Medical Image Processing for Interventional Applications

Deep Learning Computed Tomography

Online Course – Unit 52

Andreas Maier, Tobias Würfl, Frank Schebesch
Pattern Recognition Lab (CS 5)

virtuelle hochschule bayern

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

Limited Angle Reconstruction

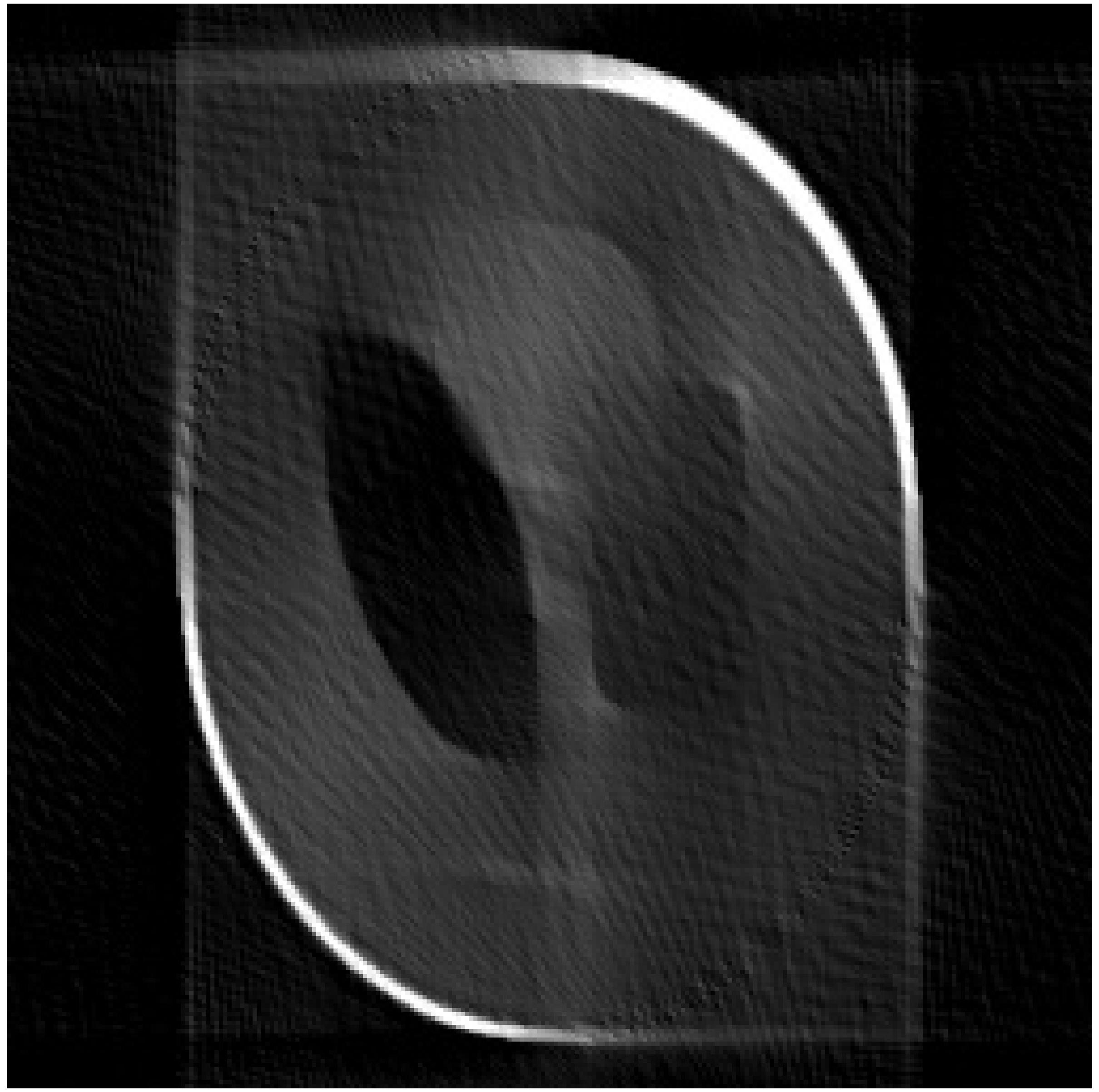


Figure 1: Limited angle reconstruction of phantom

Modifying Analytic Algorithms

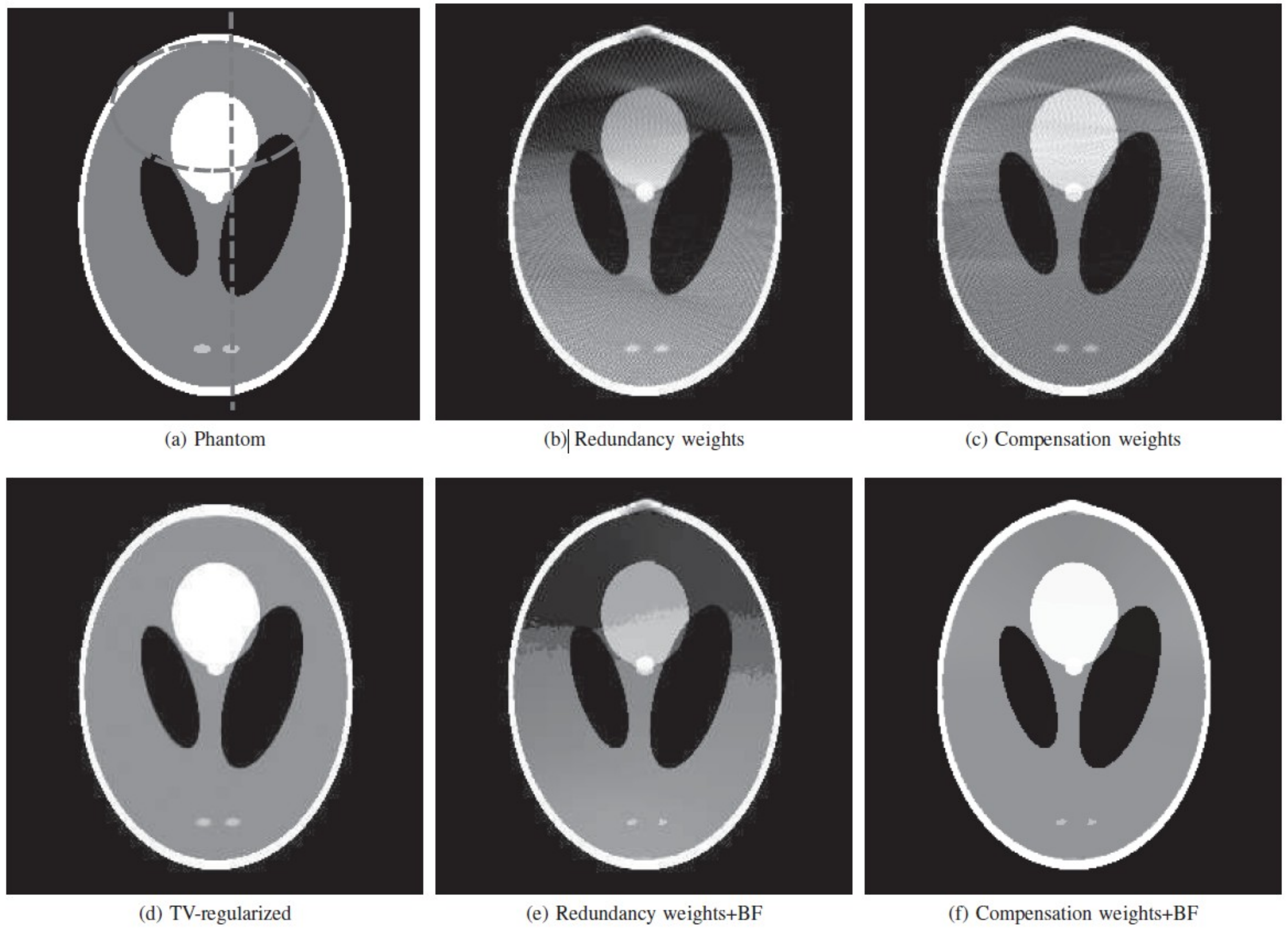


Figure 2: FBP compared to TV (Riess et al., *TV or not TV? [...]*, 2013)

Goal

Question: Can we use neural networks to learn artifact correction from data?

Goal

Question: Can we use neural networks to learn artifact correction from data?

State-of-the-art:

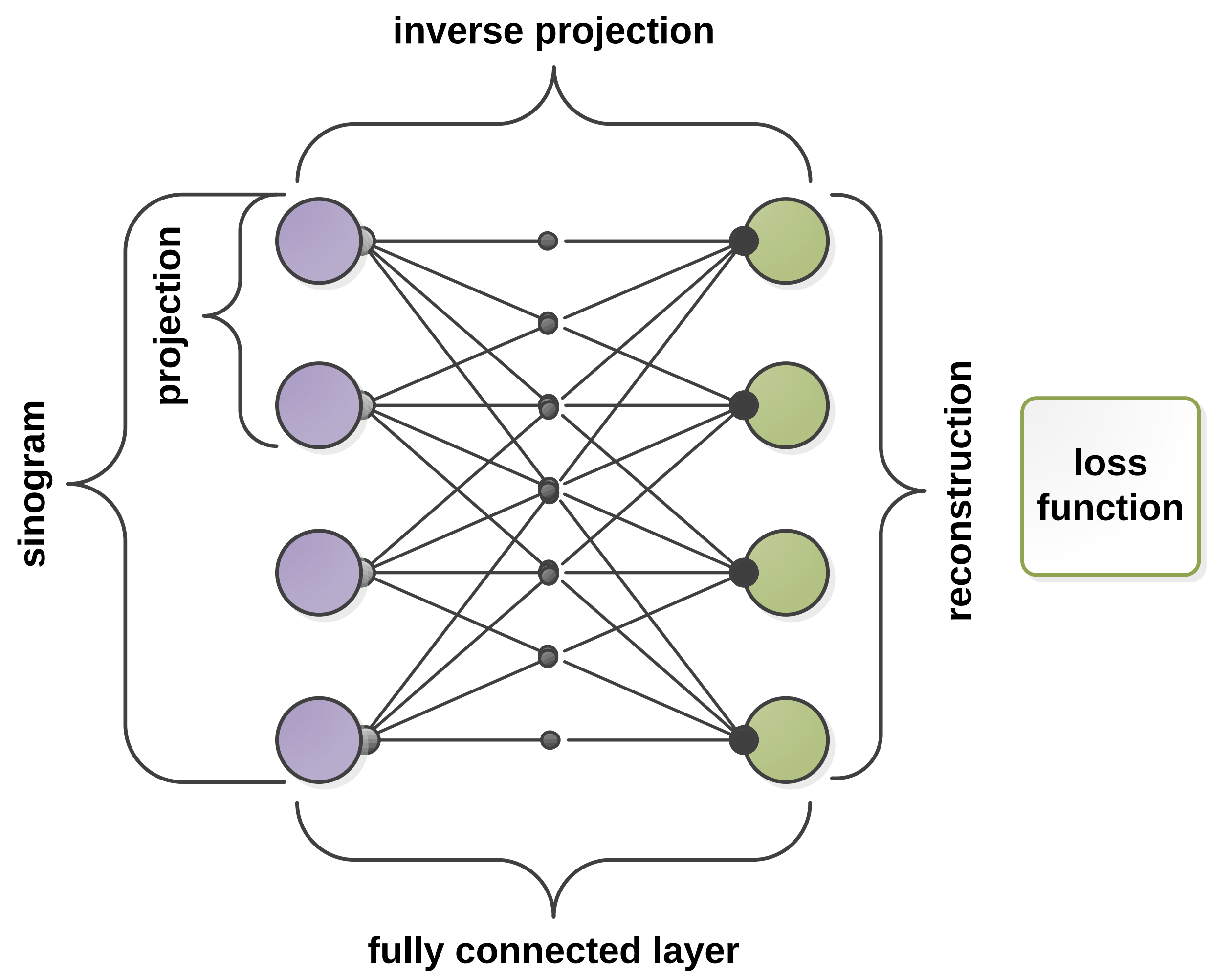


Figure 3: Neural network architecture of Argyrou et al., 2012

Parallel Beam Architecture

Can we reuse the knowledge about FBP for reconstruction networks?

Parallel Beam Architecture

Can we reuse the knowledge about FBP for reconstruction networks?

Filtered backprojection:

$$f(x,y) = \int_0^\pi p(s,\theta) * \frac{1}{-2\pi^2 s^2} \, \mathrm{d}\theta \,,$$

where $s = x\cos\theta + y\sin\theta$

Three algorithmic steps:

- Convolution along s
- Backprojection (BP) w. r. t. θ
- Suppress negative values

Parallel Beam Architecture

Can we reuse the knowledge about FBP for reconstruction networks?

Filtered backprojection:

$$f(x,y) = \int_0^\pi p(s,\theta) * \frac{1}{-2\pi^2 s^2} \, \mathrm{d}\theta \,,$$

where $s = x\cos\theta + y\sin\theta$

Three algorithmic steps:

- Convolution along s
- Backprojection (BP) w. r. t. θ
- Suppress negative values

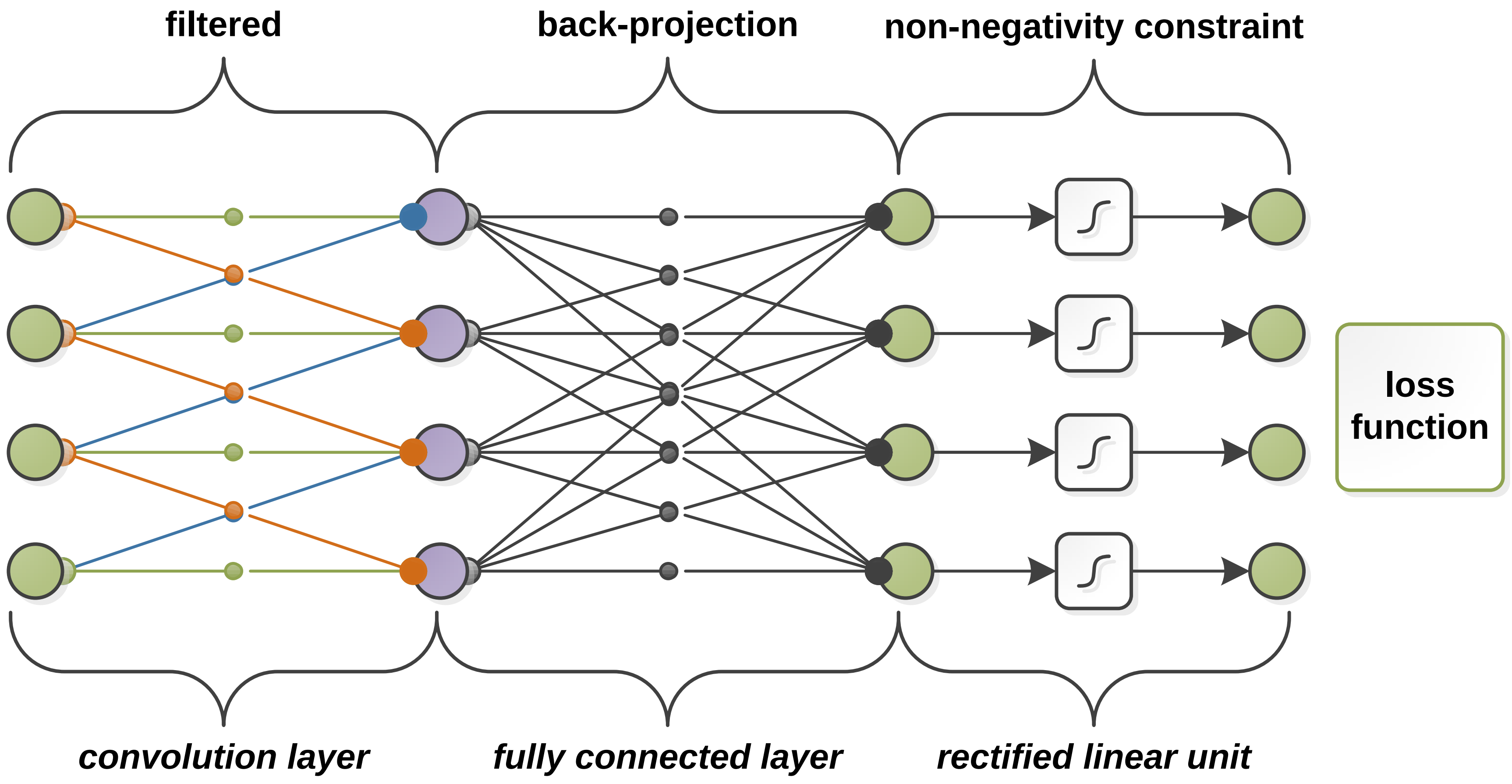


Figure 4: Architecture for parallel beam reconstruction

Layer Structure

Convolutional layer:

- Infinite support of reconstruction filters
- Fourier domain convolution

Layer Structure

Convolutional layer:

- Infinite support of reconstruction filters
- Fourier domain convolution

Fully connected layer:

- Huge dimensionality: $512 \cdot 180 \cdot 512 \cdot 512 \approx 24 \cdot 10^9$ weights
- **"Very deep networks"**: $14 \cdot 10^7$ weights
- Sparsity of the matrix **undone** in training

Layer Structure

Convolutional layer:

- Infinite support of reconstruction filters
- Fourier domain convolution

Fully connected layer:

- Huge dimensionality: $512 \cdot 180 \cdot 512 \cdot 512 \approx 24 \cdot 10^9$ weights
- **“Very deep networks”**: $14 \cdot 10^7$ weights
- Sparsity of the matrix **undone** in training

$\rightarrow$ Neither do we have the memory, nor the data!

Making It Fit

Question: How to learn reconstruction if BP does not fit into memory?
Idea: Treat BP as fixed.

Making It Fit

Question: How to learn reconstruction if BP does not fit into memory?
Idea: Treat BP as fixed.

Backprojection layer:

- Forward: **Backprojection**
- Backward: $\mathbf{E}_{n-1} = \mathbf{E}_n \cdot \mathbf{W}_n^T$

Making It Fit

Question: How to learn reconstruction if BP does not fit into memory?
Idea: Treat BP as fixed.

Backprojection layer:

- Forward: **Backprojection**
- Backward: $\mathbf{E}_{n-1} = \mathbf{E}_n \cdot \mathbf{W}_n^T$

How to transpose something we cannot fit into memory?

Making It Fit

Question: How to learn reconstruction if BP does not fit into memory?
Idea: Treat BP as fixed.

Backprojection layer:

- Forward: **Backprojection**
- Backward: $\mathbf{E}_{n-1} = \mathbf{E}_n \cdot \mathbf{W}_n^T$

How to transpose something we cannot fit into memory?

$\mathbf{W} = \mathbf{R}^T \rightarrow \mathbf{W}^T = \mathbf{R}$

(Implementation using GPU $\rightarrow$ 50$\times$ speedup)

Fan Beam Architecture

Can we extend it to fan beam geometry?

Fan Beam Architecture

Can we extend it to fan beam geometry?

