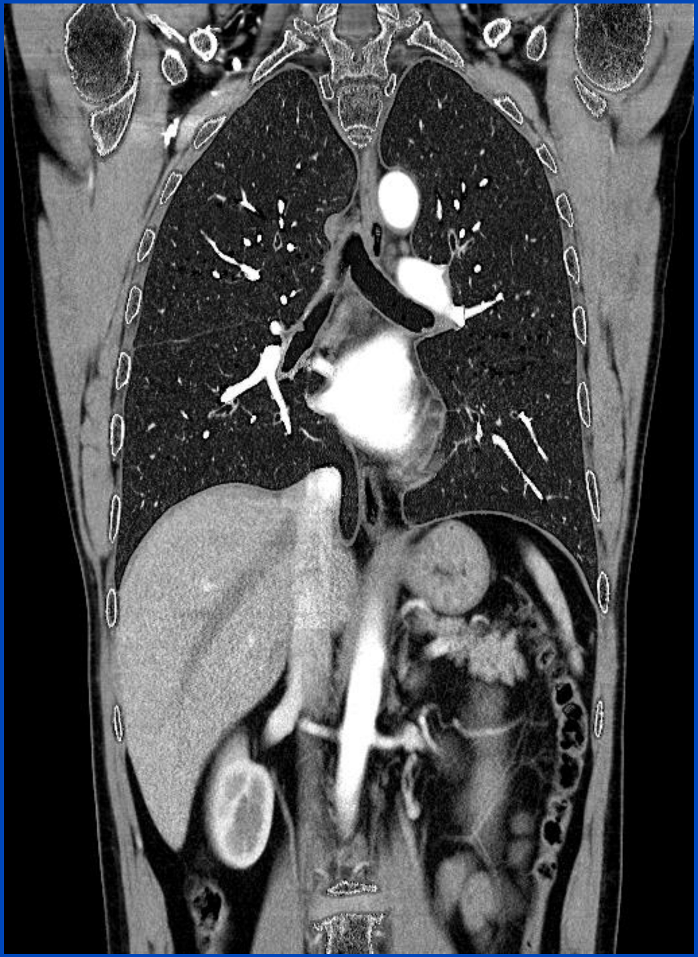
CS Display
Soft Blending

- Varying σ during the Gaussian smoothing result in different blending widths $w_l(\mathbf{r})$
- We use 3 mm blending
  - Good compromise between hard transitions and over smoothing



