SPIE 2014: Session 5, 9033-25

A New Approach to Regularized Iterative CT Image Reconstruction

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Why Iterative Reconstruction?

- Iterative image reconstruction promises to reduce image noise (and thus patient dose), to reduce artifacts, or to improve spatial resolution.
- Works for all geometries with only small adaptations.
- Allows to model any effect of the rawdata acquisition process.
- Allows to incorporate prior knowledge like image properties such as smoothness and edges (regularization).

Motivation

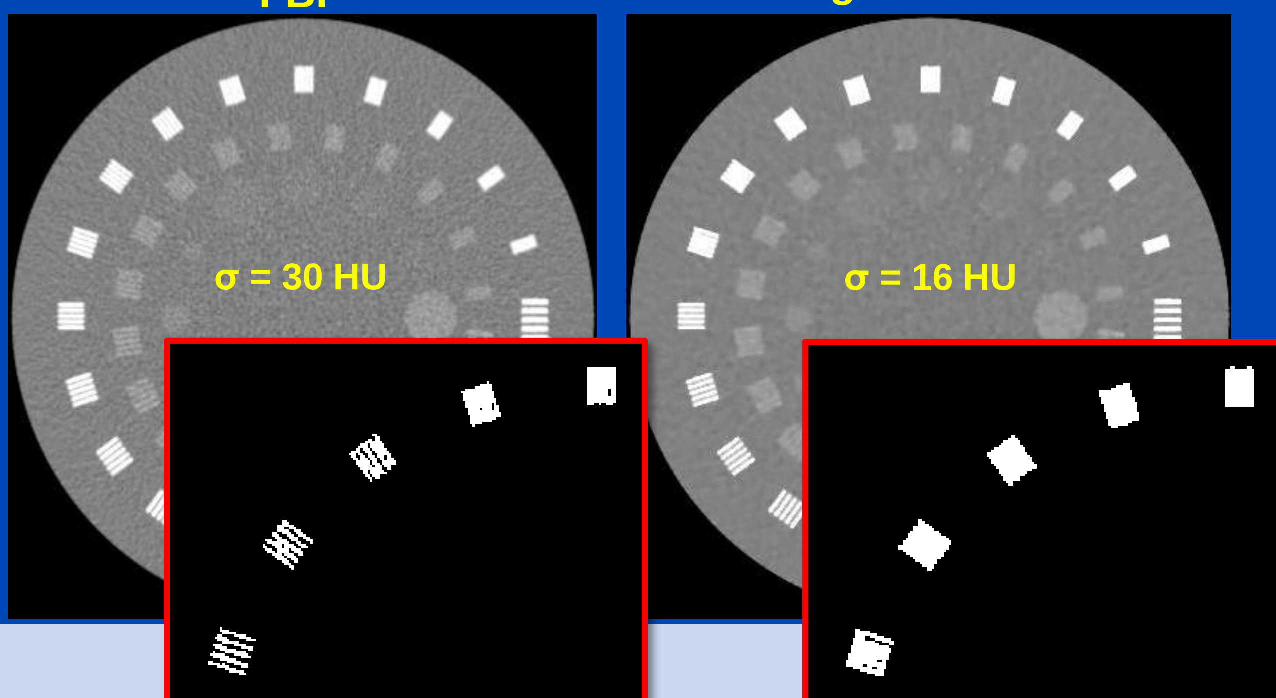
- Most common approach for regularization in iterative reconstruction:

  Cost function = Rawdata fidelity + Penalty term (1) + Penalty term (2) …

- In general the penalty terms penalize strong variations between neighboring voxels → the stronger the regularization the stronger the resolution-noise trade-off → problematic at the resolution limit or when the contrast of details is in the range of the noise level.
- Often many regularization parameters have to be chosen carefully to avoid an artificial image impression or not to alter anatomical information.

FBP

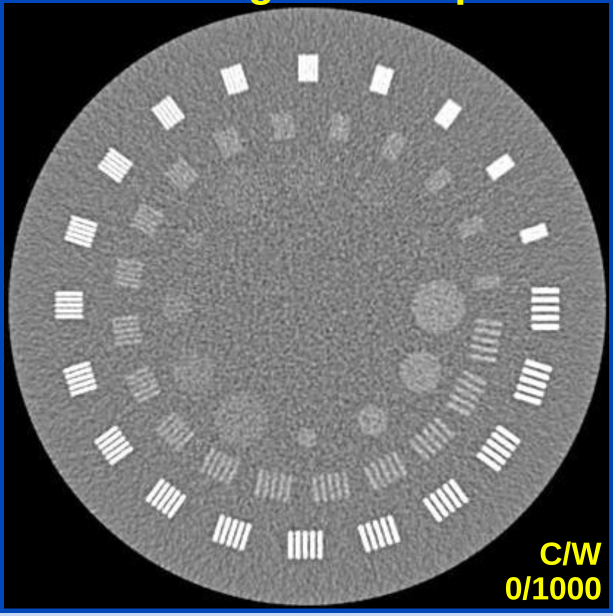
Iterative reconstruction + regularization