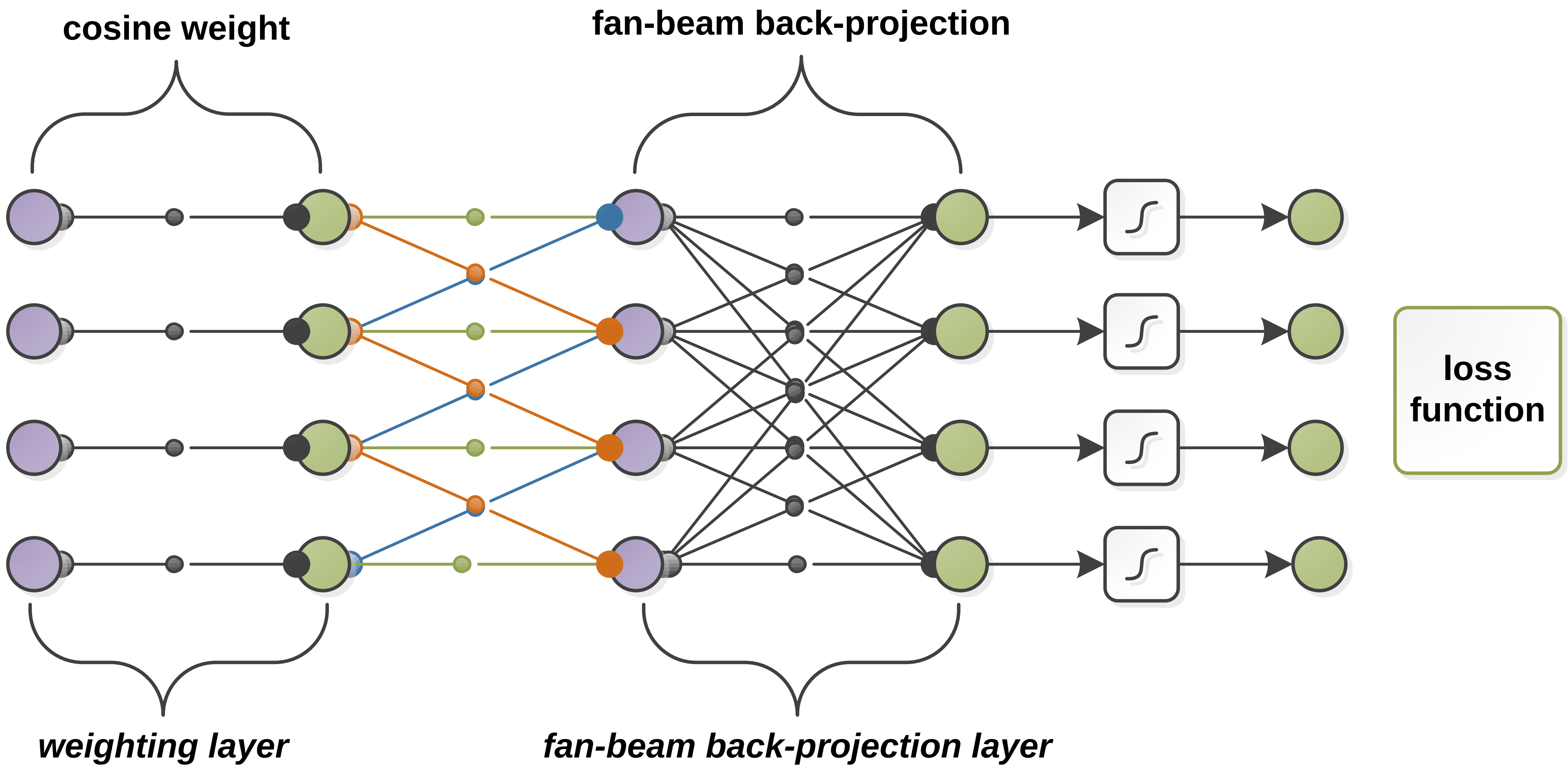


Figure 5: Architecture for fan beam reconstruction

Layer Structure

Weighting layer:

- Diagonal matrix
- Forward: Element-wise multiplication
- Backward: $\mathbf{W}^T = \mathbf{W}$ for diagonal matrices
- Update: $\Delta\mathbf{W}_n = \mathbf{E}_n \cdot \mathbf{A}_{n-1}$

Layer Structure

Weighting layer:

- Diagonal matrix
- Forward: Element-wise multiplication
- Backward: $\mathbf{W}^T = \mathbf{W}$ for diagonal matrices
- Update: $\Delta\mathbf{W}_n = \mathbf{E}_n \cdot \mathbf{A}_{n-1}$

Fan beam backprojection layer

- Same strategy as before
- **Distance weighting** incorporated

Regularization

How can we learn such a huge network?

Regularization

How can we learn such a huge network?

$\rightarrow$ Pretrain by using reconstruction results.

Topics

Reconstruction Networks

- Motivation
- Parallel Beam
- Fan Beam
- Regularization

Summary

- Take Home Messages
- Further Readings

Take Home Messages

- The reconstruction process of filtered backprojection resembles a neural network architecture.
- The backprojection operator being the transpose of the projection operator allows us to implement the backward pass easily.
- In the next unit, we will see experimental results for the presented reconstructions using neural networks.

Further Readings

This unit is based on the following conference article:

Tobias Würfl et al. “Deep Learning Computed Tomography”. In: *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part III*. ed. by Sebastien Ourselin et al. Vol. 9902. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2016, pp. 432–440. DOI: 10.1007/978-3-319-46726-9_50

References:

- Christian Riess et al. “TV or not TV? That is the Question”. In: *The 12th International Meeting on Fully Three-Dimensional Image Reconstruction in Radiology and Nuclear Medicine*. Ed. by Richard M. Leahy and Jinyi Qi. Lake Tahoe, CA, USA, 2013, pp. 341–344
- Maria Argyrou et al. “Tomographic Image Reconstruction based on Artificial Neural Network (ANN) Techniques”. In: *2012 IEEE Nuclear Science Symposium and Medical Imaging Conference Record (NSS/MIC)*. IEEE, Oct. 2012, pp. 3324–3327. DOI: 10.1109/NSSMIC.2012.6551757

Medical Image Processing for Interventional Applications

Deep Learning Computed Tomography – Experiments and Extensions

Online Course – Unit 53

Andreas Maier, Tobias Würfl, Frank Schebesch
Pattern Recognition Lab (CS 5)

virtuelle hochschule bayern

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

Experiments
- Setup
- State-of-the-Art
- Fan Beam Experiment

Beyond FBP

Summary
- Take Home Messages
- Further Readings

Setup

Data:

- From Low Dose CT Grand Challenge
- 2378 slices of 10 patient volumes
- **Simulated** projections

Setup

Data:

- From Low Dose CT Grand Challenge
- 2378 slices of 10 patient volumes
- **Simulated** projections

Caffe: Deep learning framework

- C++ framework with Matlab and Python wrappers
- Rich functionality and well known
- Easy to extend (moreover since there is Caffe2 available now)

Experiments With the State-of-the-Art Architecture

- Images downsampled to 32×32
- 18 projections in parallel beam geometry
- **One** fully connected layer
- L_1 regularization

Experiments With the State-of-the-Art Architecture

- Images downsampled to 32×32
- 18 projections in parallel beam geometry
- **One** fully connected layer
- L_1 regularization

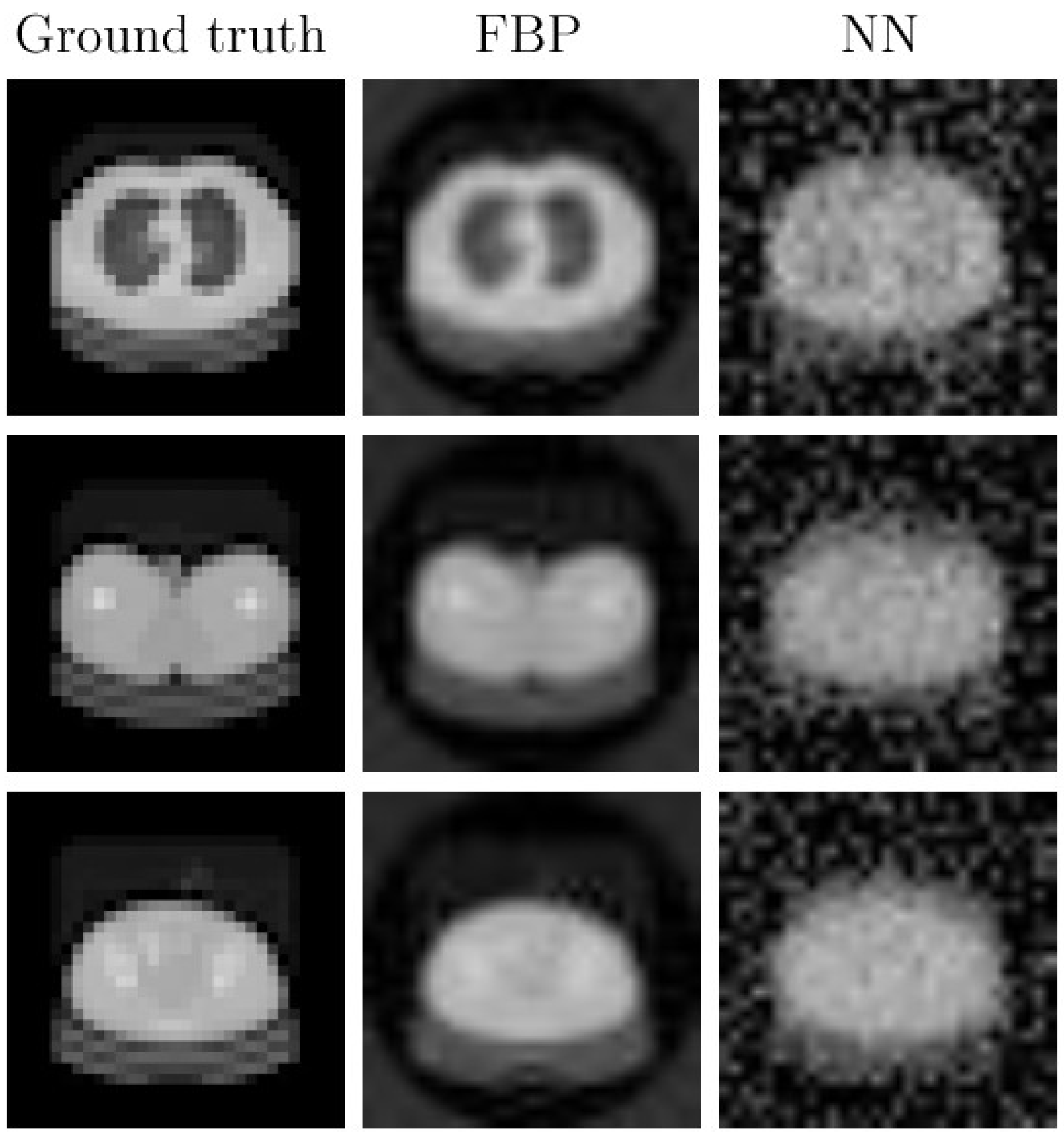


Figure 1: Sample results from the test set

Limited Angle with Fan Beam Architecture

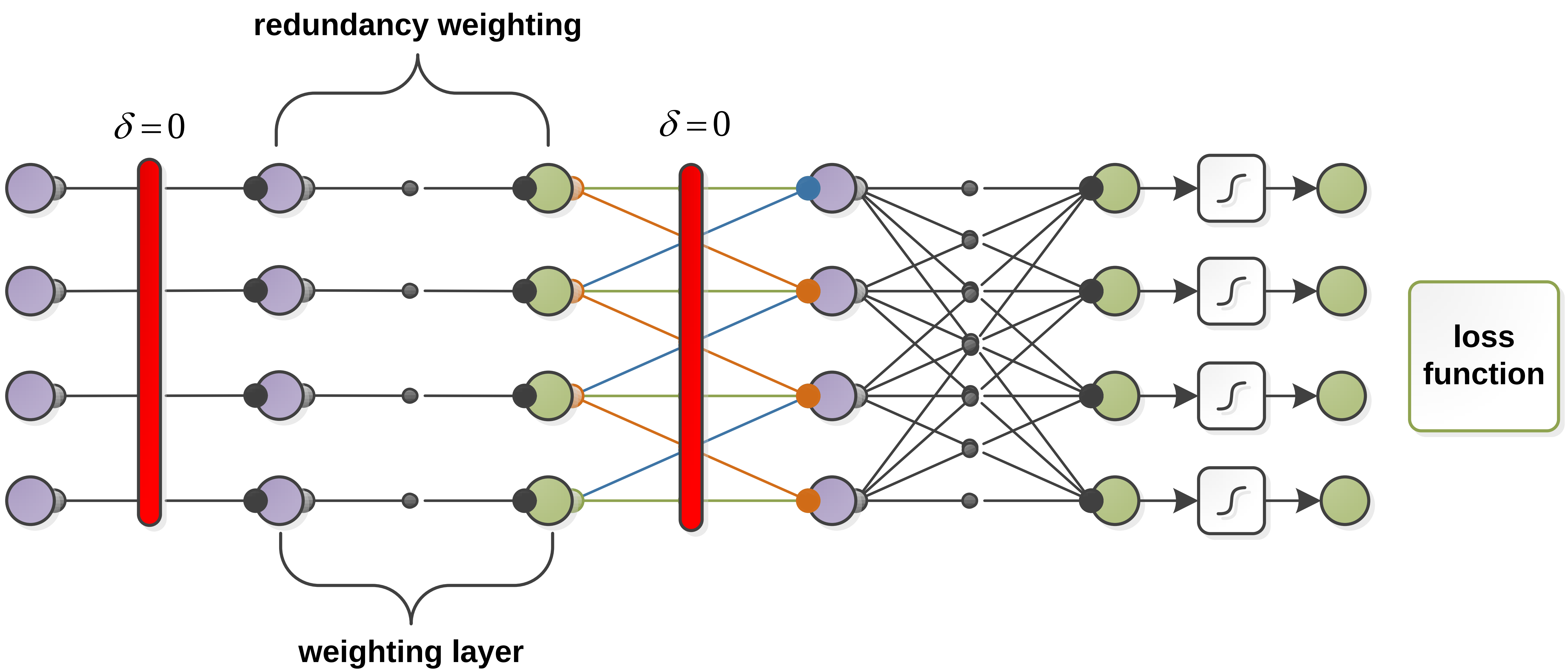


Figure 2: Architecture for the fan beam experiment

Numeric Results

- 10-fold **cross-validation**
- Performance measure: rRMSE

- Improved from $5.314 \times 10^{-3}\,\%$ for FBP to $3.923 \times 10^{-3}\,\%$
- **Every** single reconstruction **superior** to FBP!

