

Seminar New Iterative Reconstruction Methods in Medical Imaging

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Pattern Recognition Lab (CS 5)



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Requirements & Information





Course Assessment: 2 Options

● Option „Implementation“

- Implementation of a conference paper (C++ MR framework)
- Appointments by requirement
- Short report (~2 pages)
 - Implementation overview, results
- Presentation (30 min)

● Option „Review“

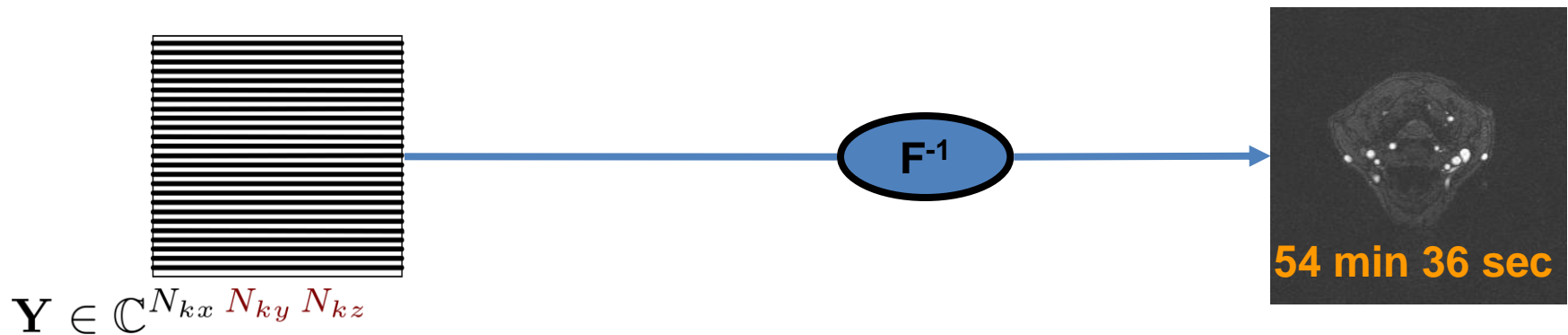
- Review of a journal paper (~10-15 pages)
- Presentation (30 min)
- Attendance of the reconstruction colloquium (Thursday 9:00 – 10:30)
- Long report (~10 pages):
 - Introduction/ Context
 - Content of the paper
 - Problems for the chosen application