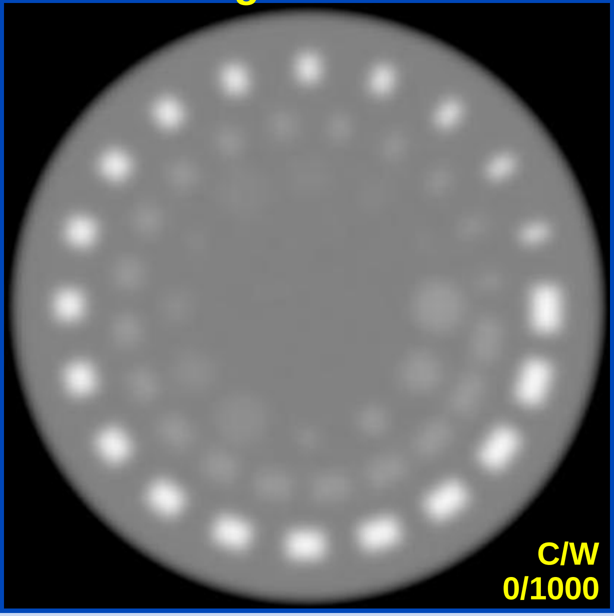
Aim

- To propose a different approach to regularization in iterative reconstruction which can improve the resolution noise trade-off.
- Basis images are generated which emphasize certain image properties like high resolution or low noise, etc. (regularization is incorporated by these basis images into the reconstruction process).
- We want to find the voxel-wise combination of the basis images to generate an image with superior resolution, and lower noise to improve the resolution noise trade-off.

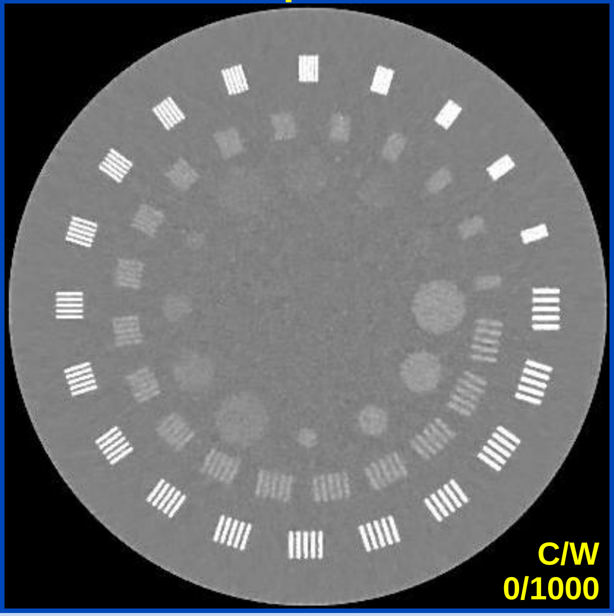
Basis image 1: Sharp FBP



Basis image 2: Smooth FBP



Proposed



Alpha Image Reconstruction (AIR)

- Generate basis images → regularization is incorporated into the reconstruction by the basis images.
  (e.g. regularized / filtered reconstructions, reference FBP reconstructions)
- Find the voxel-wise combination of these basis images best representing the real image by minimizing a cost function:

$$f_{\mathrm{AIR}} = \sum_{b=1}^{B} \boldsymbol{\alpha}_b \circ \boldsymbol{f}_b \quad , \qquad \arg\min_{\boldsymbol{\alpha}} \; \left\| \boldsymbol{R} \cdot \left(\sum_{b=1}^{B} \boldsymbol{\alpha}_b \circ \boldsymbol{f}_b \right) - \boldsymbol{p} \right\|_{\boldsymbol{W}}^2 + U(\boldsymbol{\alpha})$$

  - α_b = weighting images
  - f_b = basis images
  - $\alpha \circ f$ = Hadamard product
  - B = Number of basis images
  - R = Radon transform
  - p = rawdata
  - $U(\alpha)$ = regularization / constraints for α
  - W = statistical weights

- Determine the α – images by minimizing the above cost function
  → the minimum is reached when the weighting images α_b will have large contributions in regions of the corresponding f_b which highly correlate with the rawdata fidelity and low weighting otherwise.

Alpha Image Reconstruction (AIR)

- The regularization term is used to set certain constraints to the weighting images α_b such as continuity and smoothness:

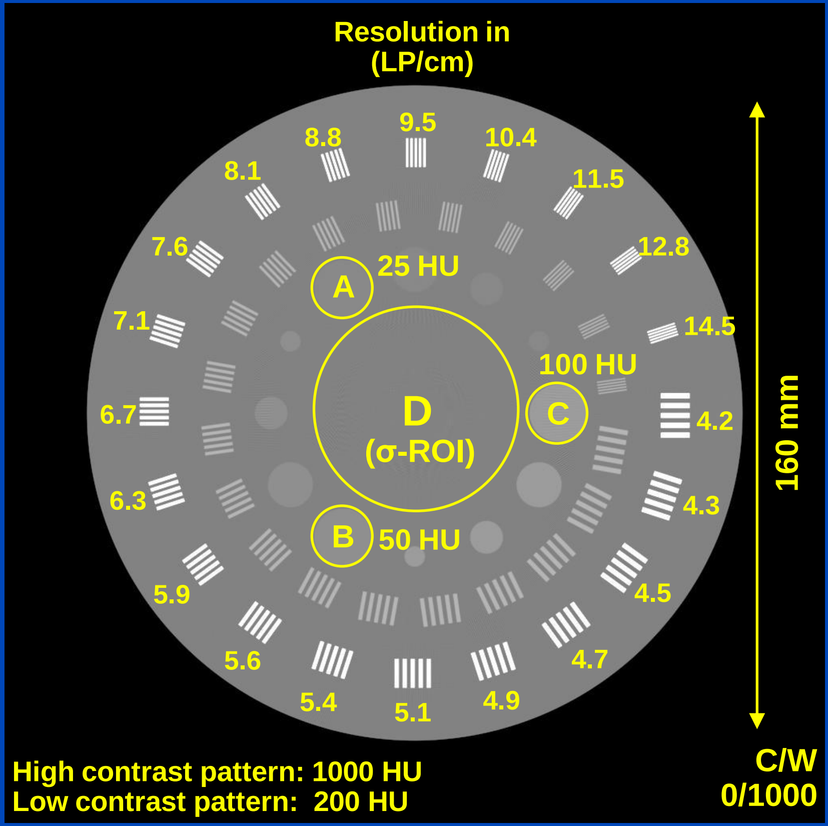
$$C(\boldsymbol{\alpha}) = \underbrace{||\boldsymbol{R}\cdot\left(\sum_{b=1}^{B}\boldsymbol{\alpha}_b\circ\boldsymbol{f}_b\right)-\boldsymbol{p}||^2_{\boldsymbol{W}}}_{\text{convex}} + \underbrace{\overbrace{\underbrace{\beta\sum_{b=1}^{B}\boldsymbol{TV}(\boldsymbol{\alpha}_b)}_{\text{convex}}}^{(1)} + \overbrace{\underbrace{\gamma\sum_{b=1}^{B}||\boldsymbol{\alpha}_b - c_b||_2^2}_{\text{strictly convex}}}^{(2)}}_{U(\boldsymbol{\alpha})}$$

- **(1)** Total variation[1]: smoothness in α_b .
- **(2)** Penalty which controls the average contribution one basis image has to the final result. We use $c_b = 1/B$ → homogeneous regions without differences with respect to the rawdata fidelity are averaged.
- β and γ are trade-off parameters (chosen as small as possible).
- Overall cost function is strictly convex → a unique global minimum exists.

[1]L. Ouyang, et al. , "Effects of the penalty on the penalized weighted least squares image reconstruction for low-dose CBCT." Phys. Med. Biol., vol. 56, no. 17, pp. 5535–5552, Sep. 2011

Phantom

- Analytical phantom
- Diameter of water cylinder = 160 mm
- High contrast (1000 HU) and low contrast (200 HU) resolution patterns (4.2 – 14.5 LP/cm)
- Low contrast disk (100, 50, 25 HU)
- D = ROI for noise measurements
- A, B, C = ROIs for CNR measurements



Assessment of Image Quality

- Image quality was quantified by computing the normalized cross correlation with ground truth,

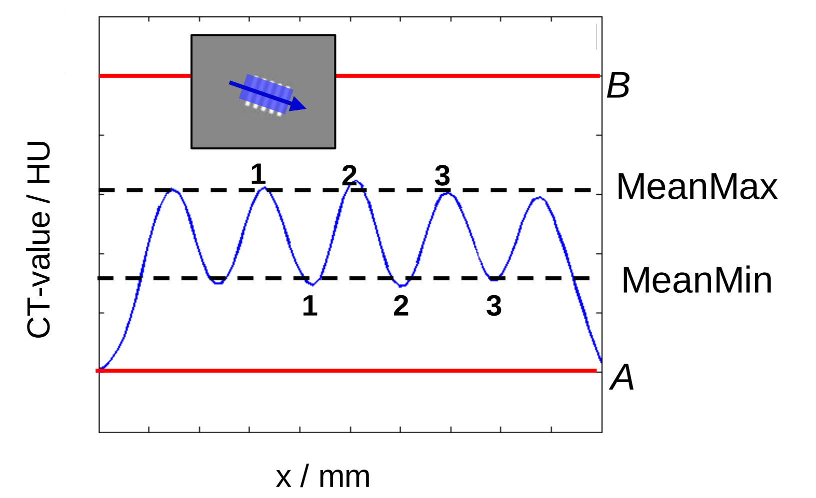
$$\mathrm{NCC} = \frac{1}{L-1}\sum_{x,y\in\Omega}\frac{(f(x,y)-\bar{f})(g(x,y)-\bar{g})}{\sigma_f\sigma_g},$$

  - *f* = reconstructed image, *g* = ground truth
  - σ_f, σ_g = corresponding standard deviations
  - Ω region for NCC analysis

- The resolution line patterns are analyzed using the contrast factor:

$$\mathrm{CF} = \frac{\mathrm{MeanMax}(i)-\mathrm{MeanMin}(i)}{B-A},$$

  - MeanMax(*i*) = mean of three inner maxima of resolution pattern *i*
  - MeanMin(*i*) = mean of three inner minima of resolution pattern *i*
  - *B* = 1000 HU, *A* = 0 HU