Results

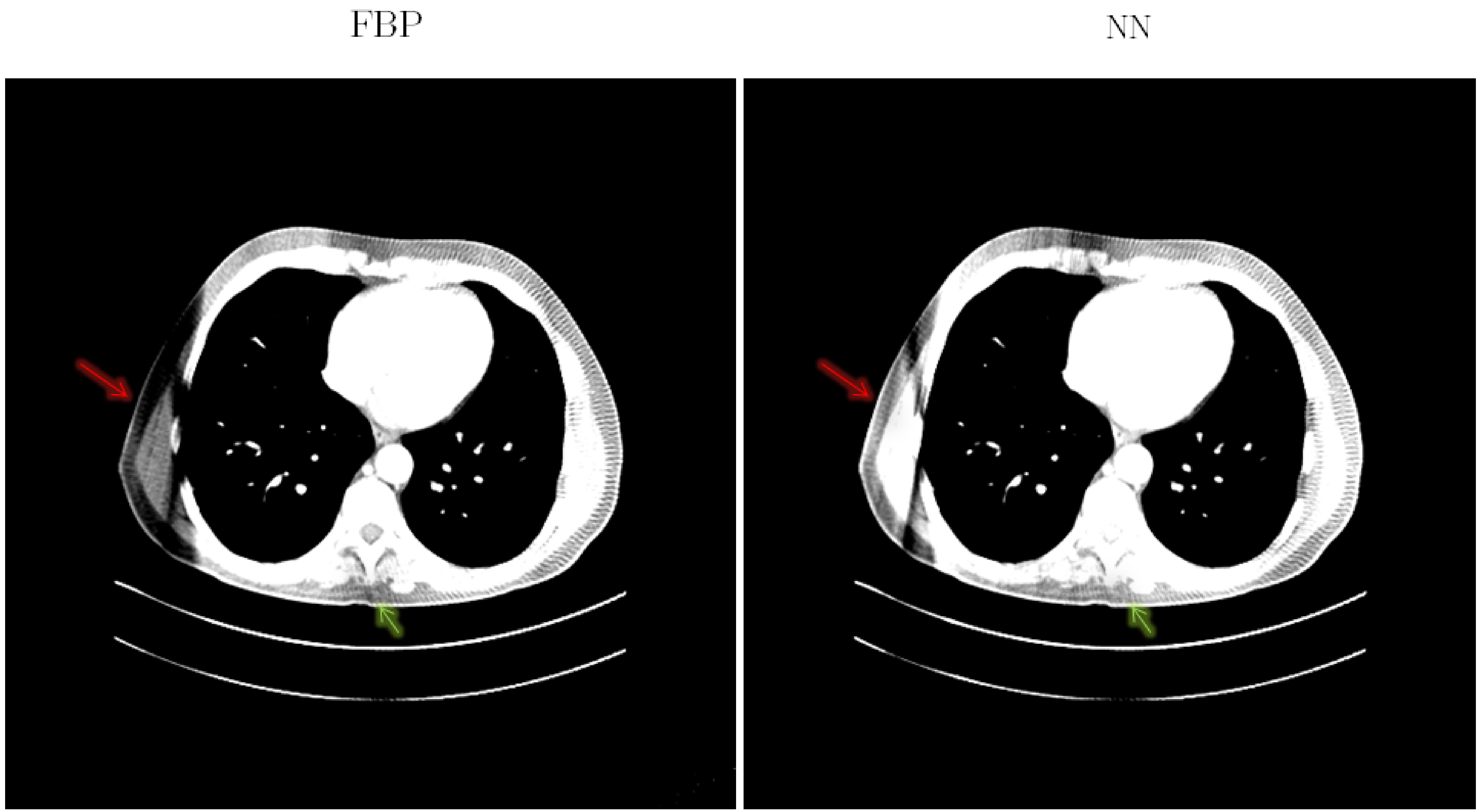


Figure 3: Sample results from the test set

Results

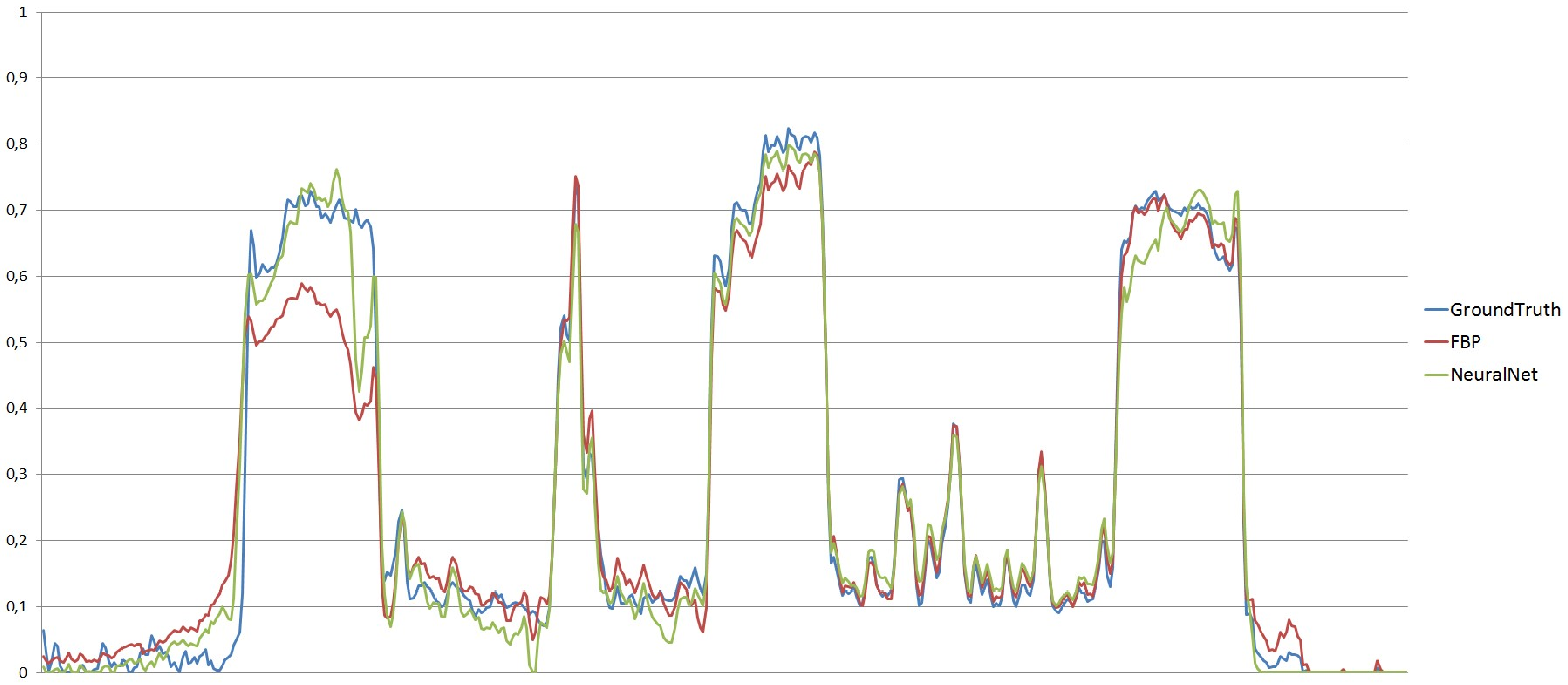


Figure 4: Profiles through the result images

Learned Compensation Weights

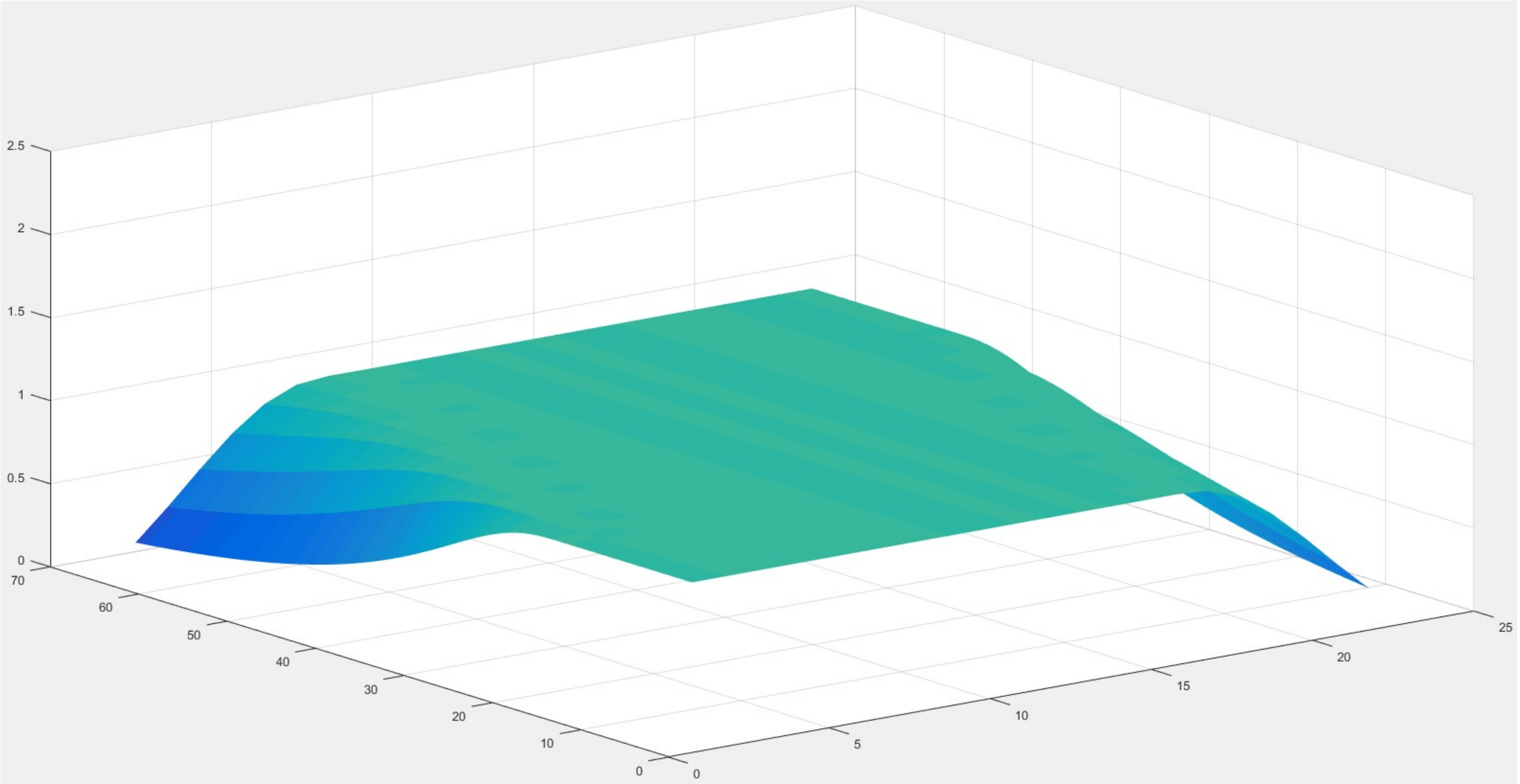


Figure 5: Parker weights

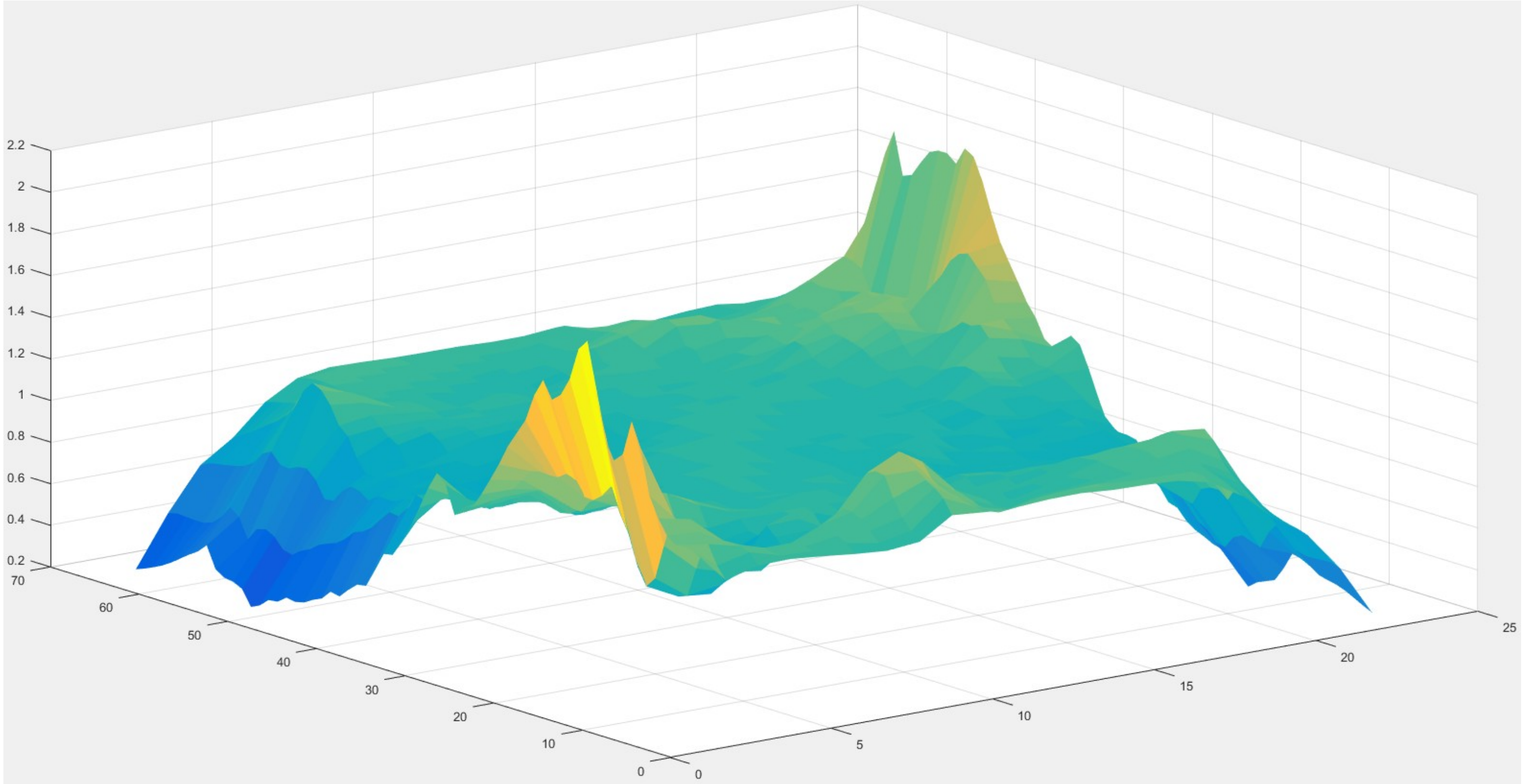
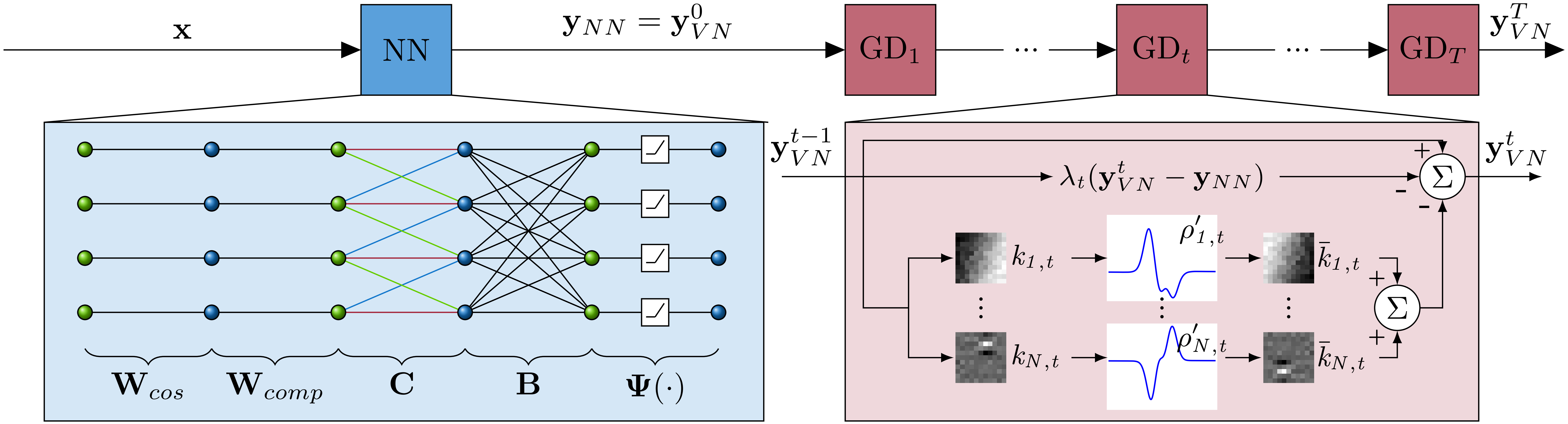


Figure 6: Compensation weights

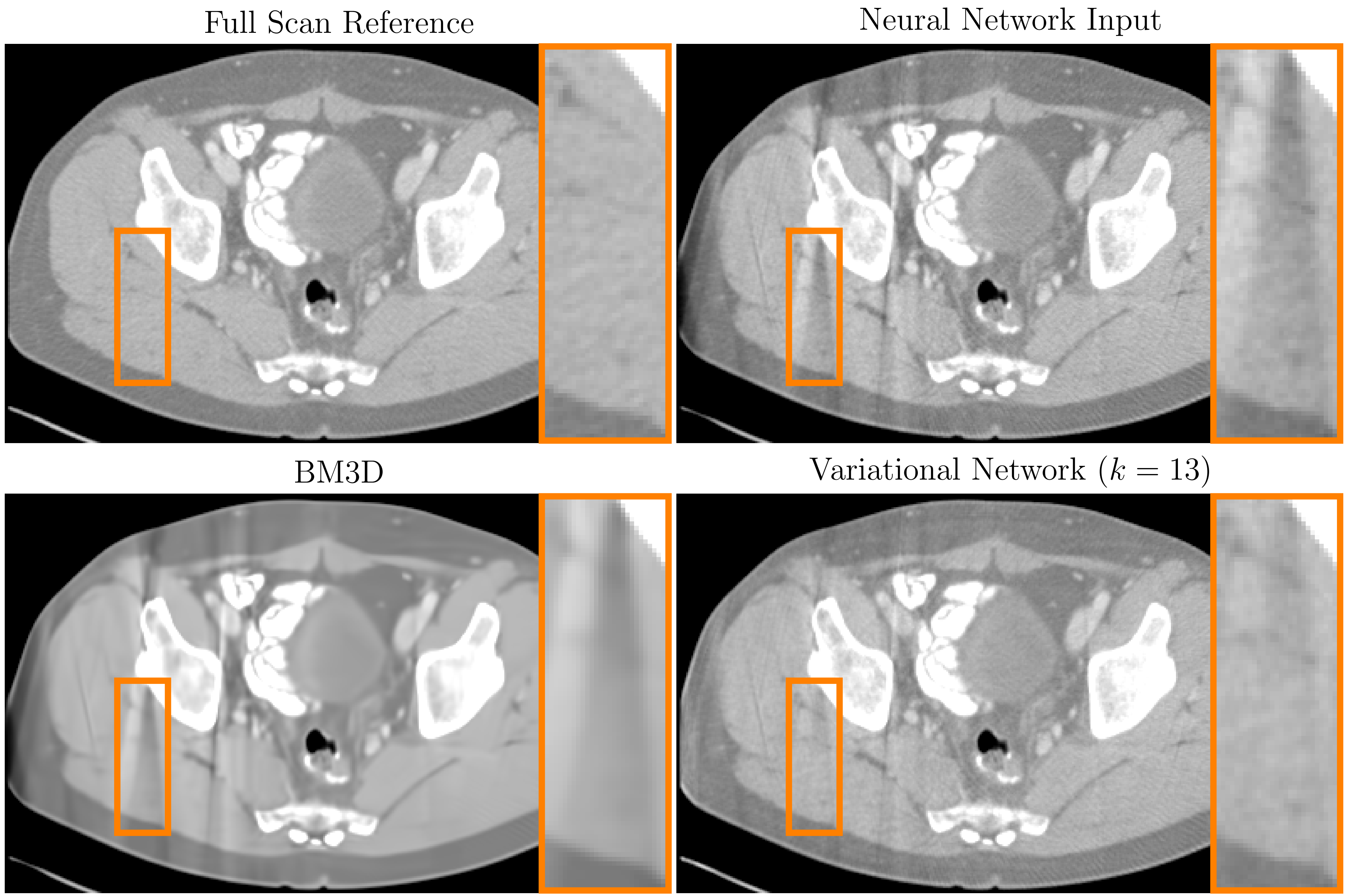
Topics

Extension via Postprocessing



Step 1: Neural network CT reconstruction Step 2: Variational network non-linear filtering

Extension via Postprocessing



Topics

Take Home Messages

- Efficiency of the shown approach is **the same** as of FBP and it is **better** compared with iterative methods.
- Image quality in the experiments is **consistently** better than FBP (comparison to iterative methods unclear).

Further Readings

This unit is based on the following two conference articles:

- Tobias Würfl et al. “Deep Learning Computed Tomography”. In: *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part III*. ed. by Sebastien Ourselin et al. Vol. 9902. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2016, pp. 432–440. DOI: 10.1007/978-3-319-46726-9_50
- Kerstin Hammernik et al. “A Deep Learning Architecture for Limited-Angle Computed Tomography Reconstruction”. In: *Bildverarbeitung für die Medizin 2017: Algorithmen - Systeme - Anwendungen. Proceedings des Workshops vom 12. bis 14. März 2017 in Heidelberg*. Ed. by Klaus Hermann Maier-Hein et al. Informatik aktuell. Berlin, Heidelberg: Springer Berlin Heidelberg, 2017, pp. 92–97. DOI: 10.1007/978-3-662-54345-0_25

Medical Image Processing for Interventional Applications

Cardiac Imaging

Online Course – Unit 54
Andreas Maier, Frank Schebesch
Pattern Recognition Lab (CS 5)

virtuelle hochschule bayern
FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

3-D Angiography

- Developed in the 90s
- Since 1999 in clinical use
- Reconstruction of static objects
  $\rightarrow$ **pretty ok**

Major achievements:

- Flat panel detectors
  $\rightarrow$ low contrast resolution
- Large object reconstruction

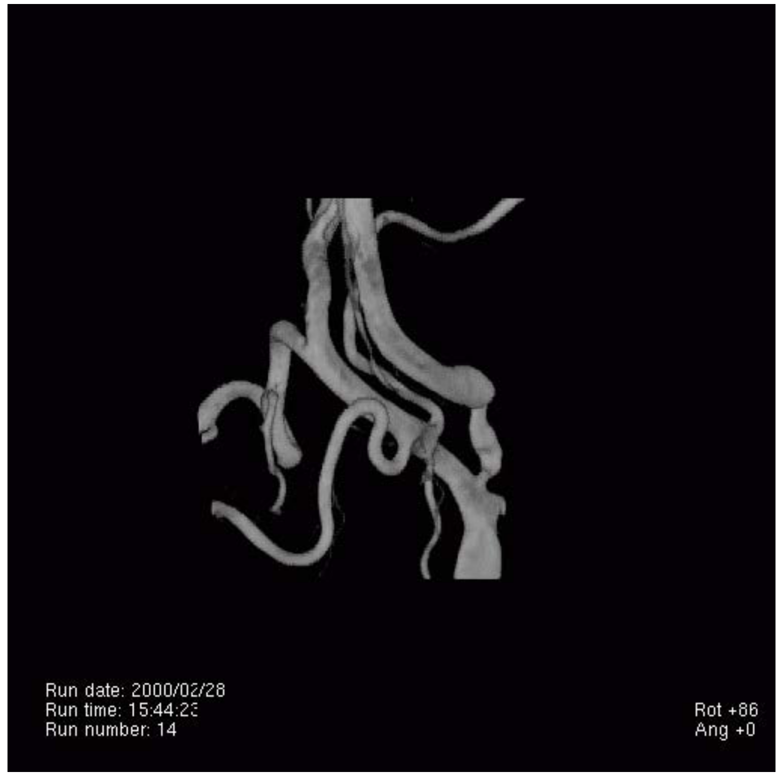


Figure 1: Image data provided by Klinikum Coburg, Germany

3-D Angiography

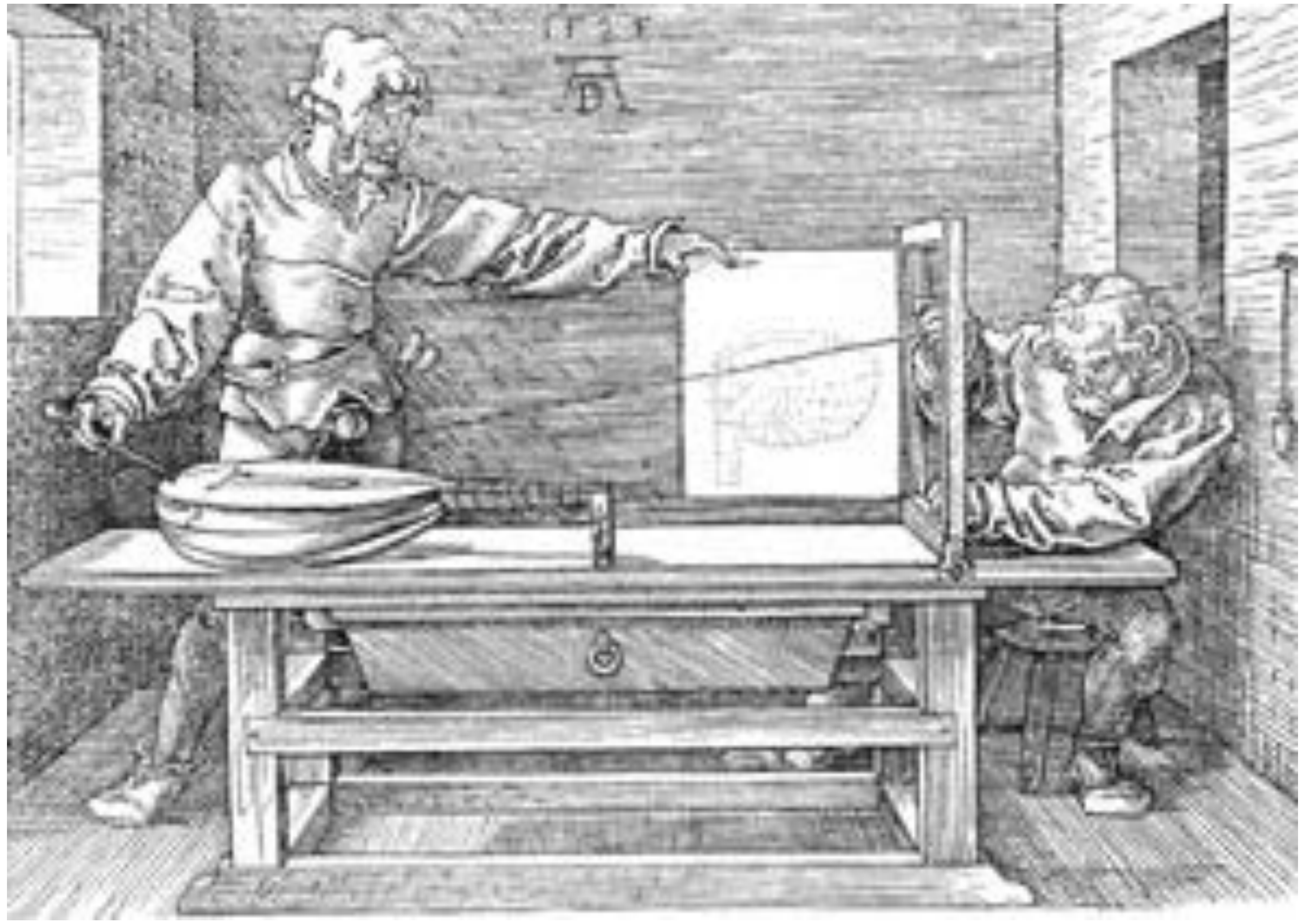


Figure 2: Albrecht Dürer, 1441-1528

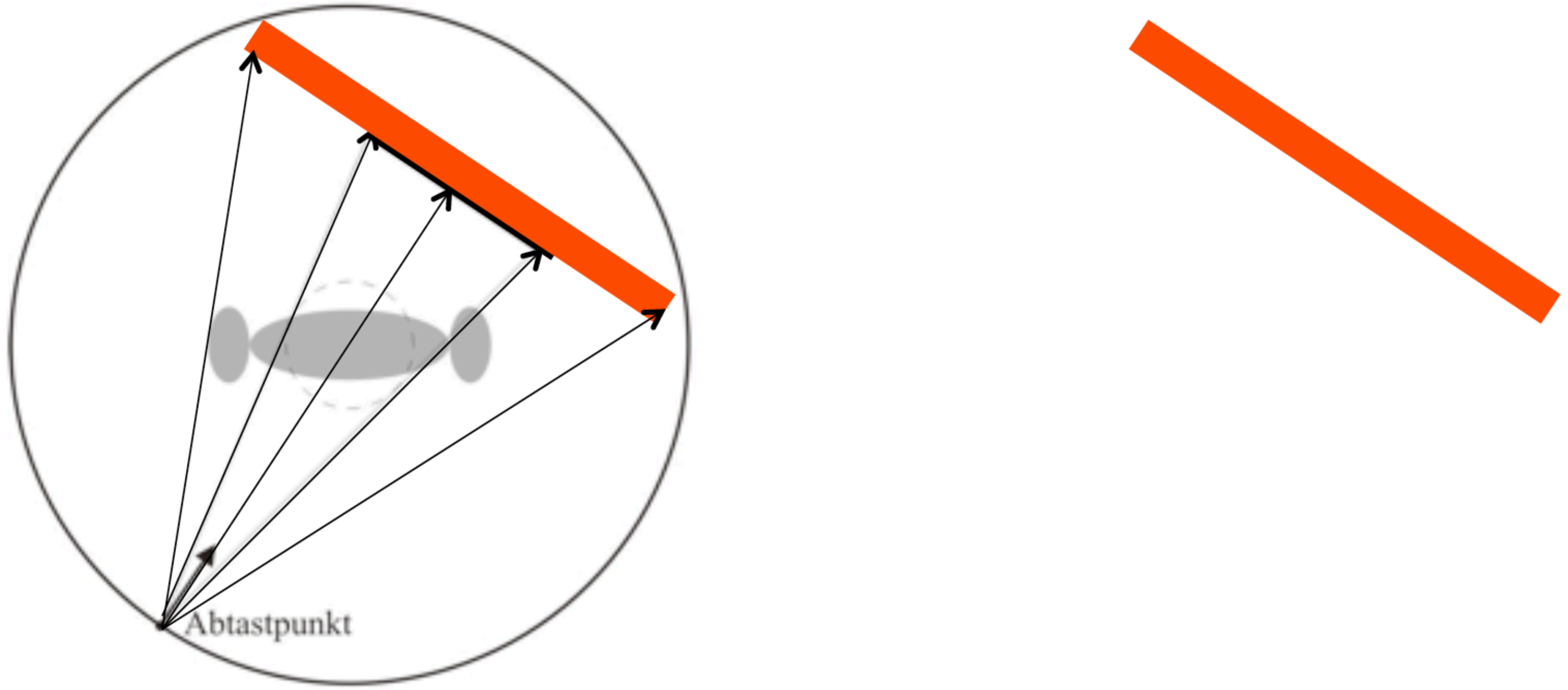


Figure 3: Rotational projections

3-D Angiography

$$f(\boldsymbol{x}) = \sum_{i=1}^{N} w(i, \boldsymbol{x}) \cdot p_F(i, A(i, \boldsymbol{x}))$$