Iterative Magnetic Resonance Reconstruction - Basics



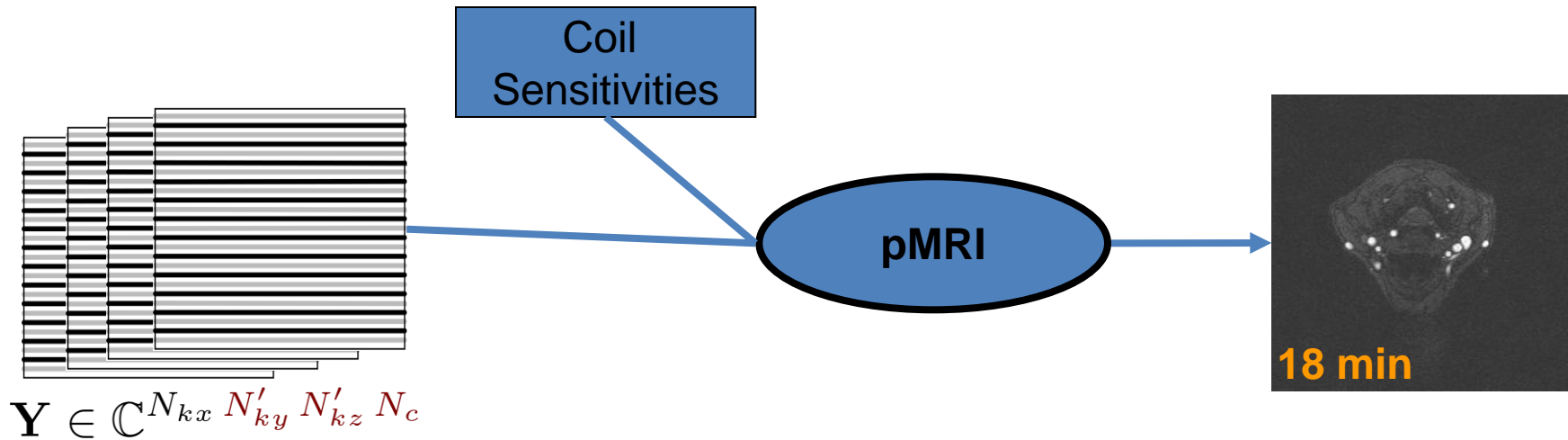


Acquisition details – Reconstruction of undersampled data



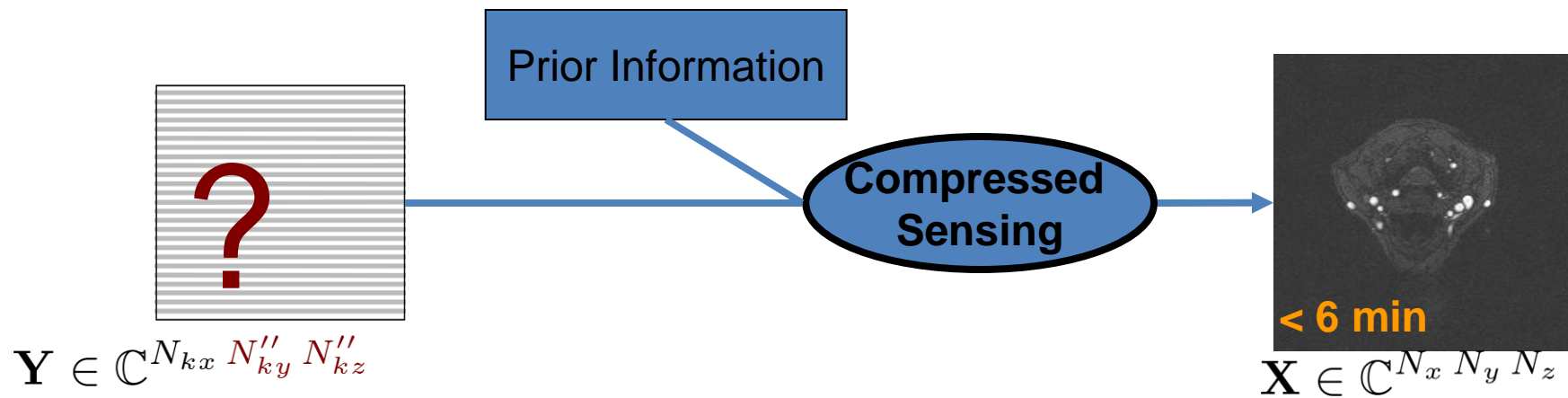


Acquisition details – Reconstruction of undersampled data





Acquisition details – Reconstruction of undersampled data





Iterative Reconstruction

$$f(\mathbf{I}) = D(\mathbf{I}) + \alpha R(\mathbf{I})$$

- The target function $f(\mathbf{I})$ is composed of the data fidelity term $D(\mathbf{I})$ and the regularization function $R(\mathbf{I})$
- The solution is found iteratively by solving the minimization problem

$$\mathbf{I}^{k+1} = \underset{\mathbf{I}^k}{\operatorname{argmin}} f(\mathbf{I}^k)$$



Iterative Reconstruction

$$f(\mathbf{I}) = D(\mathbf{I}) + \alpha R(\mathbf{I}) = \sum_j^Y \|\mathbf{PFC}^j \mathbf{I} - \mathbf{M}^j\|_2^2 + \alpha R(\mathbf{I})$$

- The data fidelity term includes the pMRI reconstruction algorithm switching between

- Multiple coil k-space data $\mathbf{M}^j \in \mathbb{C}^{N_k \times 4N_t}$
- The actual image estimate $\mathbf{I} \in \mathbb{C}^{N \times 4N_t}$

- The data fidelity term contains

- Coil Sensitivity maps $\mathbf{C}^j \in \mathbb{C}^{N \times N}$
- Fourier Coefficient Matrix $\mathbf{F} \in \mathbb{C}^{N_k \times N}$
- Sampling Pattern matrix $\mathbf{P} \in \mathbb{C}^{N_k \times 4N_t}$



MR Options

- Option „Review“

Kim D., Dyvorne H., Otazo R., Feng L., Sodickson D., Lee V.: „Accelerated Phase-Contrast Cine MRI Using k-t SPARSE-SENSE“, MRM 67:1054-1064 (2012)

- Phase Contrast MRI
- 2 step iterative reconstruction
- Special Focus on Temporal FFT + Temporal PCA