Compared Algorithms

- **Ground truth:**
  - noise-free ten-fold spatial resolution analytical reconstruction of our analytical phantom
- **FBP:**
  - Ram-Lak kernel (ramp filter till Nyquist frequency)
- **PWLS with TV:** $$C_{\mathrm{PWLSTV}}(\boldsymbol{f}) = ||\boldsymbol{R}\cdot\boldsymbol{f} - \boldsymbol{p}||^2_{\boldsymbol{W}} + \eta TV(\boldsymbol{f})$$
  - PWLS (Penalized weighted least squares): most attention in penalized CT literature
  - TV: also most attention in CT literature and only few parameters → results easy to comprehend etc.
- **AIR:** $$C(\boldsymbol{\alpha}) = ||\boldsymbol{R}\cdot\left(\sum_{b=1}^{B}\boldsymbol{\alpha}_b \circ \boldsymbol{f}_b\right) - \boldsymbol{p}||^2_{\boldsymbol{W}} + U(\boldsymbol{\alpha})$$
  - Two basis images:
    f_1 = FBP, f_2 = smooth FBP (FBP + Gaussian filtering)
  - Three basis images + anisotrop bilateral filtering[1]:
    f_1 = FBP, f_2 = FBP bilateral filtered, f_3 = sharp FBP bilateral filtered

[1]C. Tomasi and R. Manduchi, “Bilateral filtering for gray and color images,” Proc. 6th Int. Conf. Computer Vision, pp. 839–846, 1998.

Simulation and Reconstruction Setting for Phantom Simulations

<u>Rawdata:</u>

- Siemens SOMATOM Definition Flash Geometry
- N_{360} = 1160
- Poisson noise was simulated resulting in 30 HU noise in the FBP reconstruction in water-equivalent tissue.
- Monochromatic rawdata at 80 keV

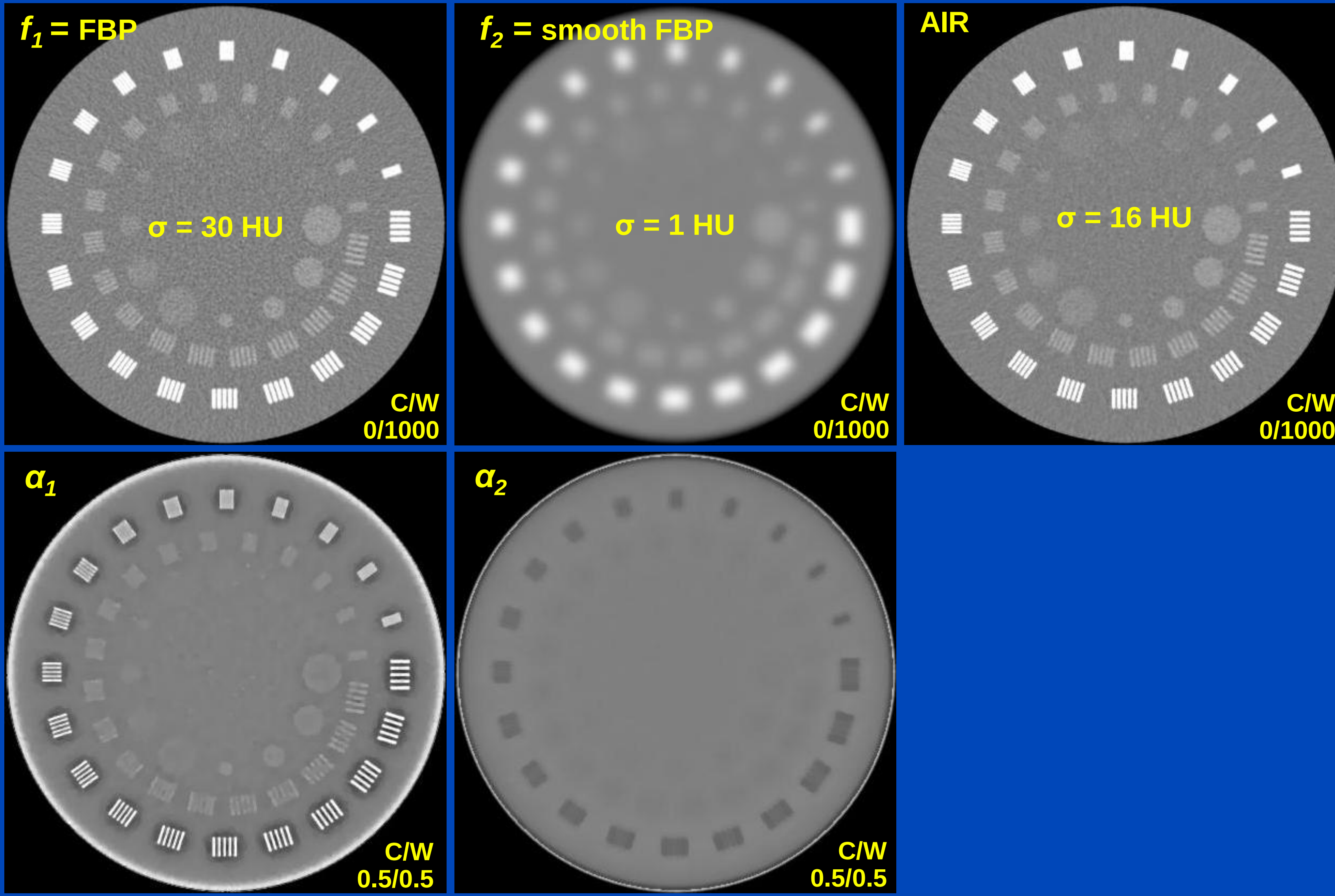
<u>Reconstruction setting:</u>

- Field of view = 200 mm
- $N_x = N_y = 512 \rightarrow \Delta x = \Delta y = 0.4$ mm