- Distance weight $w : \mathbb{N} \times \mathbb{R}^3 \rightarrow \mathbb{R}$
- Filtered / redundancy weighted $p_F : \mathbb{N} \times \mathbb{R}^2 \rightarrow \mathbb{R}$
- Projection geometry $A(i, \boldsymbol{x}) = \boldsymbol{u} \in \mathbb{R}^2$

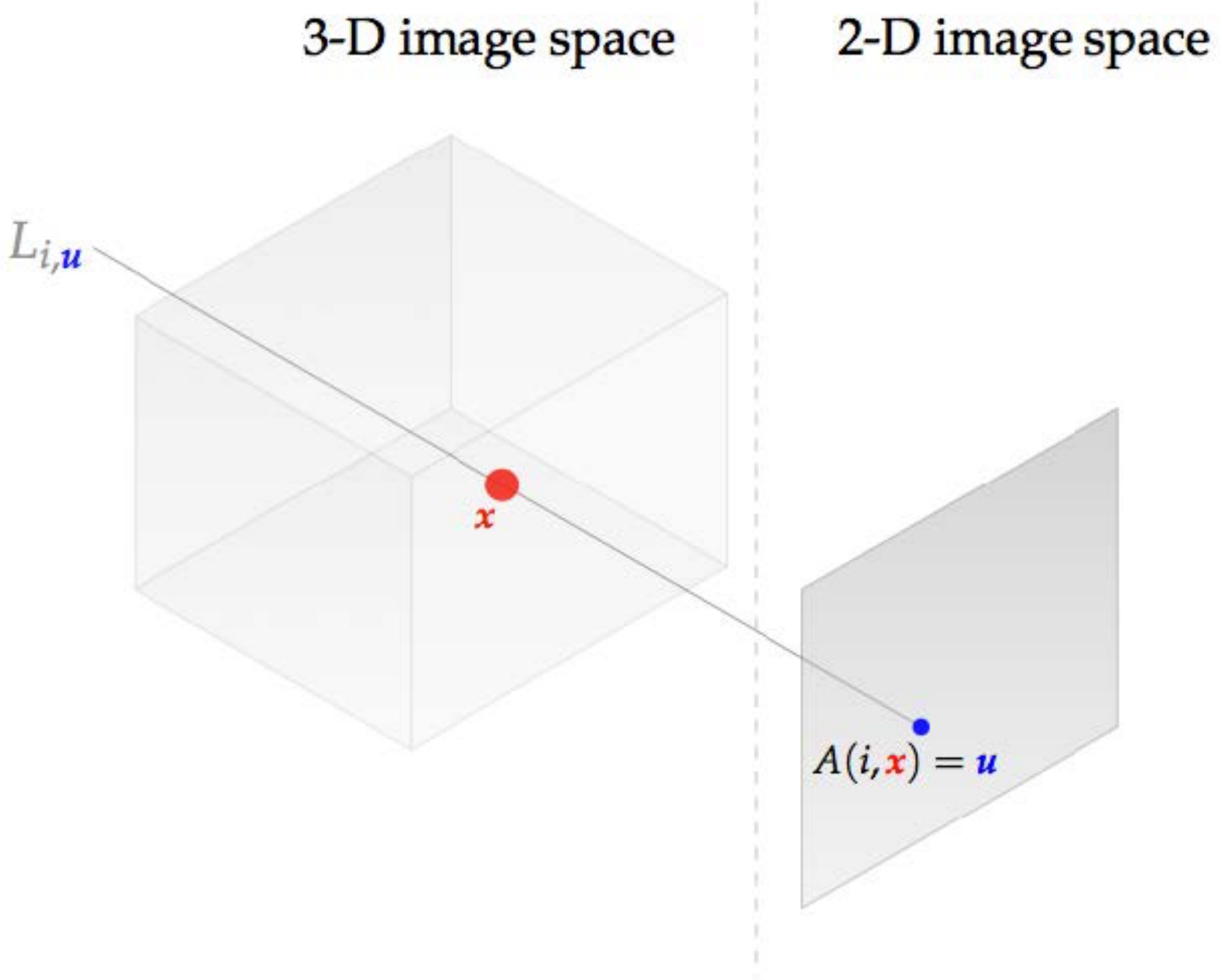


Figure 4: Projection scheme

3-D Angiography

Figure 5: Patent with Siemens, 2005

Topics

Reconstruction of Static Objects

Cardiac Reconstruction

Summary

- Take Home Messages
- Further Readings

Acquired Projection Data of the Heart

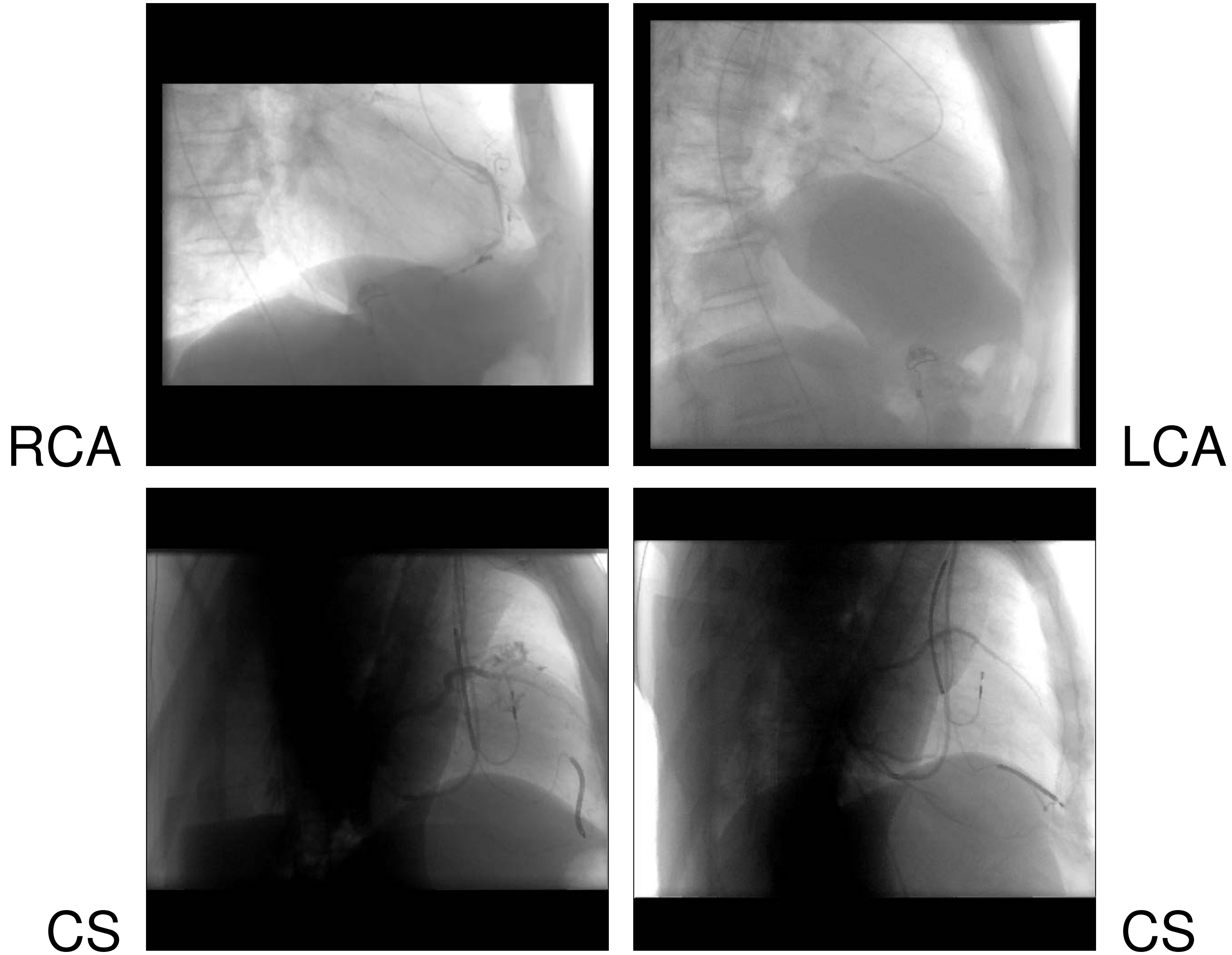


Figure 6: Image data provided by Klinikum Coburg, Germany

Cardiovascular 3-D Imaging: High Clinical Relevance

Setting:

- Intra-procedural cardiac imaging using a C-arm system
- Selective injection of contrast agent (high contrast)

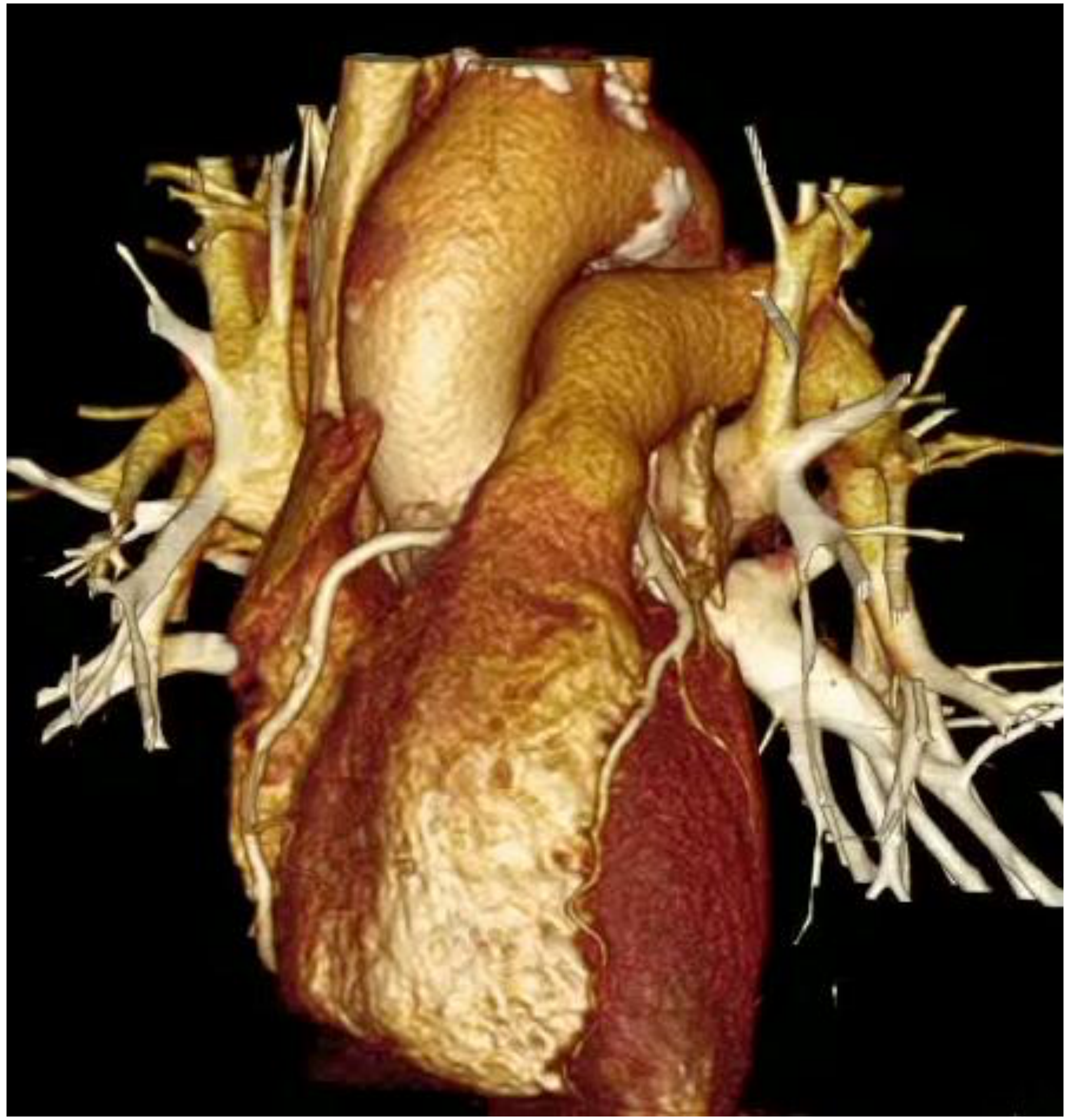


Figure 7: Rendered image of a heart

Cardiovascular 3-D Imaging: High Clinical Relevance

Setting:

- Intra-procedural cardiac imaging using a C-arm system
- Selective injection of contrast agent (high contrast)

Goal: Additional 3-D and 4-D information of the arterial and venous cardiac vascular systems

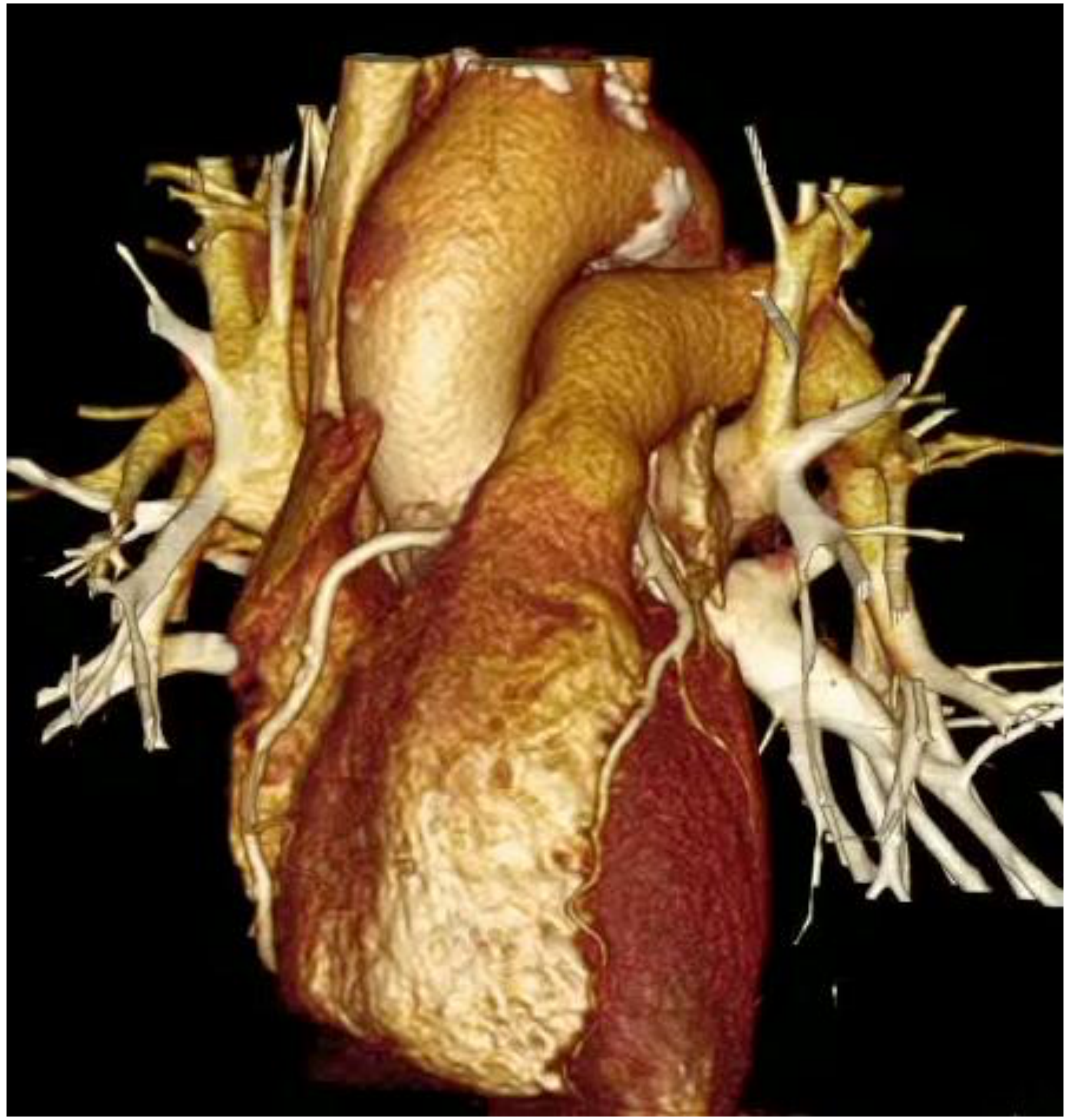


Figure 7: Rendered image of a heart

Cardiovascular 3-D Imaging: High Clinical Relevance

Setting:
- Intra-procedural cardiac imaging using a C-arm system
- Selective injection of contrast agent (high contrast)

Goal: Additional 3-D and 4-D information of the arterial and venous cardiac vascular systems

Clinical applications:
- Assessment of anatomical and functional properties, e. g., diameters, angles or velocity (**diagnostics**)
- Determination of the best fluoro-angulations (**planning**)
- Device selection, e. g., catheter size or manufacturer (**planning**)
- Image overlay during intervention for guiding the procedure (**guidance**)