MR Options

Framework Introduction
Monday 06.05. 15:00

- Option „Implementation“

Löcher: „L1-SPIRiTphase for Separate Magnitude and Phase Reconstruction with a Divergence Penalty for 3D Phase-Contrast Flow Measurements“, ISMRM (2012)

- Implementation of the divergence-free constraint into the MR framework
- Phase Contrast MRI (blood flow data)

$$f(\mathbf{I}) = D(\mathbf{I}) + \alpha R(\mathbf{I}) = \sum_j^Y \left\| \text{PFC}^j \mathbf{I} - \mathbf{M}^j \right\|_2^2 + \alpha R(\mathbf{I})$$

Wavelet ✓

PCA ✓

Total Variation ✓

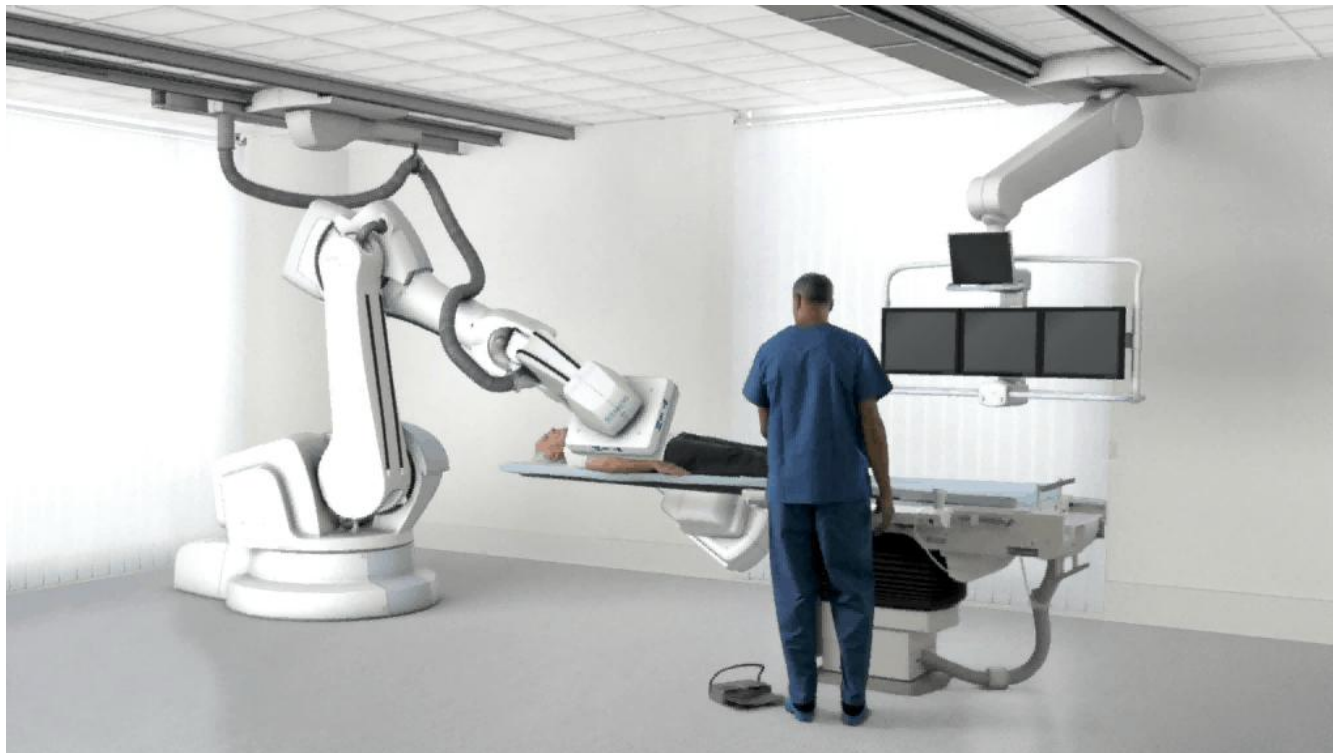
Divergence-free



Iterative Reconstruction to improve Cardiac Imaging with C-arm CT



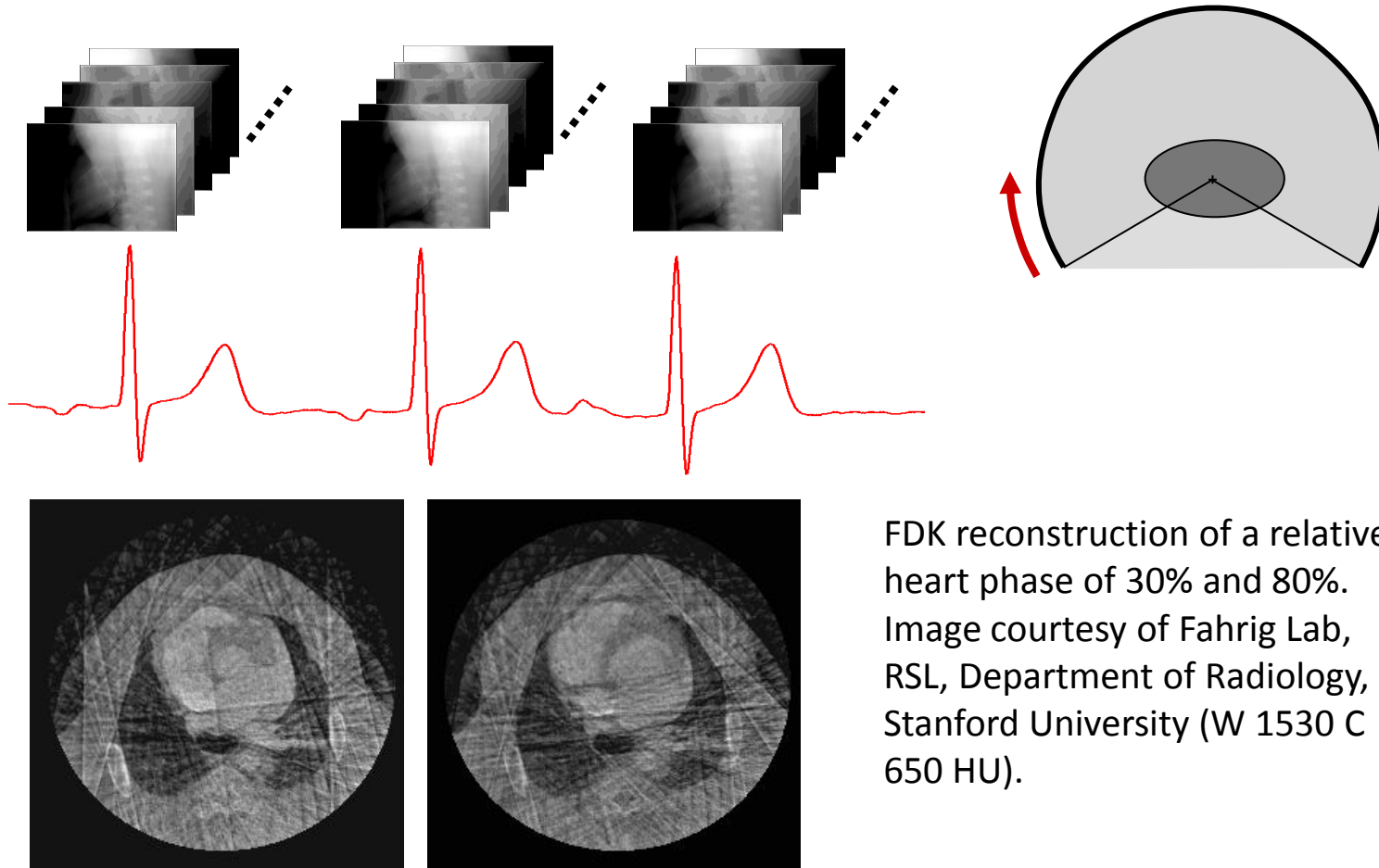
Cardiac C-arm CT imaging



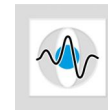
Artis zeego C-arm system. Image taken from Siemens AG, Healthcare Sector.



ECG-gating



FDK reconstruction of a relative heart phase of 30% and 80%. Image courtesy of Fahrig Lab, RSL, Department of Radiology, Stanford University (W 1530 C 650 HU).