<u>Algorithm parameters for the proposed method:</u>

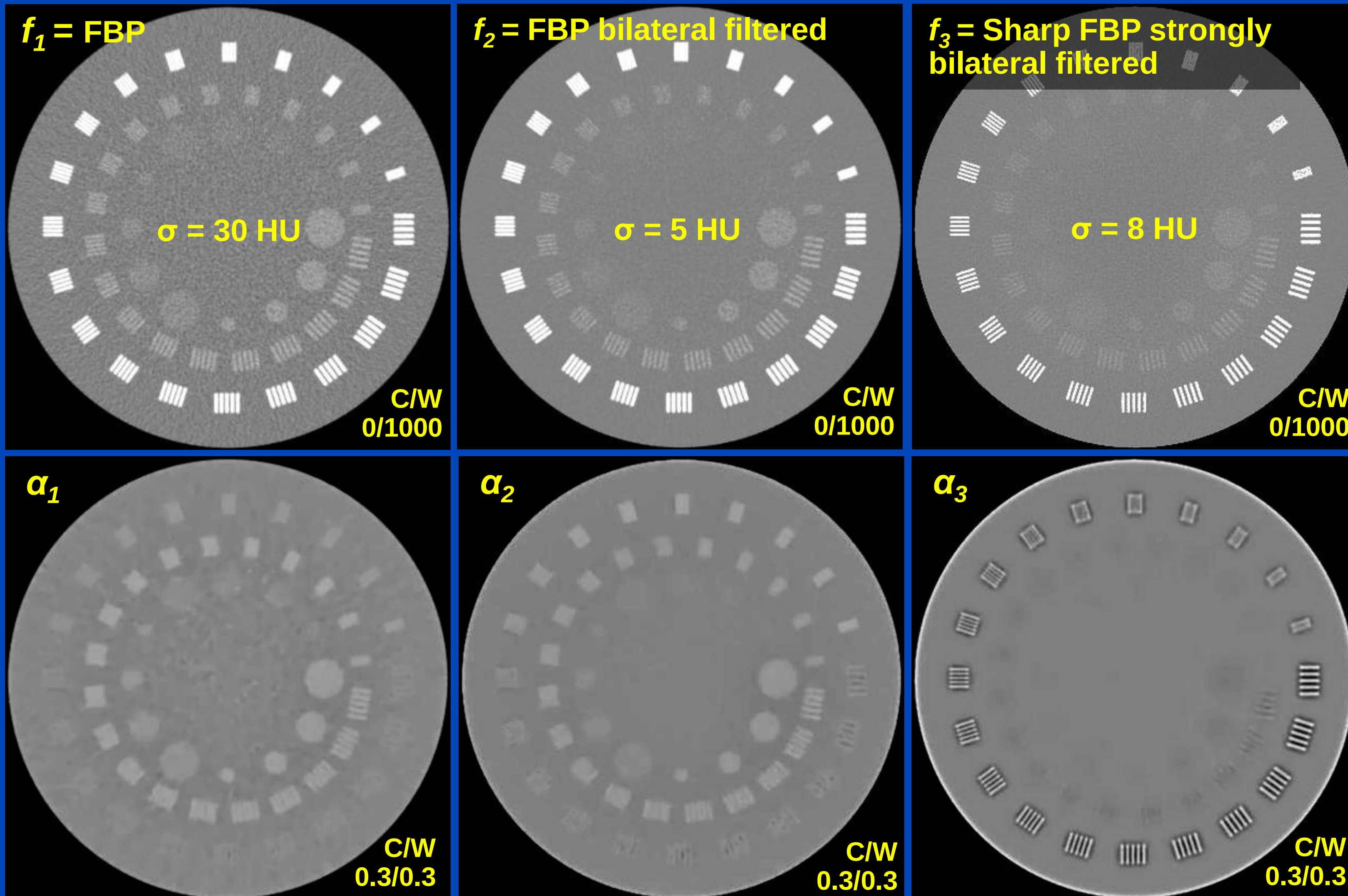
- $\beta = 0.001$, $\gamma = 0.02$, α initialized with zero
- Minimization of cost function: Gradient descent with backtracking line search
- N_{Iter} = 500 (convergence: iterated until no significant changes during further iterations)