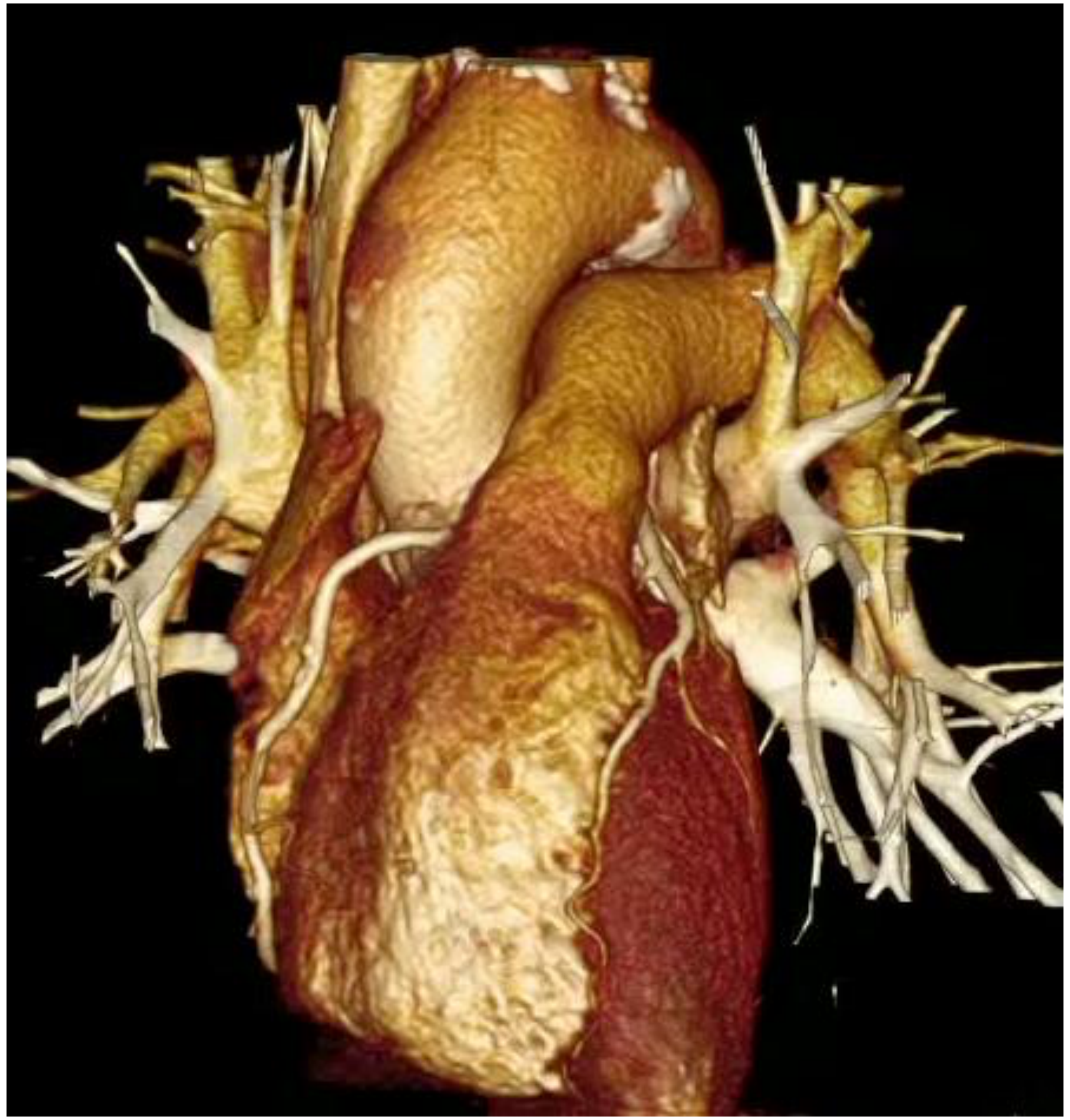


Figure 7: Rendered image of a heart

Motion Patterns

- Cardiac motion
- Respiratory motion
- Patient motion

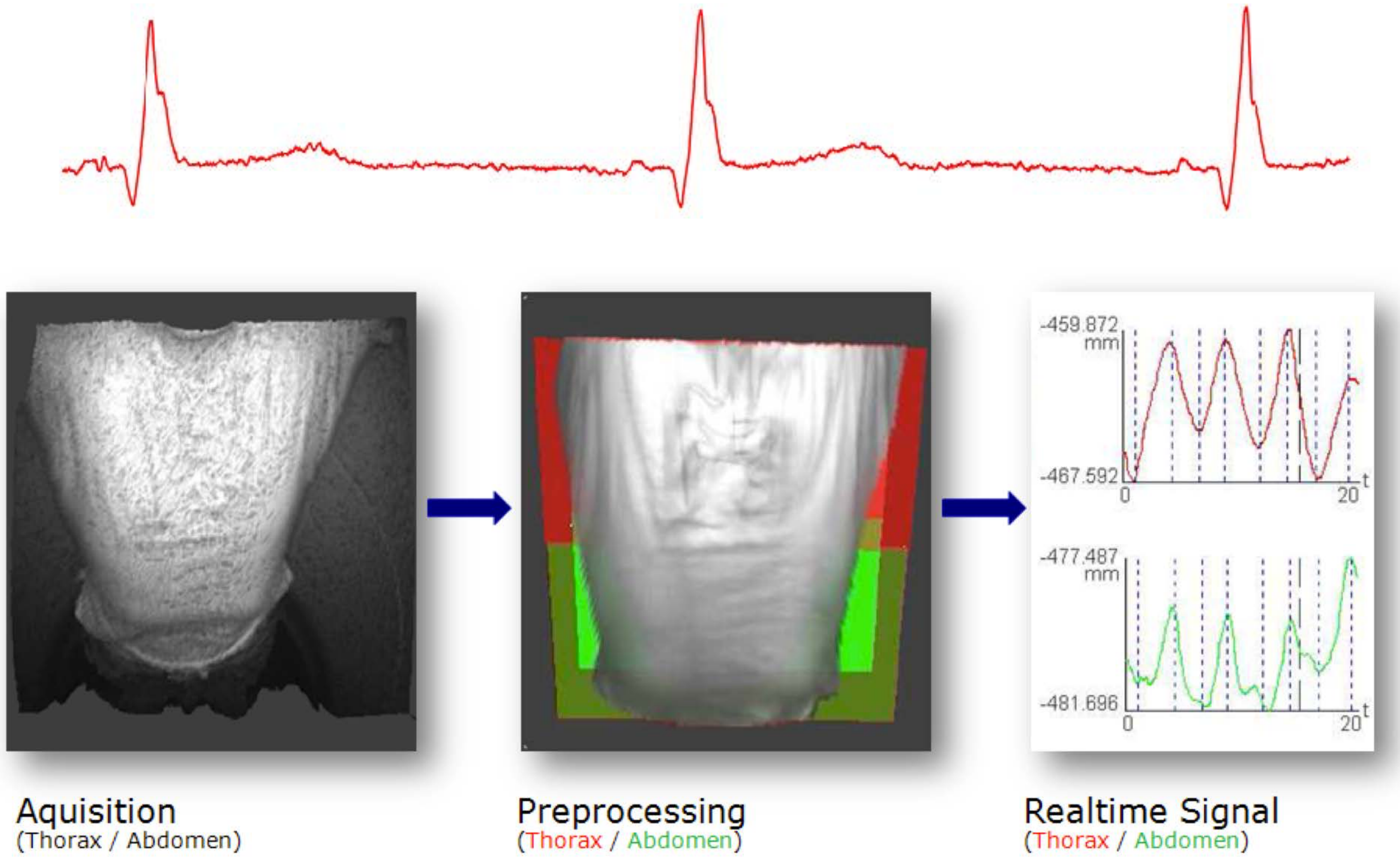


Figure 8: Motion pattern by body part

Topics

Reconstruction of Static Objects

Cardiac Reconstruction

Summary

- Take Home Messages
- Further Readings

Take Home Messages

- Cardiac imaging is used for diagnostic as well as interventional imaging.
- Cardiac, respiratory and patient motion are three different types of motion that have to be compensated for when reconstructing 3-D volumes of the heart (or certain parts of it).

Further Readings

For more information on reconstruction in cardiac imaging, you can start here:

- Günter Lauritsch et al. "Towards Cardiac C-Arm Computed Tomography". In: *IEEE Transactions on Medical Imaging* 25.7 (July 2006), pp. 922–934. DOI: 10.1109/TMI.2006.876166
- C. Schwemmer et al. "Residual Motion Compensation in ECG-gated Interventional Cardiac Vasculature Reconstruction". In: *Physics in Medicine and Biology* 58.11 (2013), pp. 3717–3737. DOI: 10.1088/0031-9155/58/11/3717

Reference:

Albrecht Dürer. *Underweysung der Messung, mit dem Zirckel und Richtscheyt, in Linien, Ebenen unnd gantzen corporen*. Nüremberg: [Hieronymus Andreae], 1525

Medical Image Processing for Interventional Applications

Gating Methods

Online Course – Unit 55

Andreas Maier, Frank Schebesch
Pattern Recognition Lab (CS 5)

virtuelle hochschule bayern

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

ECG-Based Gating

Image-Based Gating
- Algorithm
- Experimental Studies
- Conclusions

Summary
- Take Home Messages
- Further Readings

ECG-Gated C-arm CT (cf. Lauritsch et al., 2006)

- Low-contrast reconstruction of the heart using a C-arm system
- Quasistatic object required for reconstruction
- Series of N forward and backward short scan sweeps
- ECG-gating to generate a complete data set of almost motion-free projection images

Figure 1: C-arm system (image courtesy of Siemens Healthcare)

The Principle of ECG-Gating

First forward sweep of a three-sweep acquisition:

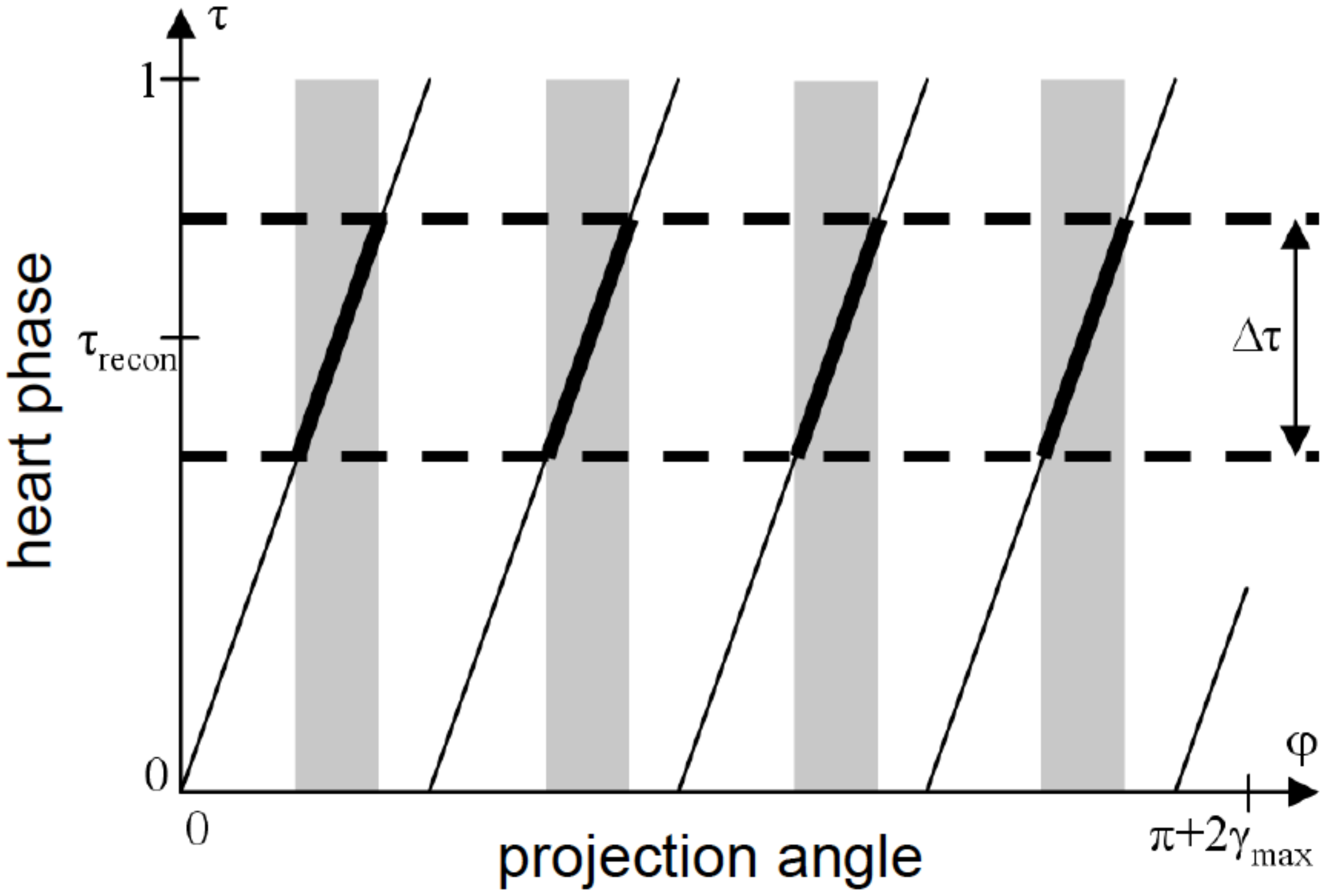


Figure 2: Desired time window characterized by its **center** τ_{recon}, and **width** $\Delta\tau$ (reconstruction time)

The Principle of ECG-Gating

First forward sweep of a three-sweep acquisition:

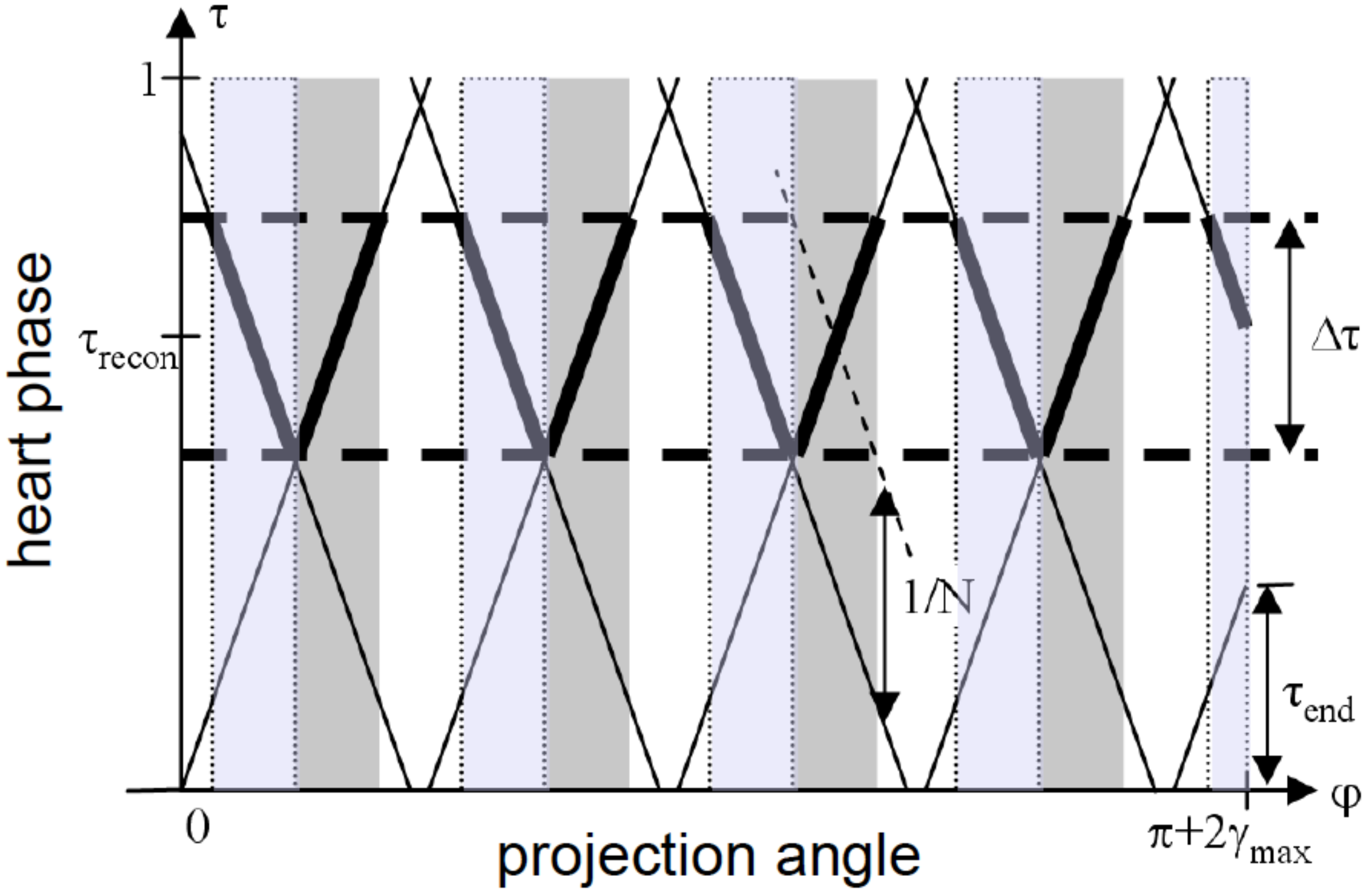


Figure 2: Desired time window characterized by its **center** τ_{recon}, and **width** $\Delta\tau$ (reconstruction time)

The Principle of ECG-Gating

First forward sweep of a three-sweep acquisition:

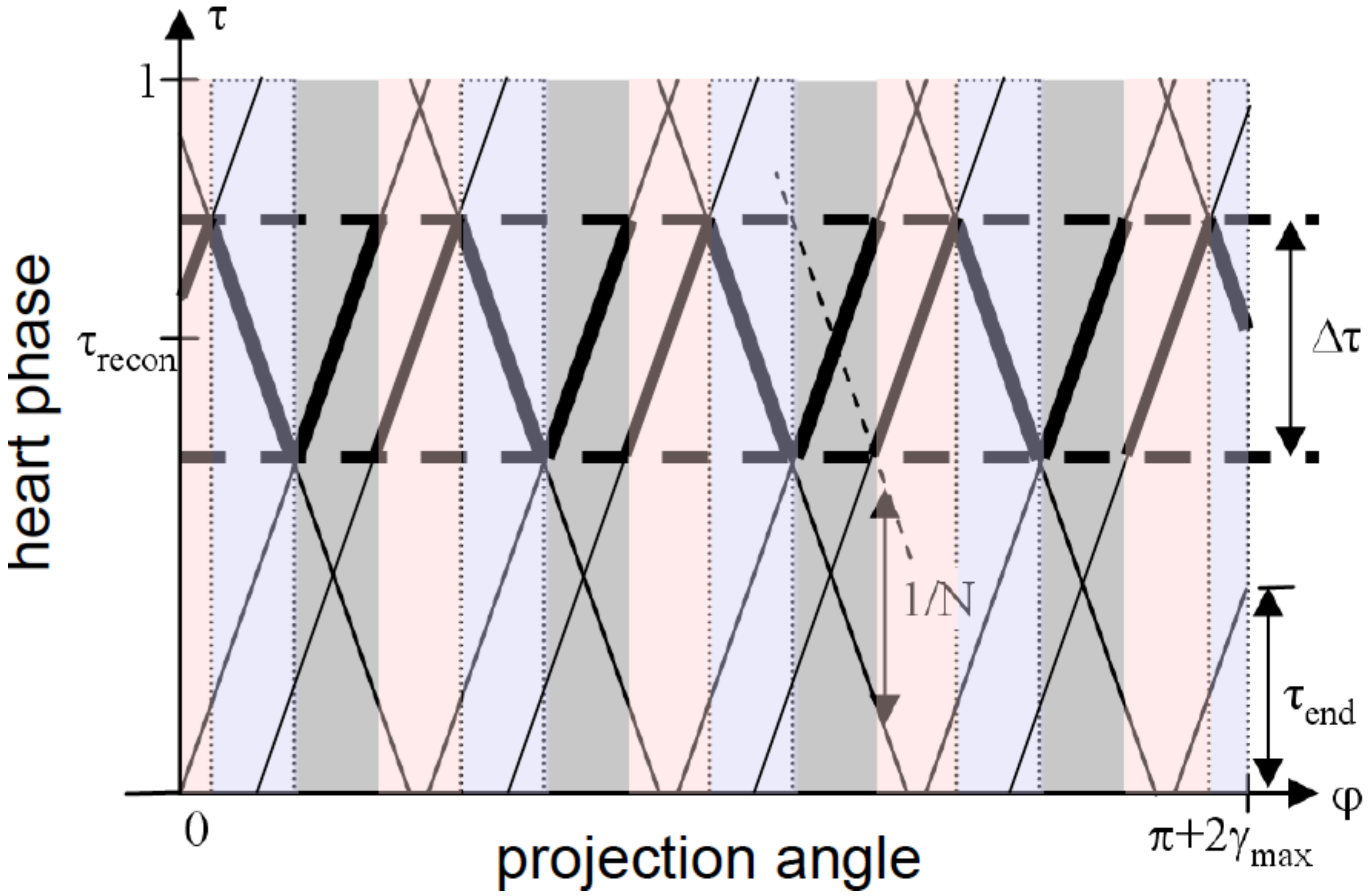


Figure 2: Desired time window characterized by its **center** τ_{recon}, and **width** $\Delta\tau$ (reconstruction time)

ECG-Based Gating

- **Today:** Product in clinical use
- **Single sweep:** Data sufficiency condition violated
- **Multiple sweeps:** No 3-D angiograms
- ECG measures the electrical cardiac activity only:
  $\rightarrow$ derivation of an electrical cardiac phase,
  $\rightarrow$ no direct measure of the physiological cardiac phase.
- Correlation between electrical and physiological phase can be weak, for instance, at:
  - non-stable heart rates,
  - non-sinus rhythms,
  - cardiac arrhythmia.

Topics

Image-Based Gating

Physiological cardiac phase is encoded in the projection data.
$\rightarrow$ Perform gating based on the image information.