Geometry: Cone-beam geometry

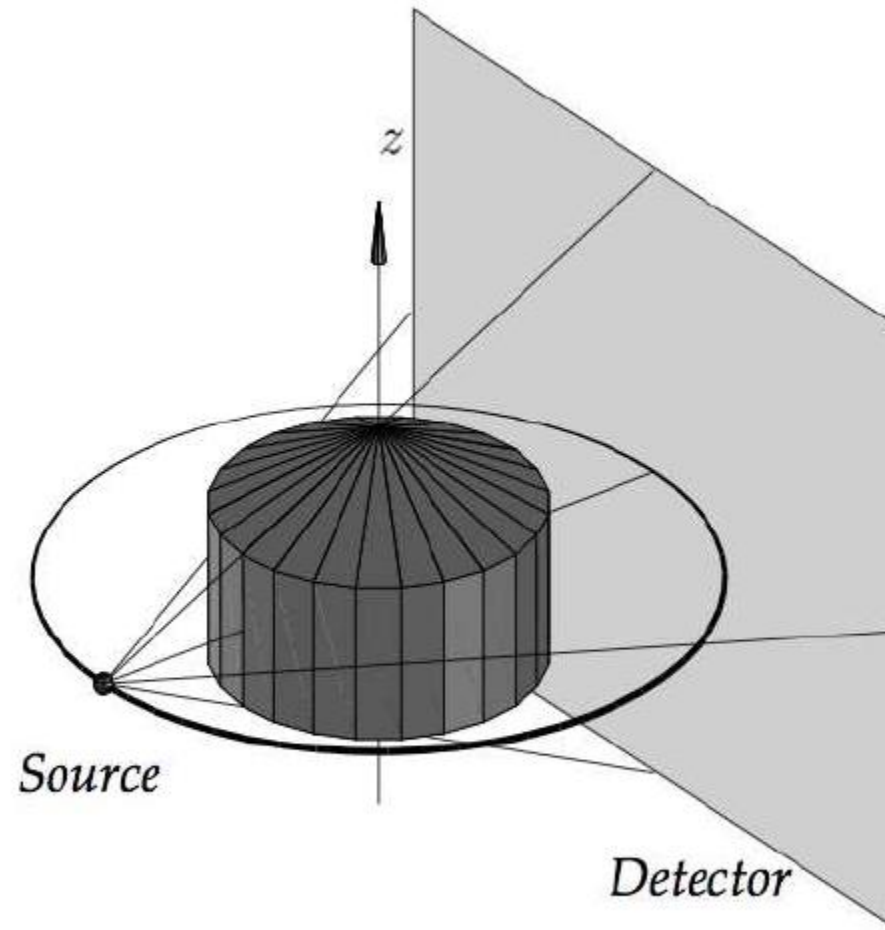
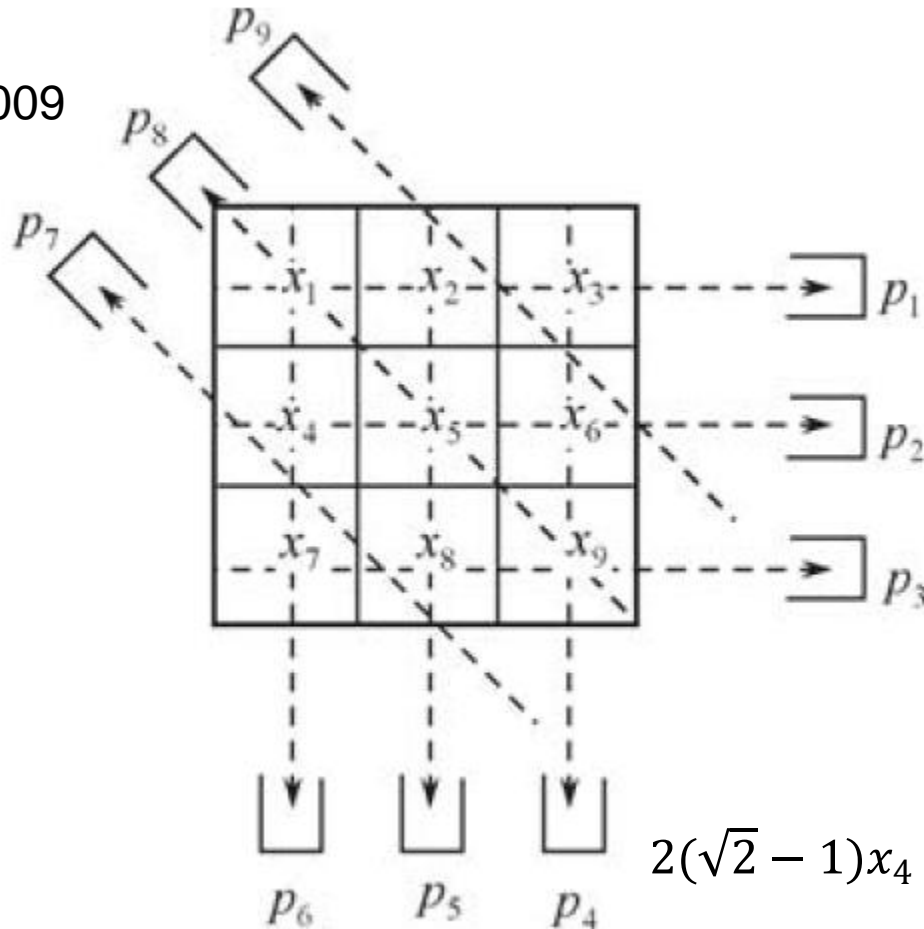