TWO BASIS IMAGES

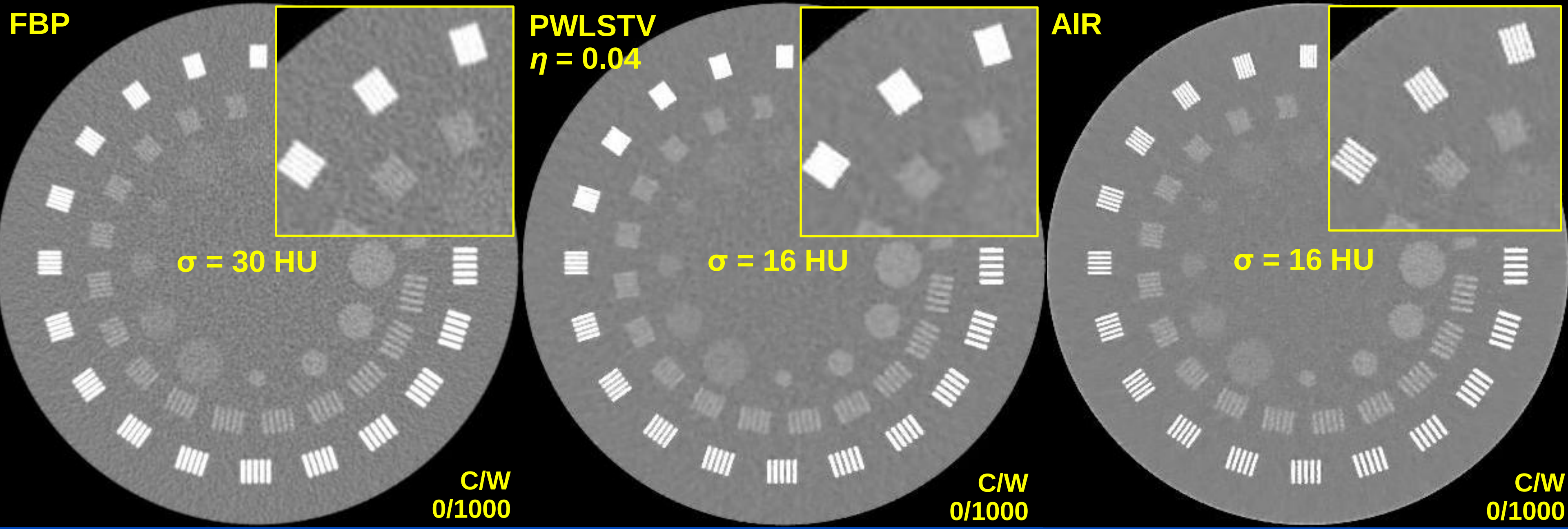


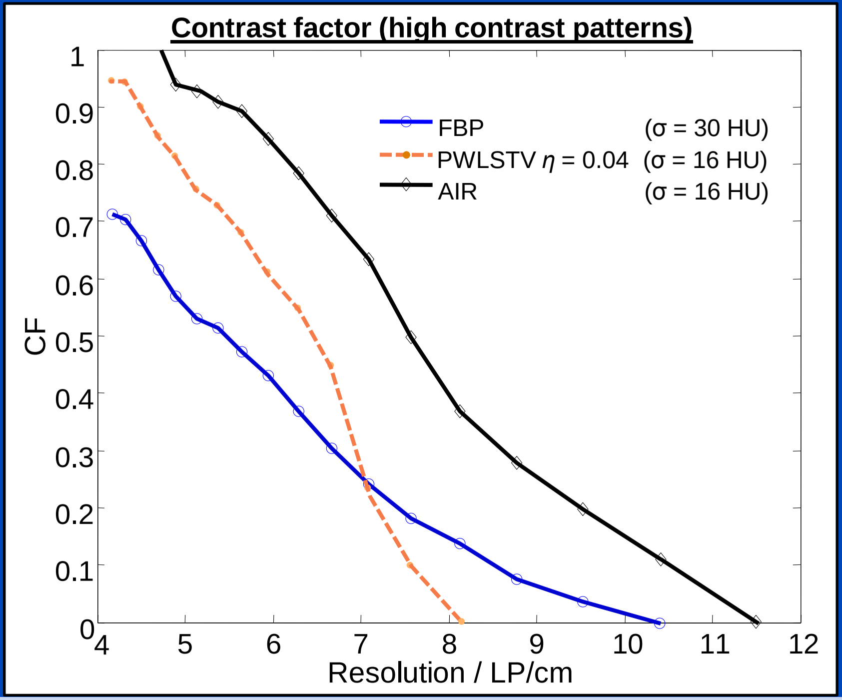
- **High weights in regions which highly correlate with the rawdata fidelity**
- **Low weights in regions with low correlation**
- **Regions which have the same correlation with the rawdata are averaged**

THREE BASIS IMAGES WITH BILATERAL FILTERING



- **Low contrast detail information has the highest correlation with the ground truth in basis images f_1 and f_2 → weights are high in α_1 and α_2.**
- **High contrast detail information has the highest correlation with the ground truth in basis images f_3 → weights are high in α_3.**





Proposed method has the highest correlation with the ground truth:

$\mathrm{NCC}_{\mathrm{FBP}}$ < $\mathrm{NCC}_{\mathrm{PWLSTV}}$ < $\mathrm{NCC}_{\mathrm{AIR}}$

0.920 0.955 0.971

PATIENT DATA

Rawdata:

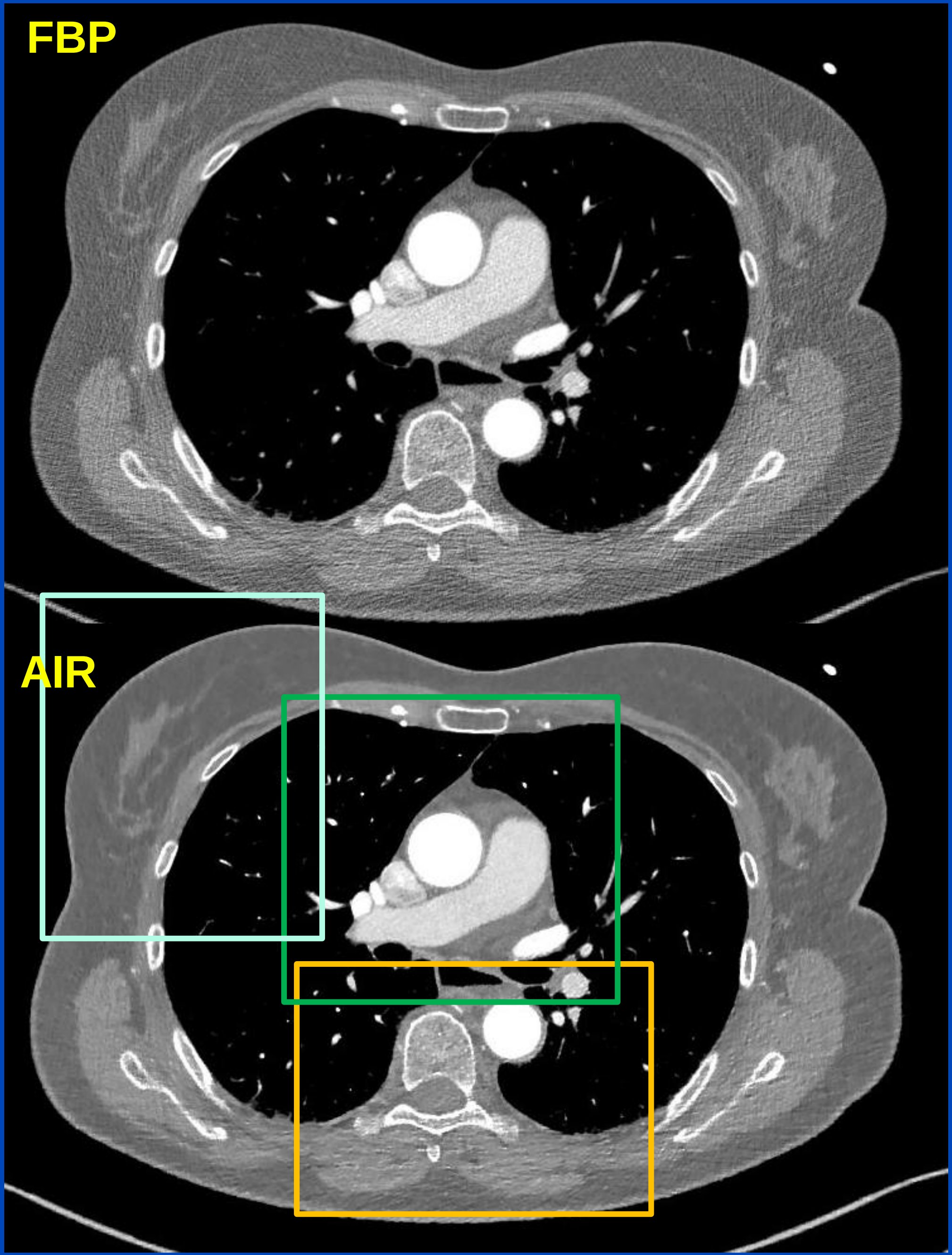
- Siemens SOMATOM Definition Flash Scanner
- Sequence scan, single source
- Scan parameters: N_{360} = 1160, tube voltage = 100 kV

Reconstruction setting:

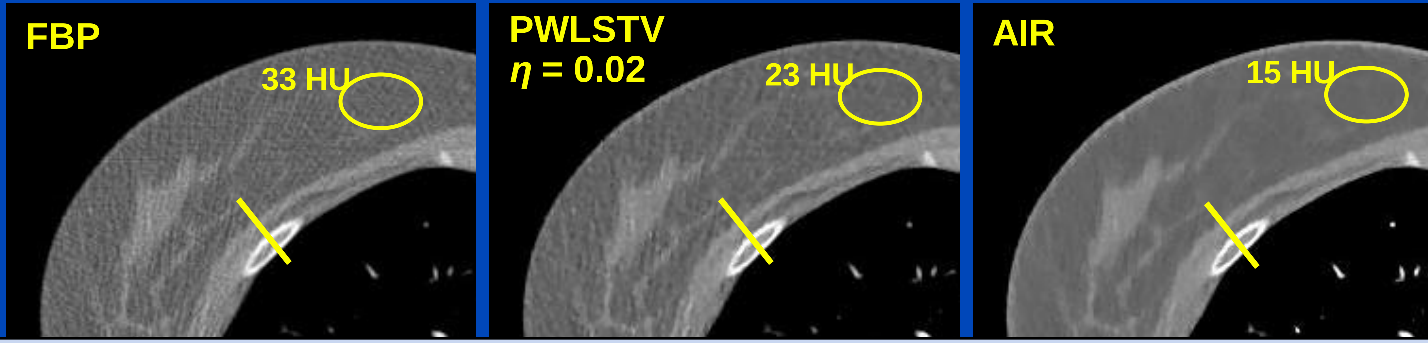
- Field of view = 500 mm
- $N_x = N_y = 1024$
  → $\Delta x = \Delta y$ = 0.5 mm

Parameters for proposed method:

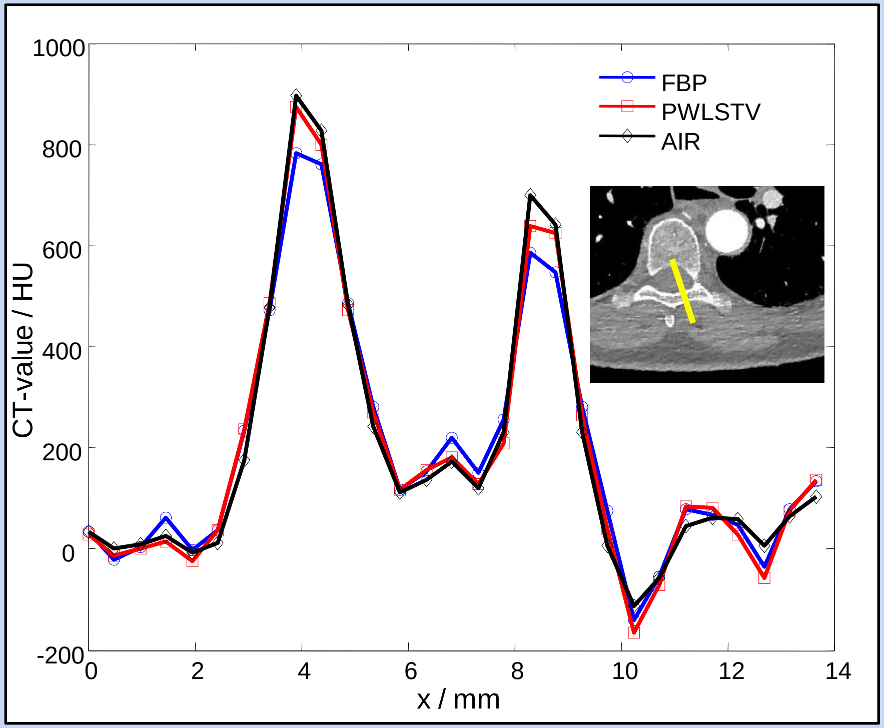
- Same parameters as for the phantom
- AIR with three basis images and bilateral filtering



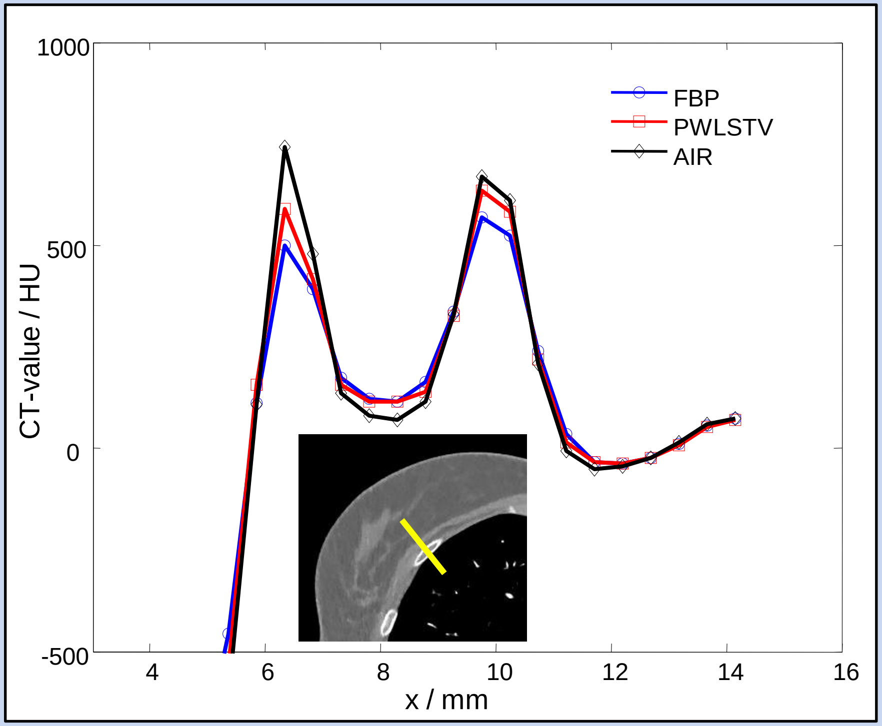
C = 0 HU, W = 1000 HU

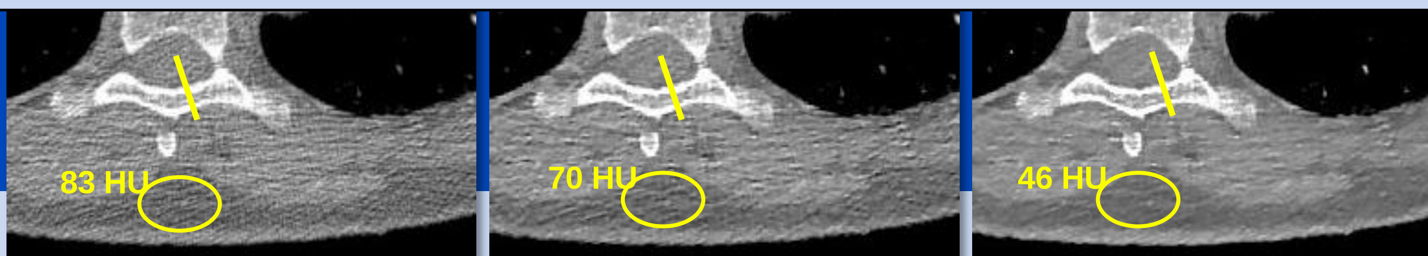


Line profile through vertebra



Line profile through Rib





C = 0 HU
W = 1000 HU

Summary & Conclusion

- In our experiments the AIR algorithm reduces noise by up to 50% and at the same time has the potential to improve the resolution.
- Any image filter or regularization approach can be used to generate the basis images which makes the method very flexible.
- Future research will be concerned with finding optimal choices for the basis images.
- Outlook – Special application cardiac CT
  Basis images:
  - Sharp FBP to avoid blooming
  - FBP with high temporal resolution and low CNR
  - FBP with low temporal resolution and high CNR

Thank You!

This work was funded by the Deutsche Forschungsgemeinschaft DFG under grant KA 1678/3-1. Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.

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