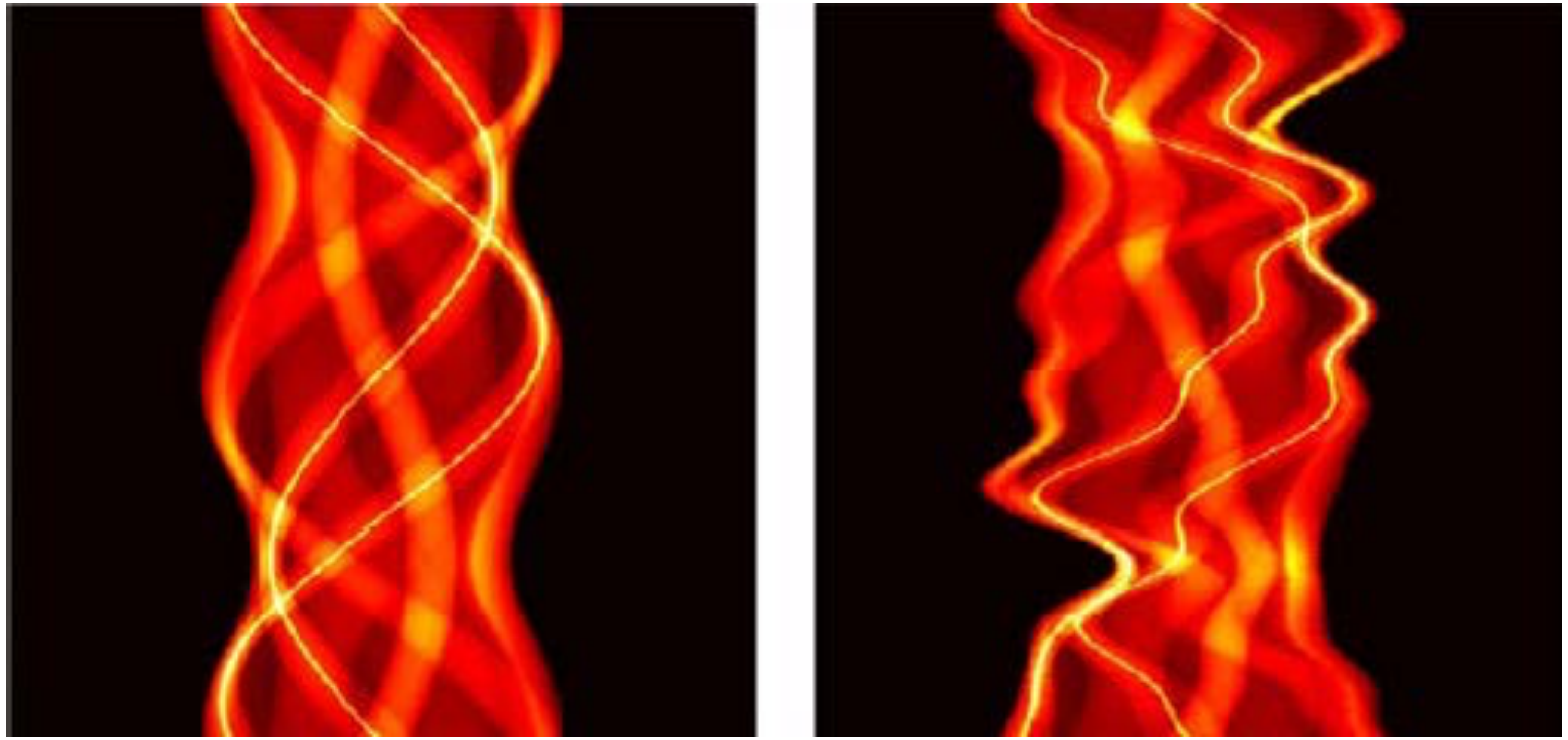


Figure 3: Static (left) vs. motion affected sinogram (right)

One Approach to Image-Based Gating

Core Idea:

Projection images of neighboring C-arm angulations:

Change of image content = *Sinogram motion* + ***Cardiac motion***

(constant for all sweeps) **(varies between sweeps)**

Implication:

- Adjacent projection images of the **same** cardiac phase are more **similar**.
- Find a gating that minimizes the change of image content between adjacent C-arm angulations in multiple sweep sequences.

One Approach to Image-Based Gating

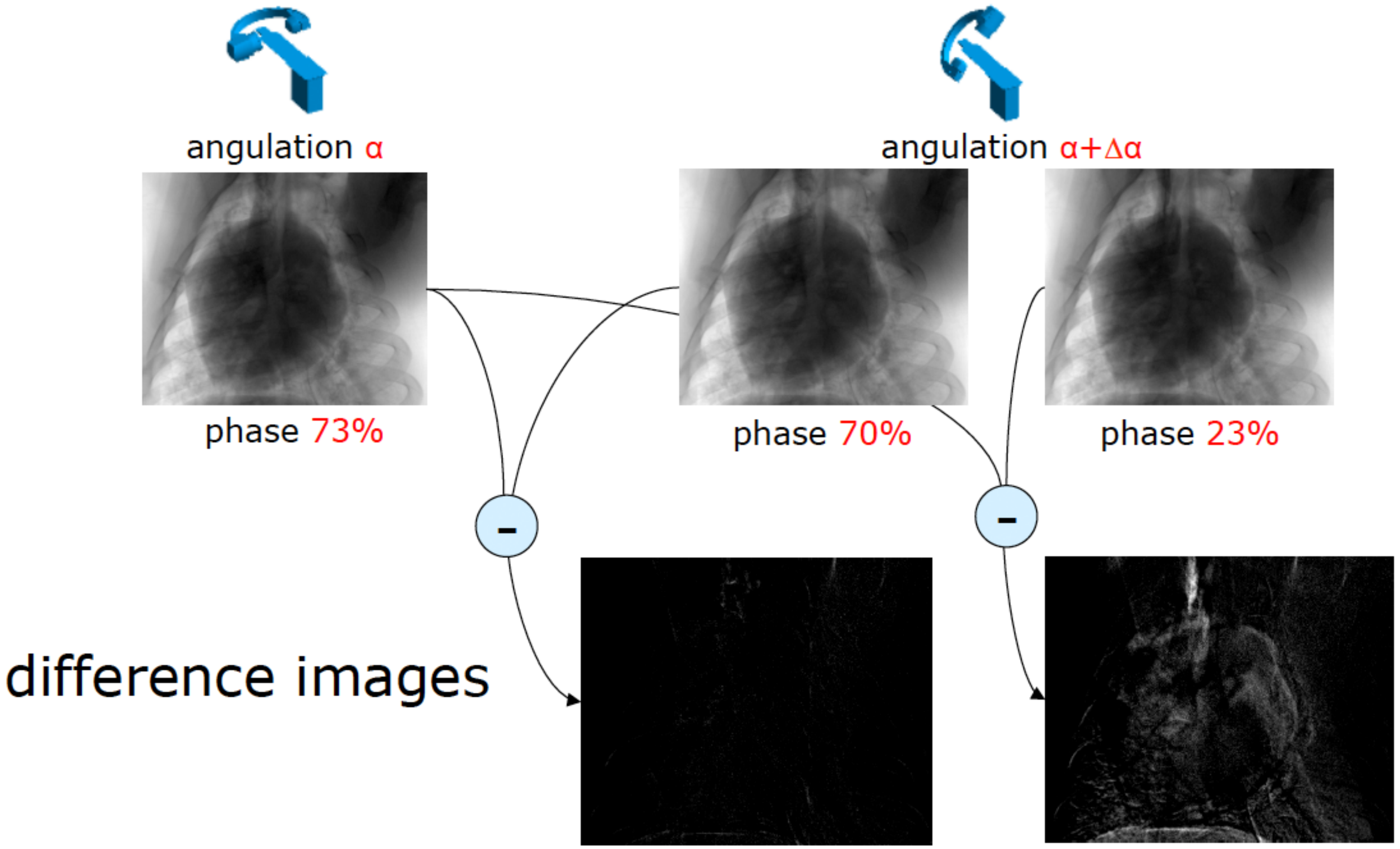
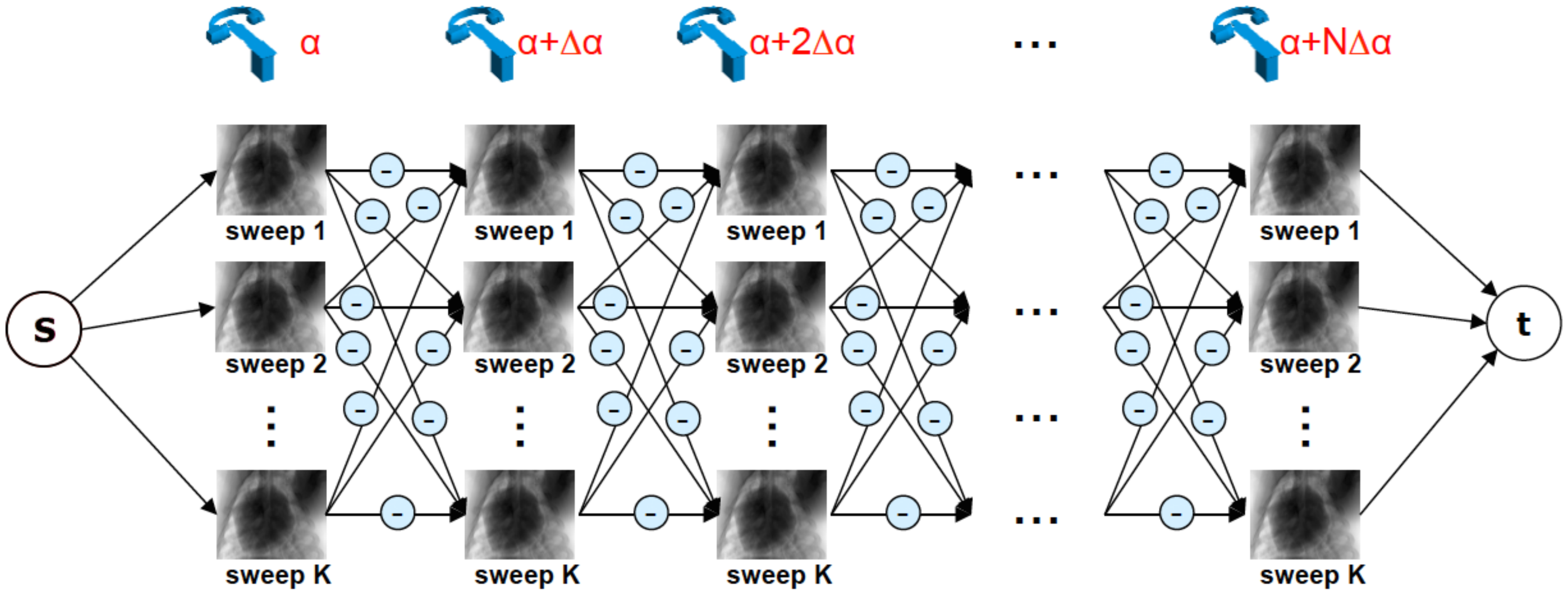


Figure 4: Analysis of different heart phases

Image-Based Gating Algorithm

- Preprocessing of images
- Mapping the space of all gatings to a **projection graph**:



- The projection images along the shortest path from **s** to **t** (using Dijkstra) form the **image-based gating**.