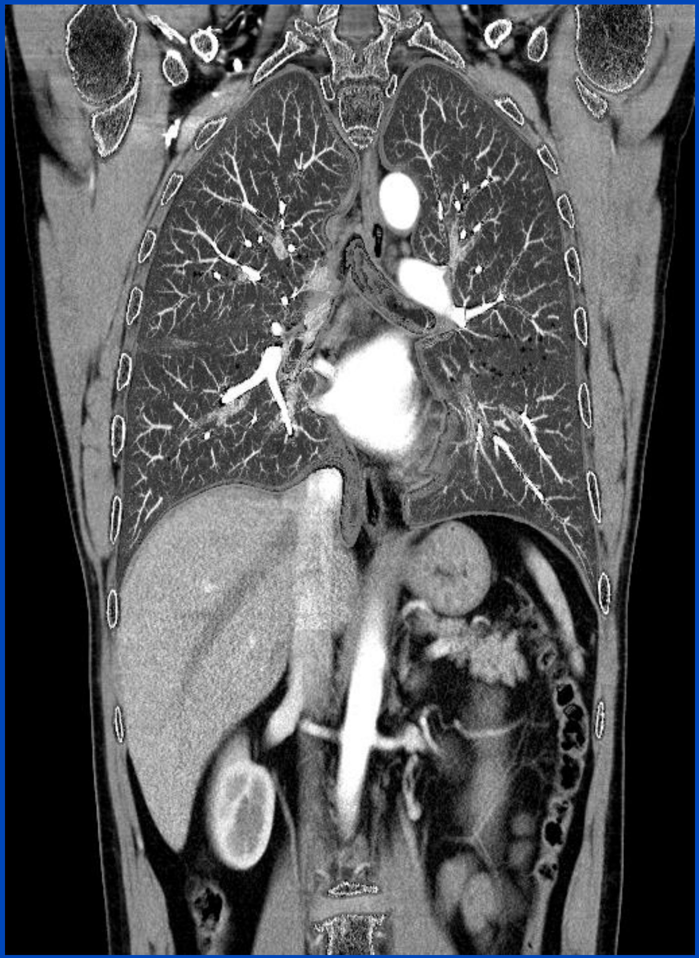
CS Display
Sliding Thin Slab

- **STS mean in soft tissue (5 mm)**
  - **Less noise in soft tissue**



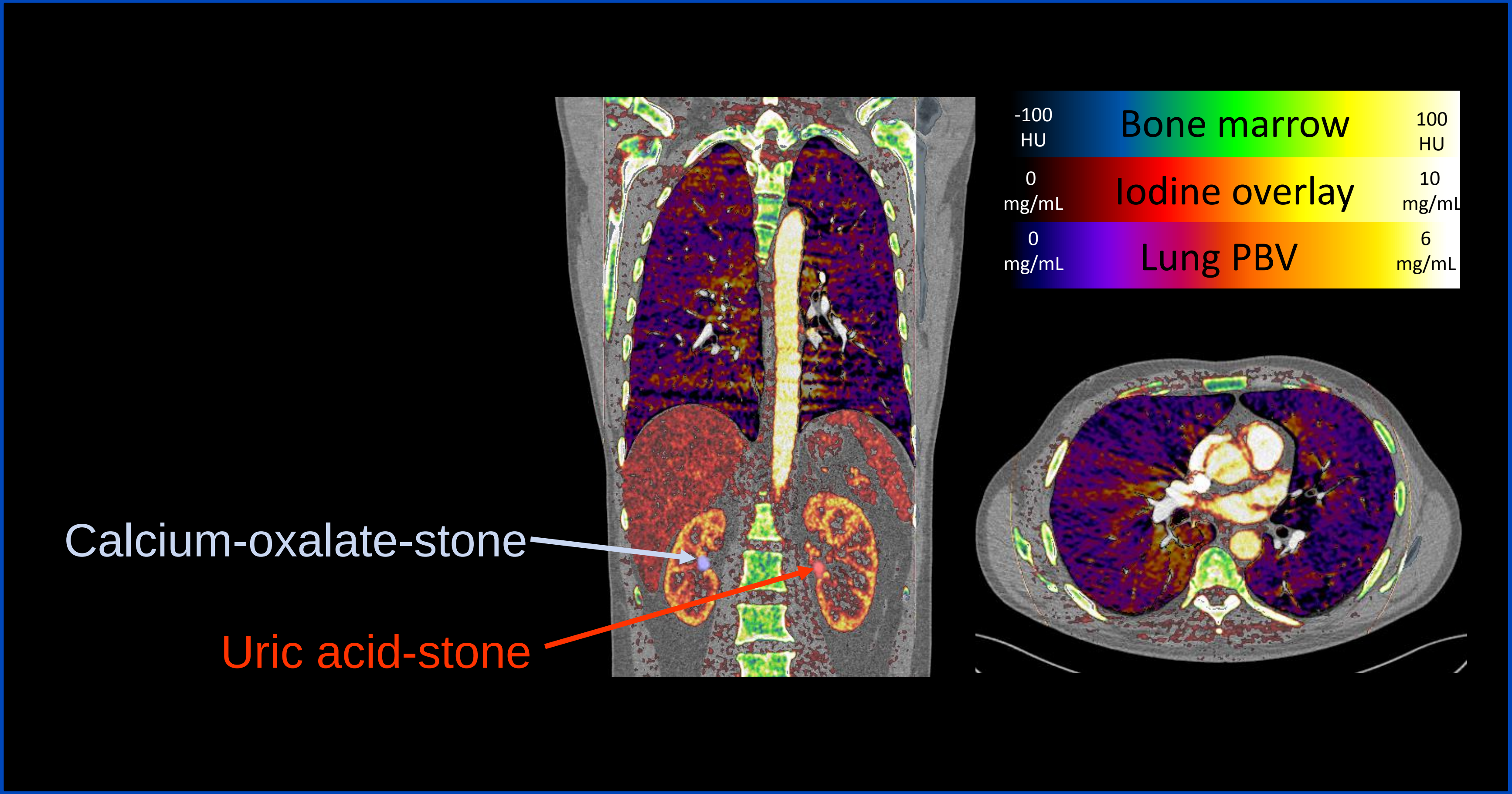
CS Display
Sliding Thin Slab

- **STS MIP in lung (10 mm)**
  - **Better visualization of lung vessels**



Context-Sensitive Dual Energy

- Simultaneous DE evaluation with commonly used applications



Conclusions

- Method strongly depends on the segmentation accuracy
  - Still needs improvement
- Context-sensitive reconstruction
  - Combines mutually exclusive image properties
    - » High spatial resolution in bone and lung
    - » Low noise in soft tissue
- Context-sensitive display
  - Able to present significantly more information to the reader simultaneously
  - Dealing with multiple image stacks may be no longer necessary

Outlook

- Development of GUI for CS reconstruction and display
- Method readily extendable to multi energy data as well as to other modalities

Thank You!

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This presentation will soon be available at www.dkfz.de/ct.

Job opportunities through DKFZ’s international PhD or Postdoctoral Fellowship programs (www.dkfz.de), or directly through Marc Kachelriess (marc.kachelriess@dkfz.de).

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