Image:
Zeng, 2009



$$x_1 + x_2 + x_3 = p_1$$

$$x_4 + x_5 + x_6 = p_2$$

$$x_7 + x_8 + x_9 = p_3$$

$$x_3 + x_6 + x_9 = p_4$$

$$x_2 + x_5 + x_8 = p_5$$

$$x_1 + x_4 + x_7 = p_6$$

$$2(\sqrt{2} - 1)x_4 + (2 - \sqrt{2})x_4 + 2(\sqrt{2} - 1)x_8 = p_7$$

$$(\sqrt{2})x_1 + (\sqrt{2})x_5 + (\sqrt{2})x_9 = p_8$$

$$2(\sqrt{2} - 1)x_2 + (2 - \sqrt{2})x_3 + 2(\sqrt{2} - 1)x_6 = p_9$$



Linear Equation System

- Rewrite to

$$\mathbf{A}\mathbf{X} = \mathbf{P}$$

with

$$\mathbf{X} = (x_1, x_2, \dots, x_9)^\top$$

$$\mathbf{P} = (p_1, p_2, \dots, p_9)^\top$$

- \mathbf{A} is the system matrix with elements a_{ij}
- The a_{ij} describe the contribution of each voxel to each ray



Linear Equation System

- For larger systems solutions of

$$AX = P$$

with

$$X = A^{-1}P$$

$$X = (A^T A)^{-1} A^T P$$

$$X = A^T (A A^T)^{-1} P$$

are infeasible (Gauss-Seidel, SVD, etc.)

⇒ Solution that does not require the inversion of A or a product of A is desirable



Algebraic Reconstruction Technique (ART)

- Idea: Find an iterative solution of

$$\mathbf{AX} = \mathbf{P}$$

using Kaczmarz' method:

- For each pixel p_i and each row \mathbf{A}_i of \mathbf{A} perform the following update:

$$\mathbf{X}^{k+1} = \mathbf{X}^k + \frac{p_i - \mathbf{A}_i \mathbf{X}^k}{\mathbf{A}_i \mathbf{A}_i^\top} \mathbf{A}_i^\top$$

- Repeat until convergence



ART Extensions

- Slow convergence is the main drawback of ART
- Extensions aim at improving convergence speed
- Compute update using more than one projected pixel:
 - Simultaneous ART (SART): Multiple updates at the same time and combine the result
 - Simultaneous Iterative Reconstruction Technique (SIRT): Compute update once per iteration
- Use intelligent methods to select the order of the update equations (Ordered Subsets)
- Use more realistic models within the system matrix



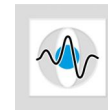
Regularizations

- Introduction of additional information into the reconstruction process to enforce a certain property of the solution
- Advantageous, if the problem is underdetermined
- Additional weighting terms used to suppress noise or artifacts



Papers

- Option „Review“
 - Jia et al., „4D Tomography Reconstruction from Few-Projection Data via Temporal Non-local Regularization“, MICCAI (2010)*
 - 4D-CT reconstruction
 - Temporal Non-local Means (TNLM)
 - Alternating two step algorithm

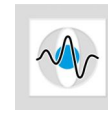


Papers

- Option „Review“

Jia et al., GPU-based Iterative Cone Beam CT Reconstruction Using Tight Frame Regularization“, PMB (2011)

- Cone-beam CT (CBCT)
- Iterative tight frame (TF) based algorithm



Papers

- Option „Review“
 - *Sidky et al., „A constrained, total-variation minimization algorithm for low-intensity x-ray CT“, MP (2011)*
- Low intensity x-ray CT
- Based on steepest-descent and projection onto convex sets (SD-POCS)