Image-Based Gating Algorithm

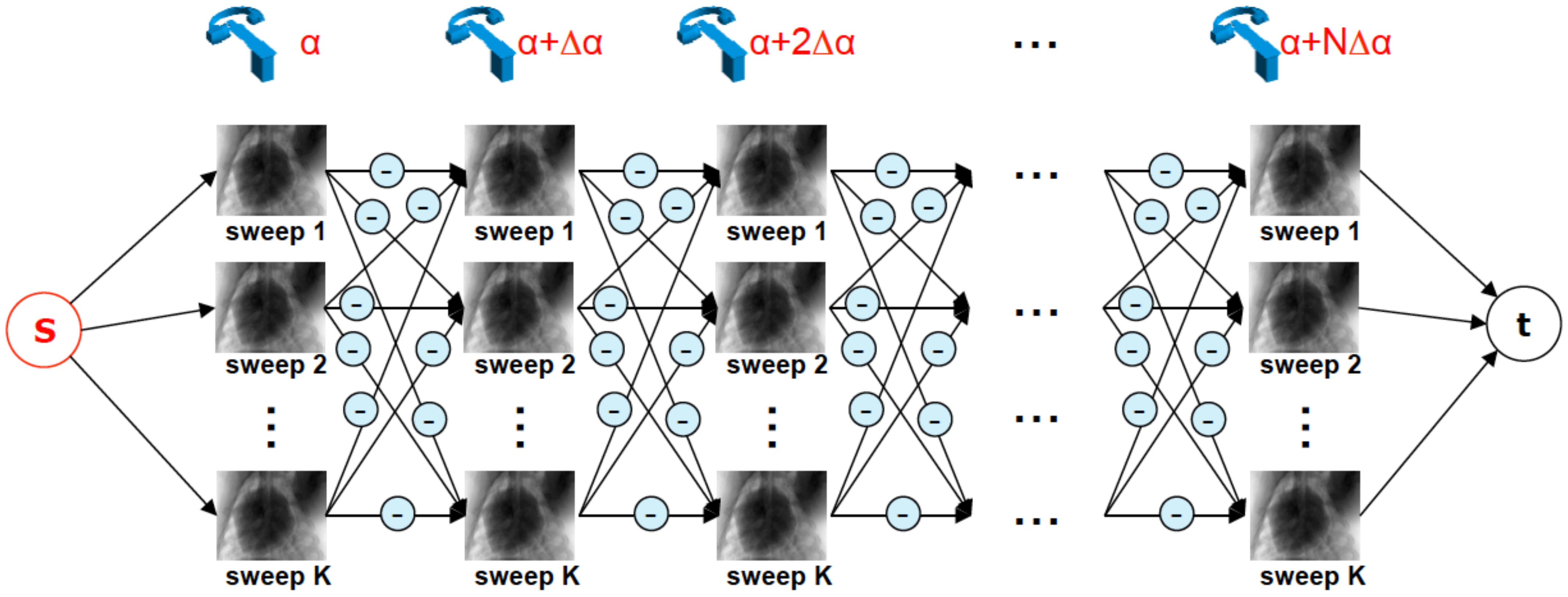


Figure 6: Graph search for shortest path through all projections

Image-Based Gating Algorithm

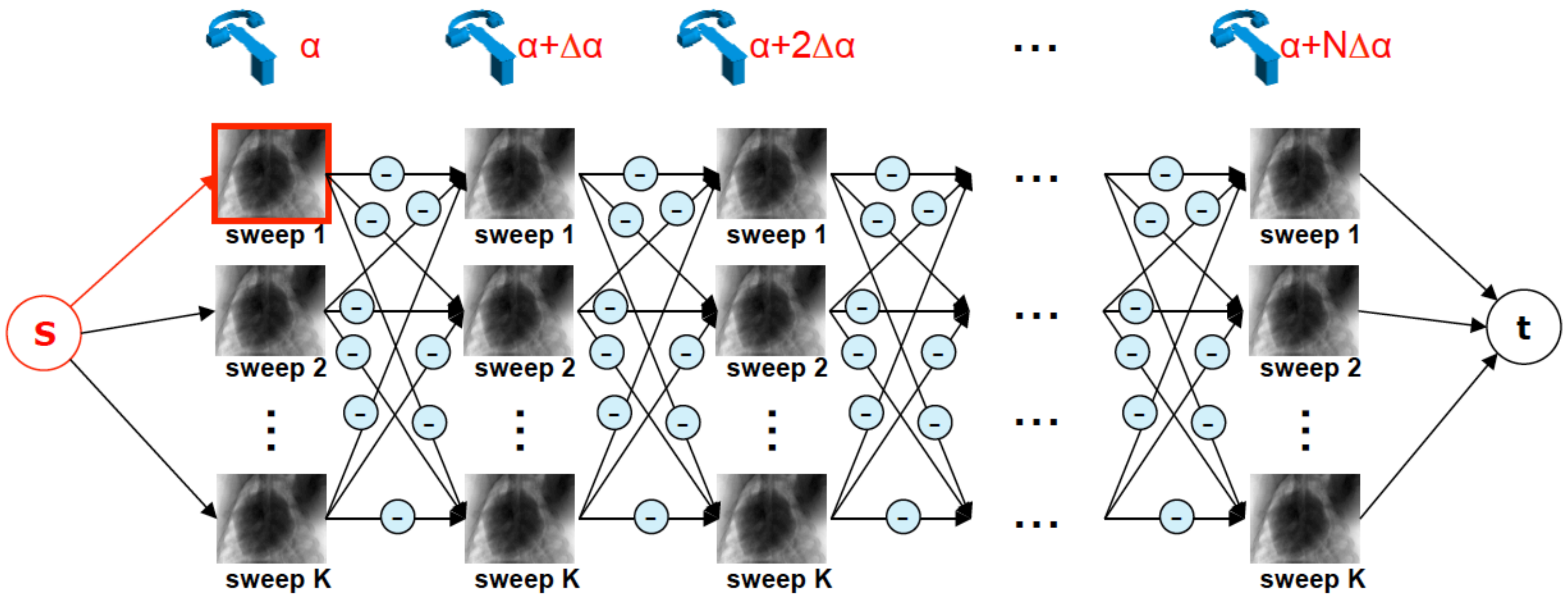


Figure 6: Graph search for shortest path through all projections

Image-Based Gating Algorithm

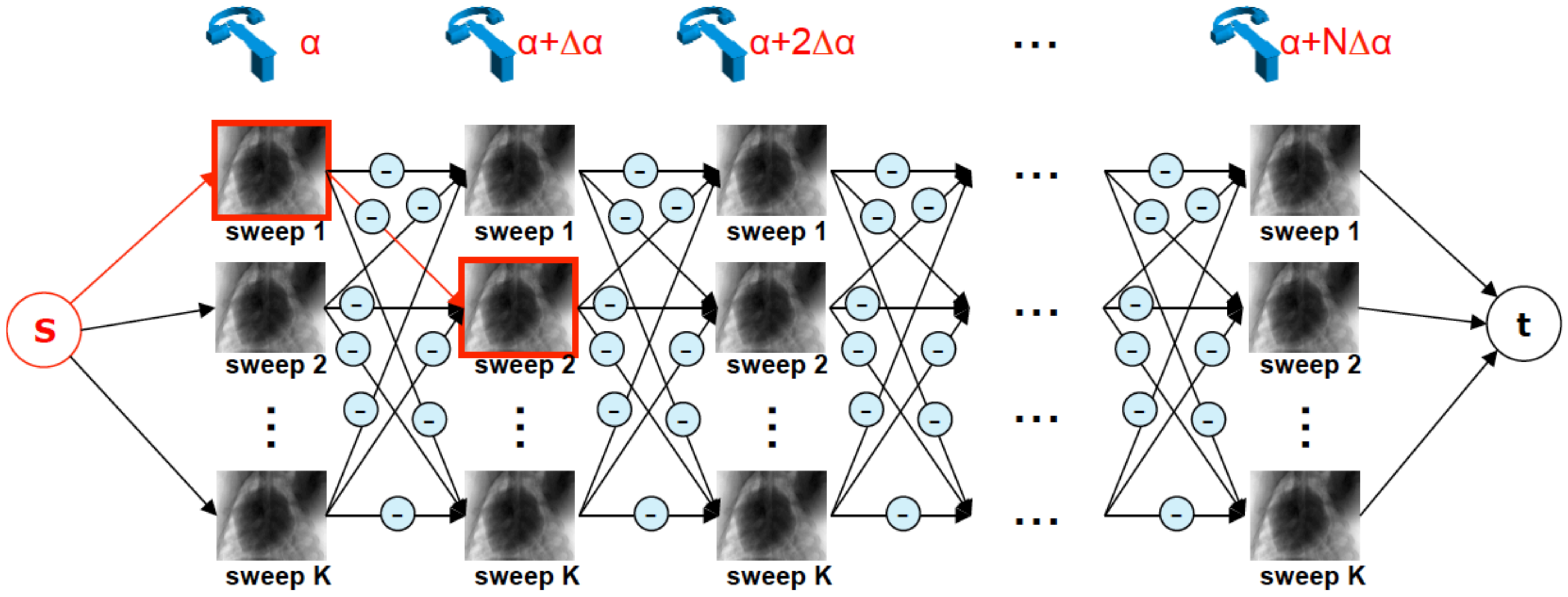


Figure 6: Graph search for shortest path through all projections

Image-Based Gating Algorithm

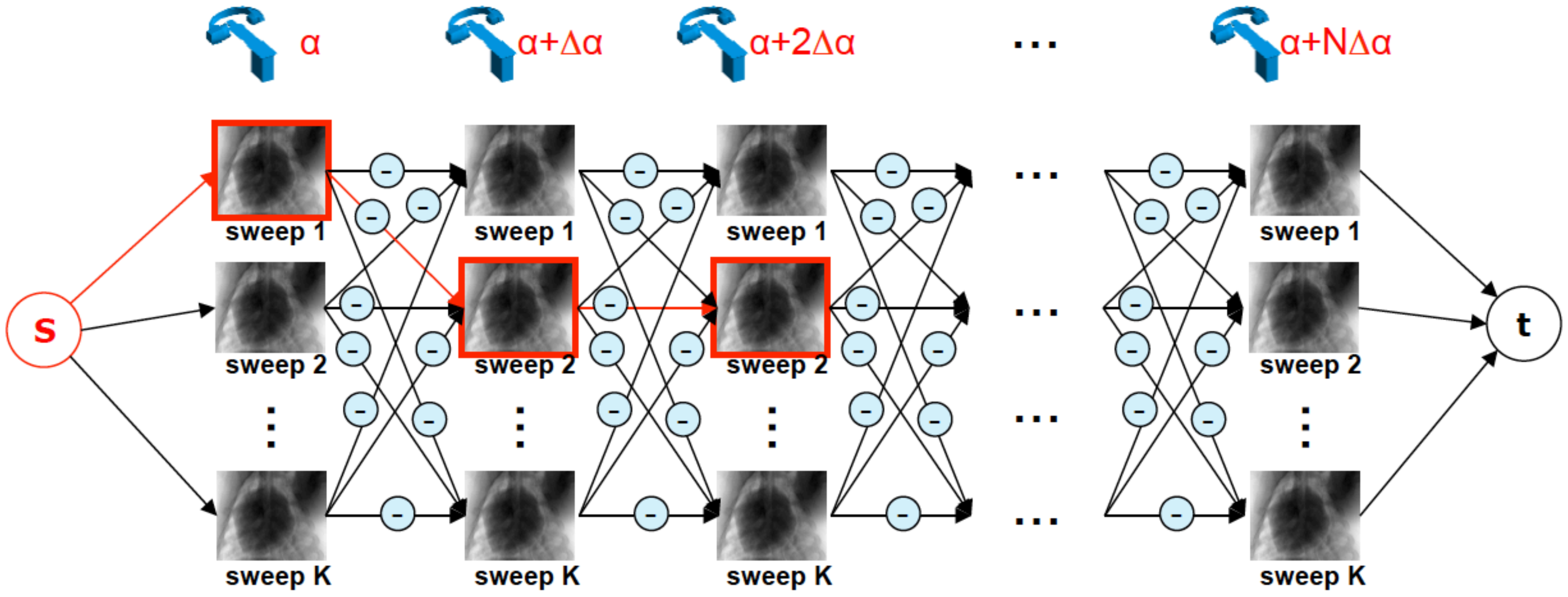


Figure 6: Graph search for shortest path through all projections

Image-Based Gating Algorithm

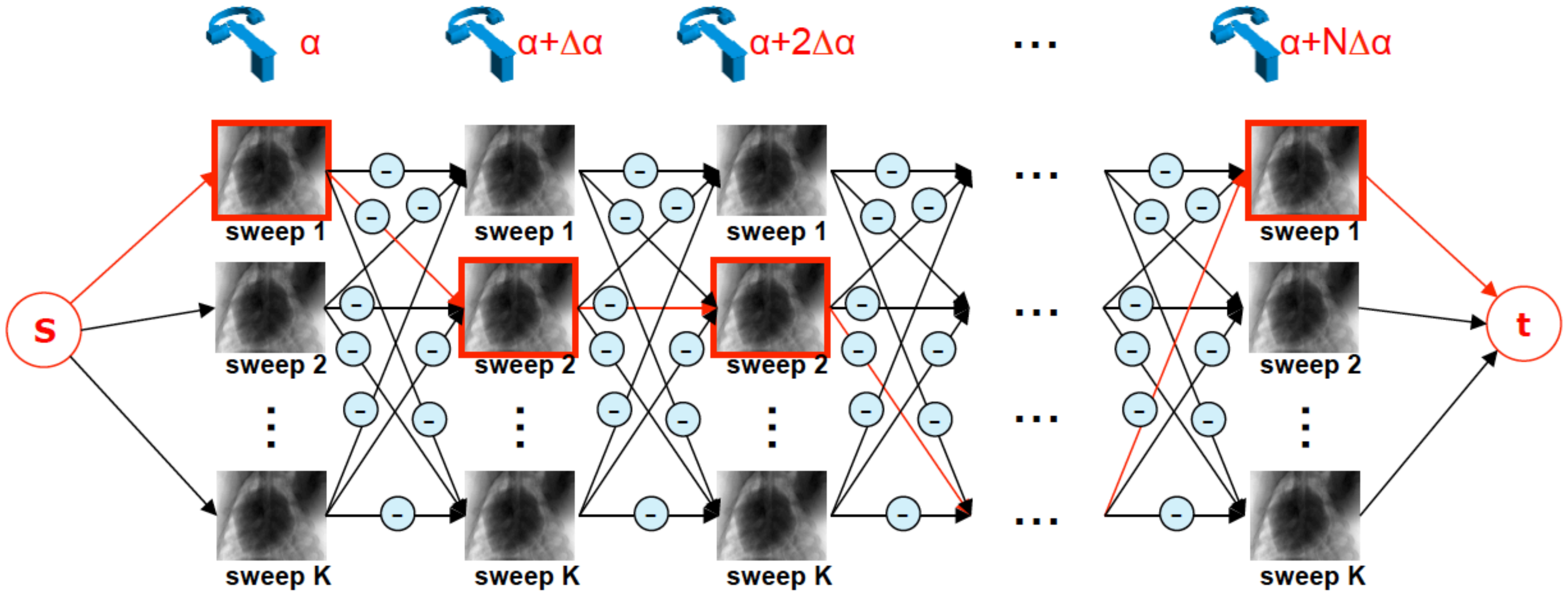
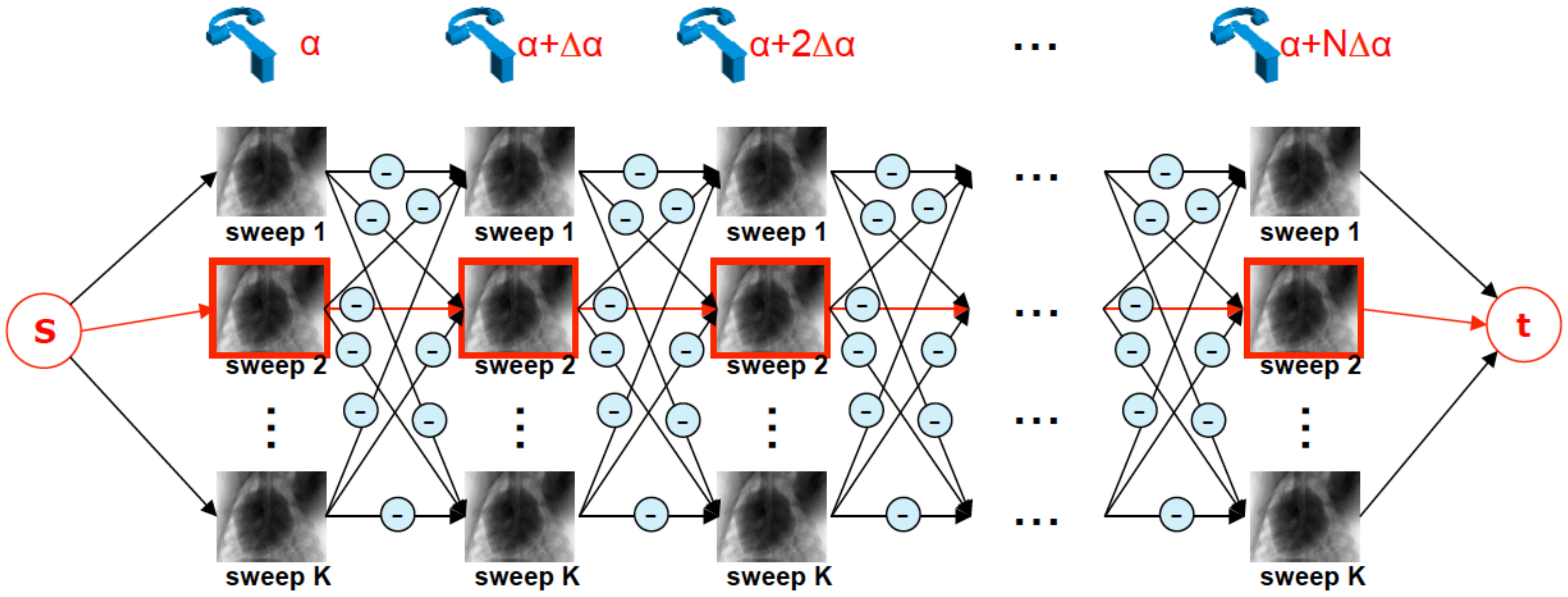


Figure 6: Graph search for shortest path through all projections

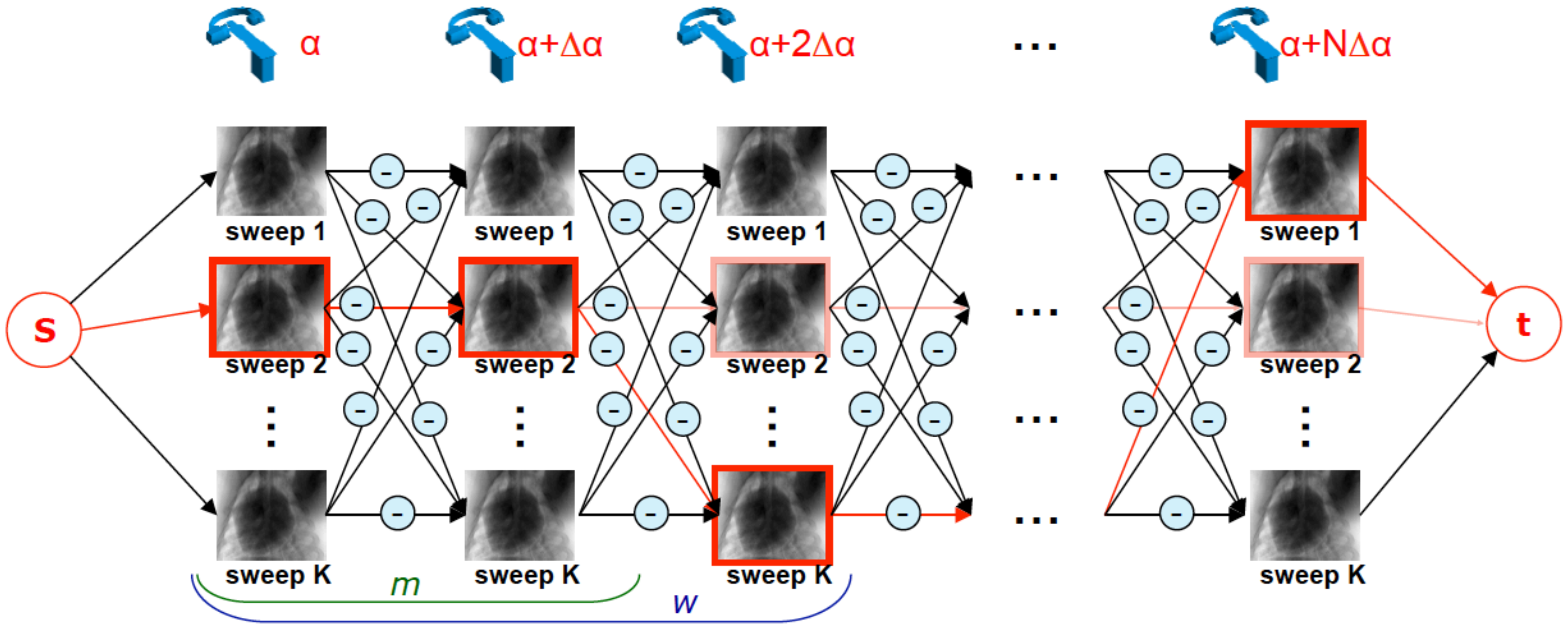
Gating Constraints

Problem: Paths are preferred with minimal jumps across sweeps.



Gating Constraints

Problem: Paths are preferred with minimal jumps across sweeps.



Solution: Within a time-frame *w* at maximum *m* projections from a particular sweep can be selected.

Parametrization is based on the mean heart rate → image-based method.

Animal Study: Setup

- 9 porcine cases
- Performed at Axiom lab, Stanford University (regulatory)
- 6 sweeps, 191 projections per 4 second sweep
- Matrix size 620×480
- Regular heart rates: $75 - 95$ bpm

Animal Study: Results

- Image quality survey:
  - Four experts were asked to blindly rate image quality.
  - Rating: -3 to $+3$ image improvement (compared to non-gated)

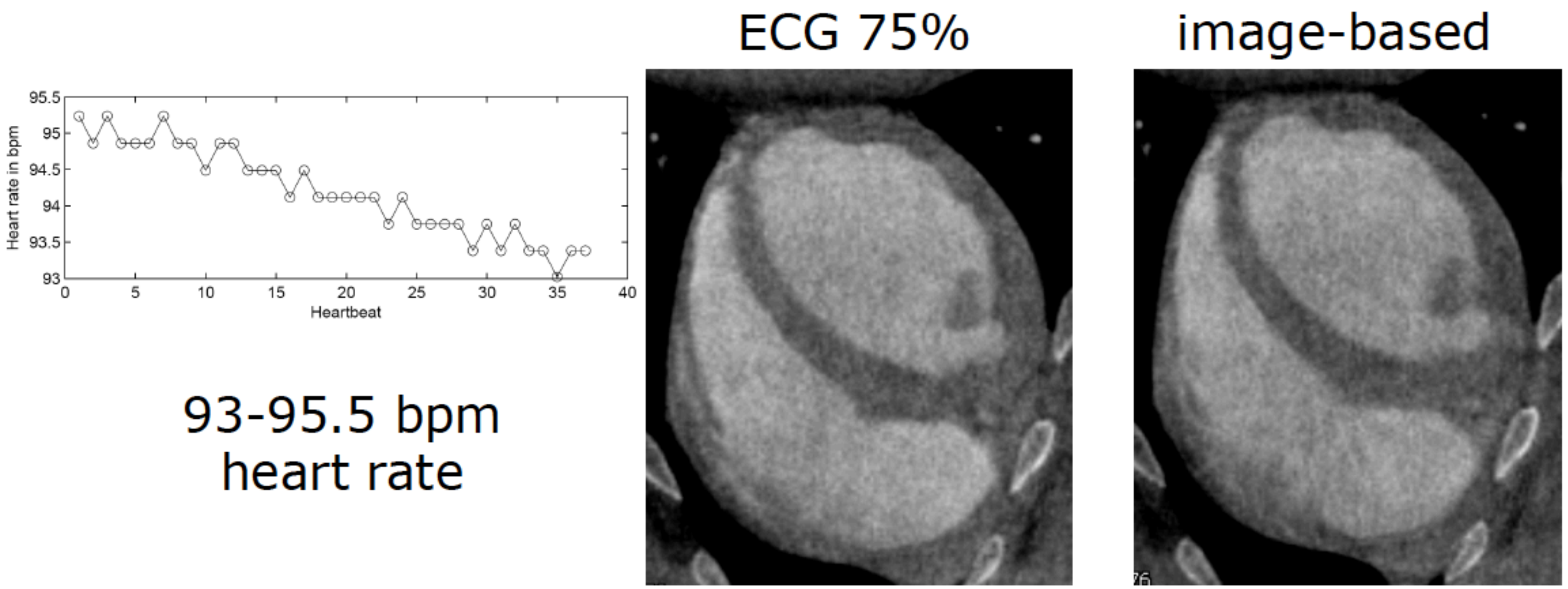
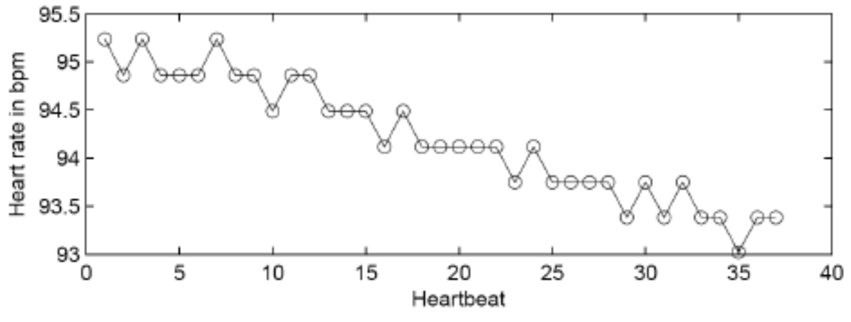


Figure 8: In-vivo porcine model (Subj. 1)

Animal Study: Results

- Image quality survey:
  - Four experts were asked to blindly rate image quality.
  - Rating: -3 to $+3$ image improvement (compared to non-gated)
- Average scores:
  - End-diastolic ECG-gating at 75 %: **2.50**
  - Image-based gating: **2.00**



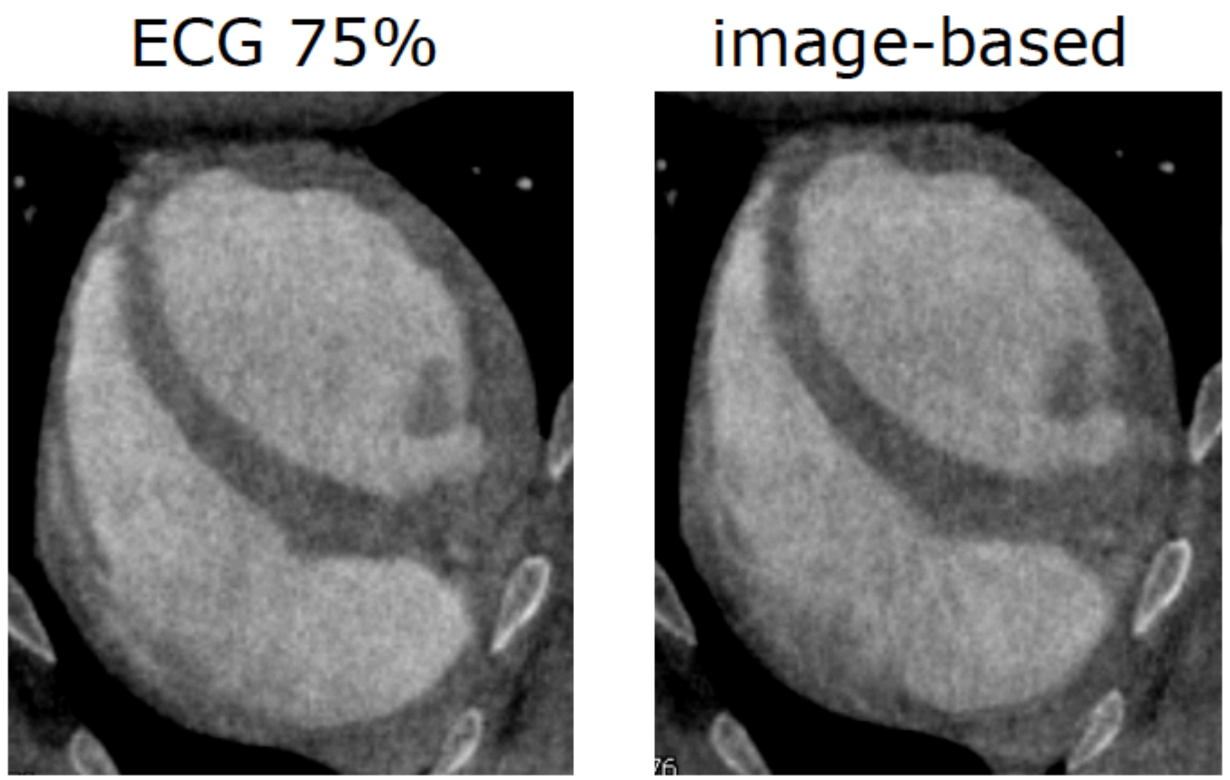


Figure 8: In-vivo porcine model (Subj. 1)

Animal Study: Results

- Image quality survey:
  - Four experts were asked to blindly rate image quality.
  - Rating: -3 to $+3$ image improvement (compared to non-gated)
- Average scores:
  - End-diastolic ECG-gating at 75 %: **2.50**
  - Image-based gating: **2.00**

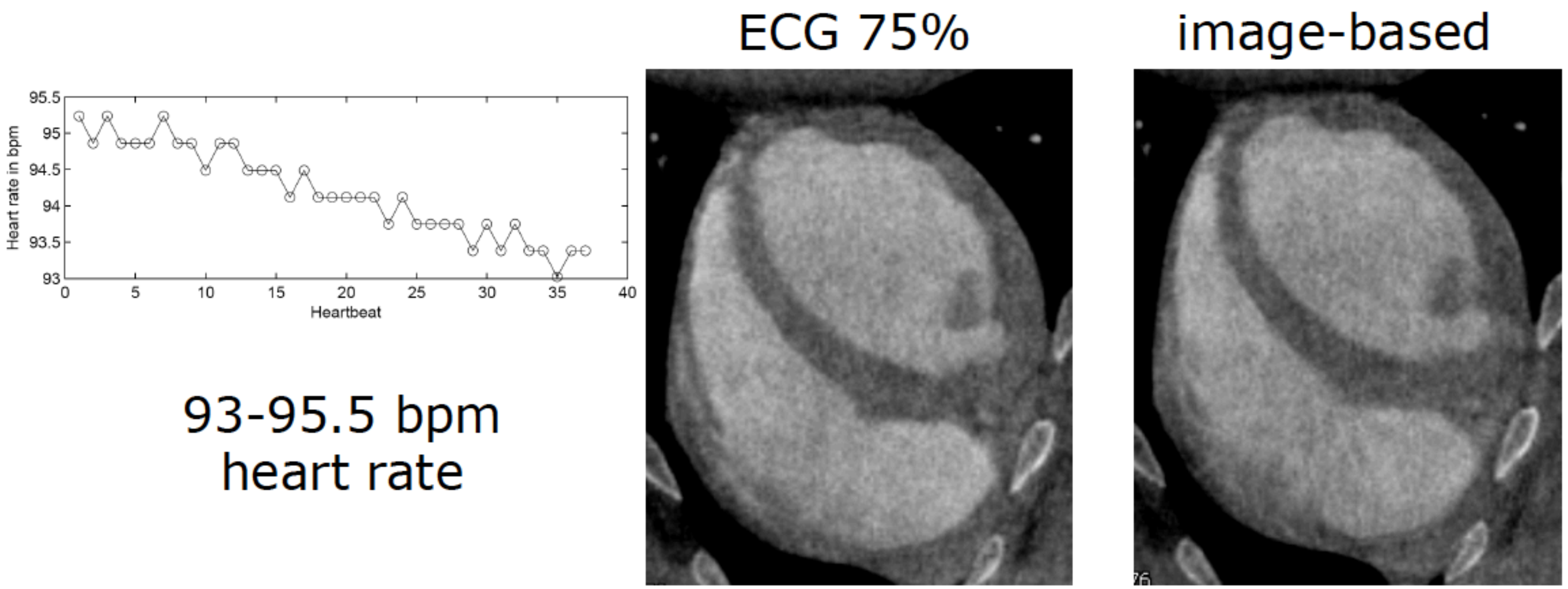
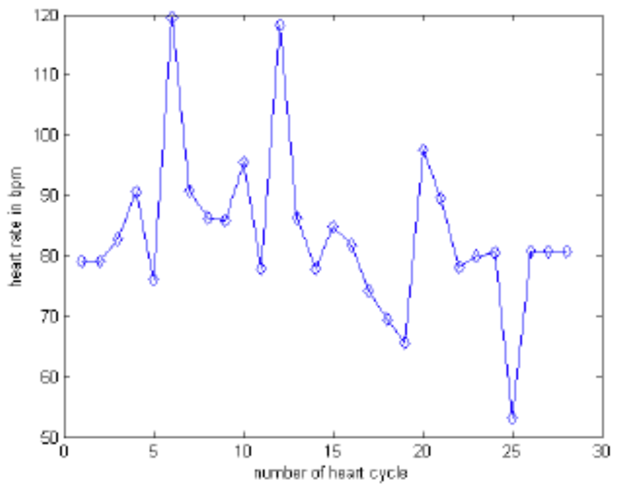


Figure 8: In-vivo porcine model (Subj. 1)

→ Excellent image quality

→ At stable heart rates ECG-gating seems to yield slightly superior image quality.

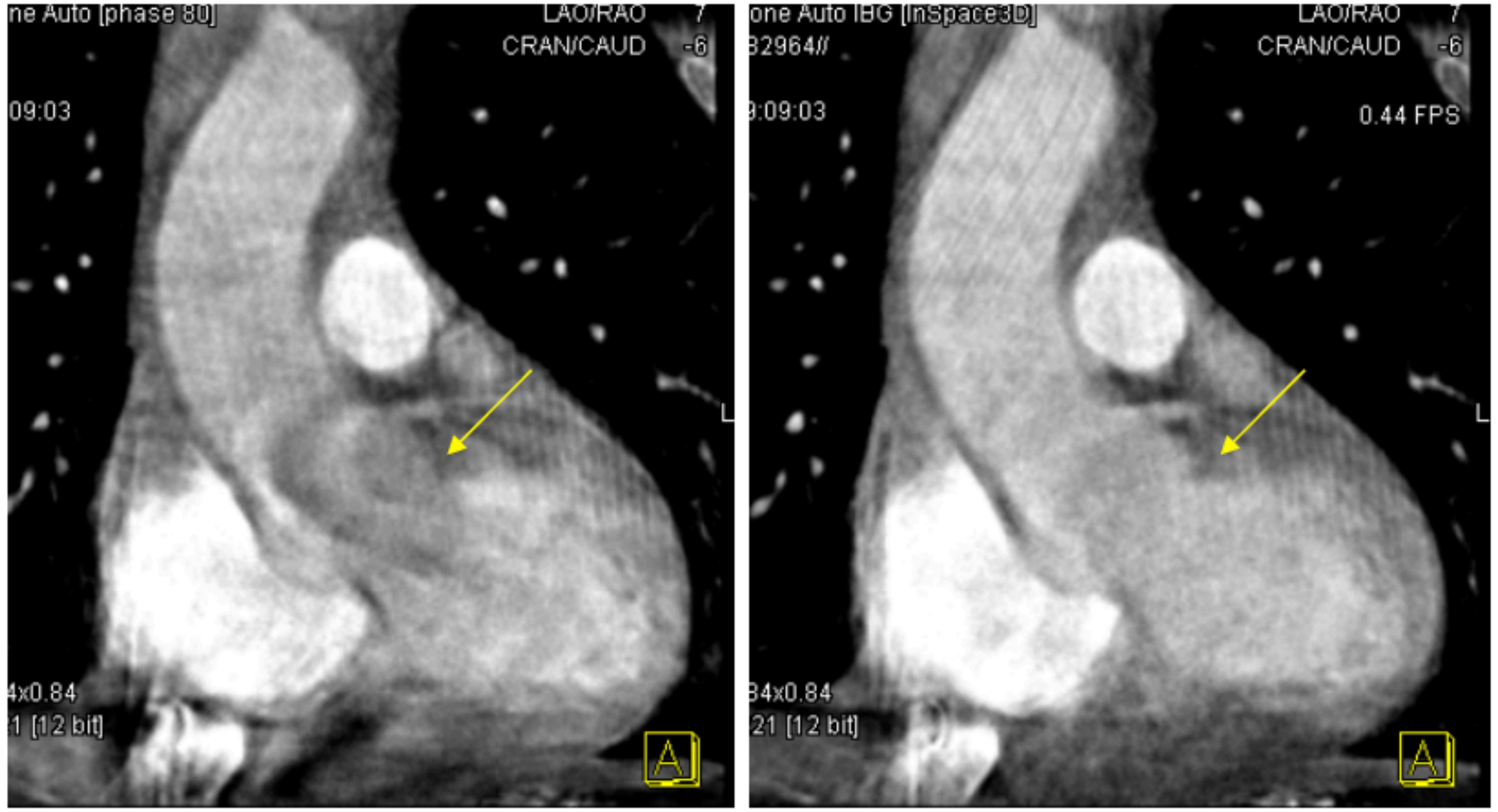
Clinical Human Case



60-105 bpm
heart rate

ECG 80%

image-based



by courtesy of Klinikum Coburg, Prof. Brachmann

→ Since image-based gating better reflects physiological information, it seems to handle cases with irregular heart rates better.

Conclusions From the Experiments

- With regular heart rates, ECG-gating appears to be better.
- With irregular heart rates, image-based gating can be superior to ECG-gating.
- **Drawback:** Not all projections used for a single reconstruction!

Topics

Take Home Messages

- For ECG-gating, we use data from several sweeps and selected for a specific heart phase.
- Image-based gating makes use of physiological information.
- Image-based gating employs a simple projection graph method to automatically find the physiological phase with smallest motion.

Further Readings

For more information on reconstruction in cardiac imaging, you can start here:

- Günter Lauritsch et al. "Towards Cardiac C-Arm Computed Tomography". In: *IEEE Transactions on Medical Imaging* 25.7 (July 2006), pp. 922–934. DOI: 10.1109/TMI.2006.876166
- C. Schwemmer et al. "Residual Motion Compensation in ECG-gated Interventional Cardiac Vasculature Reconstruction". In: *Physics in Medicine and Biology* 58.11 (2013), pp. 3717–3737. DOI: 10.1088/0031-9155/58/11/3717

Medical Image Processing for Interventional Applications

ECG-Gated Reconstruction

Online Course – Unit 56
Andreas Maier, Frank Schebesch
Pattern Recognition Lab (CS 5)

Topics

Optimal ECG windowing

- Model
- ECG-Gated Reconstruction
- Optimization
- Results

Summary

- Take Home Messages
- Further Readings

Model Assumptions

State-of-the-art model assumptions: ECG and motion periodicity

Problems in an interventional environment:

- Patients have cardiac diseases $\rightarrow$ arrhythmias, electrophysiological problems.
- Patients can be sedated $\rightarrow$ cannot hold breath.

$\rightarrow$ Assumption 1: ECG motion
$\rightarrow$ Assumption 2: Motion periodicity **?**

Model Assumptions

State-of-the-art model assumptions: ECG and motion periodicity

Problems in an interventional environment:

- Patients have cardiac diseases → arrhythmias, electrophysiological problems.
- Patients can be sedated → cannot hold breath.

→ ~~Assumption 1: ECG motion~~
→ ~~Assumption 2: Motion periodicity~~

New model assumption: Continuous and temporally smooth motion

ECG-Gated Reconstruction

$$\lambda(i, \boldsymbol{s}_{\text{ga}}) = \begin{cases} \cos\alpha\left(\frac{d_h(h(i),h_r)}{w}\pi\right) & \text{if } d_h(h(i), h_r) \leq \frac{w}{2} \\ 0 & \text{otherwise} \end{cases}$$

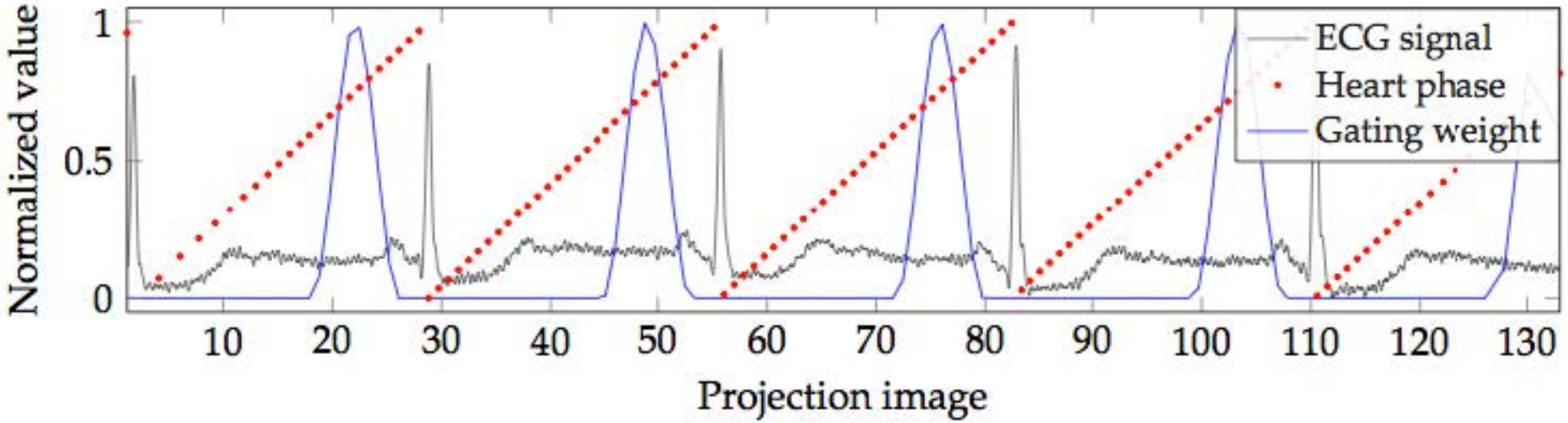


Figure 1: Gating weights by ECG signal

ECG-Gated Reconstruction

Reconstruction formula for a given set of gating parameters:

$$f(\boldsymbol{x}, \boldsymbol{s}_{\text{ga}}) = \sum_{i=1}^{N} \lambda(i, \boldsymbol{s}_{\text{ga}}) \cdot h_{\text{fdk}}(i, \boldsymbol{x}) = \sum_{i=1}^{N} h_{\text{gfdk}}(i, \boldsymbol{x}, \boldsymbol{s}_{\text{ga}})$$

where

$$h_{\text{fdk}}(i, \boldsymbol{x}) = w(i, \boldsymbol{x}) \cdot p_F(i, A(i, \boldsymbol{x}))$$

ECG-Gated Reconstruction

Idea: Find the best parameters for ECG windows.

Objective function:

1. Render reconstructed volume:
$$r(i,\boldsymbol{u},\boldsymbol{s}) = \sum_{\boldsymbol{x} \in L_{i,\boldsymbol{u}}} f(\boldsymbol{x},\boldsymbol{s}).$$
2. Compare rendered image with measured projection:
$$q(i,\boldsymbol{s}) = \sum_{\boldsymbol{u}} \left(p(i,\boldsymbol{u}) - r(i,\boldsymbol{u},\boldsymbol{s})\right)^2.$$
3. Compute the weighted sum for all images:
$$\mathcal{L}(\boldsymbol{s}_{\mathrm{ga}}) = \frac{1}{\sum\limits_{i=1}^{N} \lambda(i,\boldsymbol{s}_{\mathrm{ga}})} \sum_{i=1}^{N} \lambda(i,\boldsymbol{s}_{\mathrm{ga}}) \cdot q(i,\boldsymbol{s})$$

ECG-Gated Reconstruction

Optimization problem:

$$\hat{\boldsymbol{s}}_{\text{ga}} = \arg\min_{\boldsymbol{s}_{\text{ga}}} \mathcal{L}\left(\boldsymbol{s}_{\text{ga}}\right)$$

Degrees of freedom:

- Preprocessing: background segmentation
- Forward projection: DRR, MIP
- Similarity measure: NCC, RMSE, NMI, PI, GD

Optimization:

- Grid search: 300 sample points
- Local gradient descent

Example: Visual Comparison

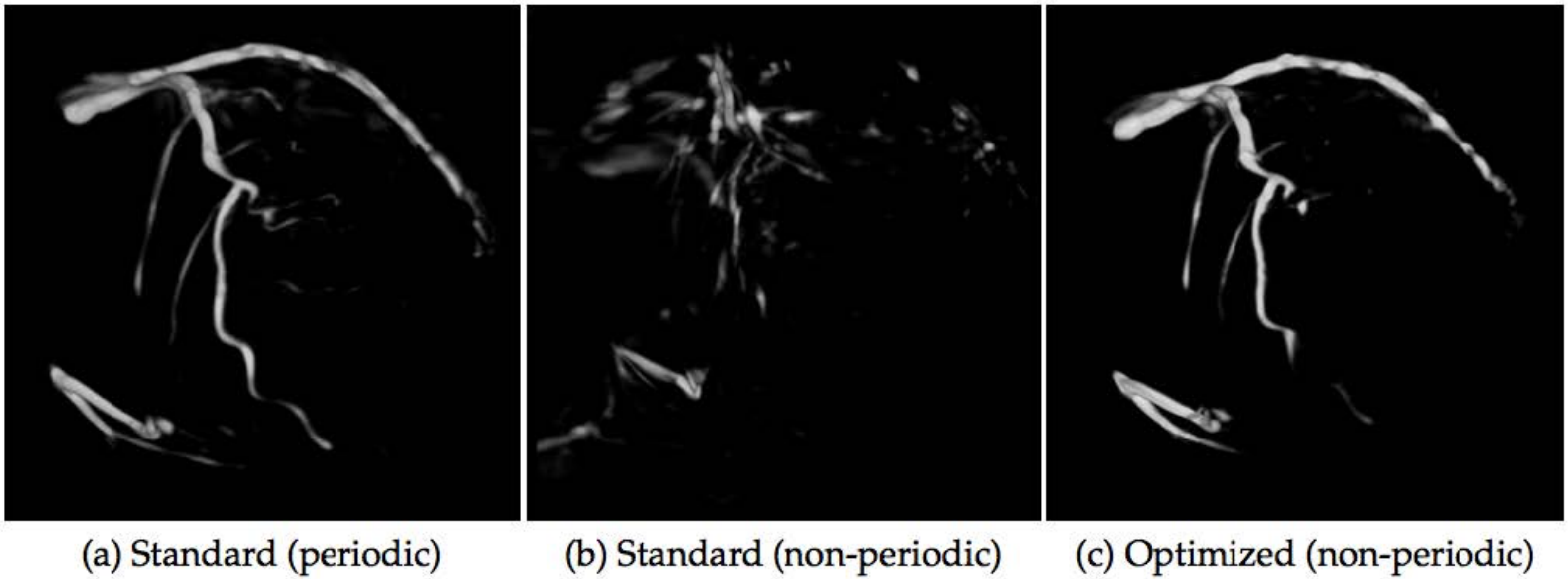


Figure 2: Standard gating versus optimized version

Example: Spearman’s Rank Correlation

	NBR, SRC	NBR, MRC	WBR, SRC	WBR, MRC
NCC	0.61	0.56	0.49	**0.90**
RMSE	0.43	0.49	0.50	0.56
NMI	0.07	0.22	0.56	**0.82**
PI	0.48	0.54	0.58	0.58
GD	0.44	0.50	0.50	0.57

NCC: normalized cross correlation
RMSE: root mean square error
NMI: normalized mutual information
PI: pattern intensity
GD: gradient difference

NBR: no background removal
WBR: with background removal
SRC: standard ray casting
MRC: maximum intensity ray casting

Topics

Take Home Messages

- For automatic parameter selection of ECG-gating, estimate a reference heart phase or the phase window width.
- Proper windowing with help of the ECG signal can improve image quality, especially for non-periodic heart motion.

Further Readings

For more information on reconstruction in cardiac imaging, you can start here:

- Günter Lauritsch et al. “Towards Cardiac C-Arm Computed Tomography”. In: *IEEE Transactions on Medical Imaging* 25.7 (July 2006), pp. 922–934. DOI: 10.1109/TMI.2006.876166
- C. Schwemmer et al. “Residual Motion Compensation in ECG-gated Interventional Cardiac Vasculature Reconstruction”. In: *Physics in Medicine and Biology* 58.11 (2013), pp. 3717–3737. DOI: 10.1088/0031-9155/58/11/3717

Medical Image Processing for Interventional Applications

Motion Compensation

Online Course – Unit 57
Andreas Maier, Frank Schebesch
Pattern Recognition Lab (CS 5)

virtuelle hochschule bayern

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

ECG-Gated Motion Compensation

Motion Compensated Reconstruction

Summary

- Take Home Messages
- Further Readings

ECG-Gated Motion Compensation

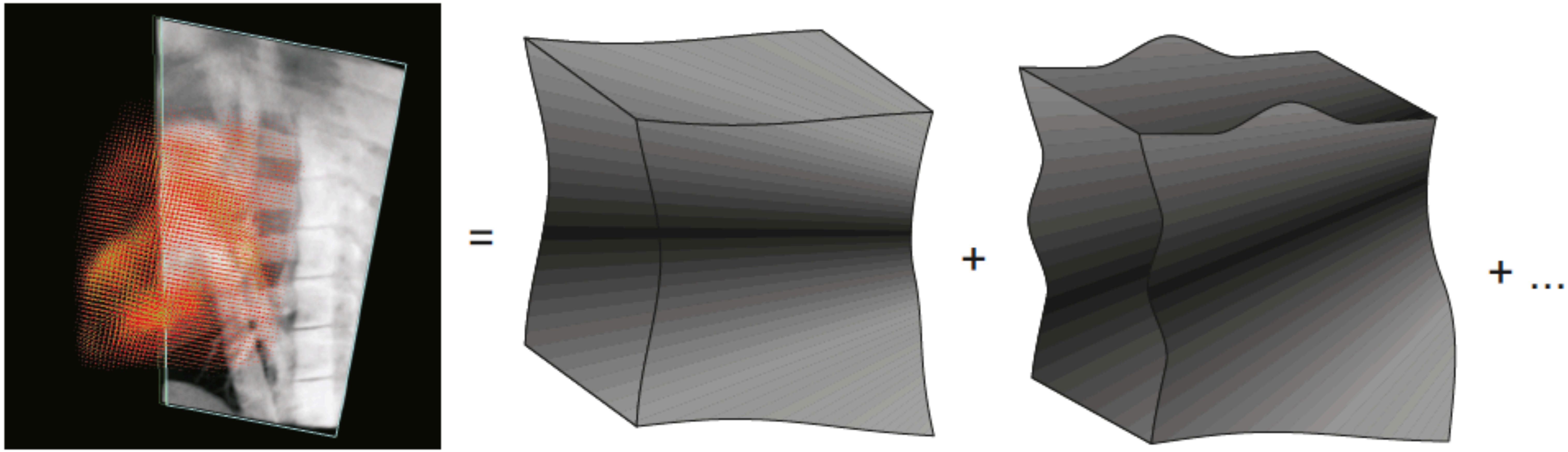
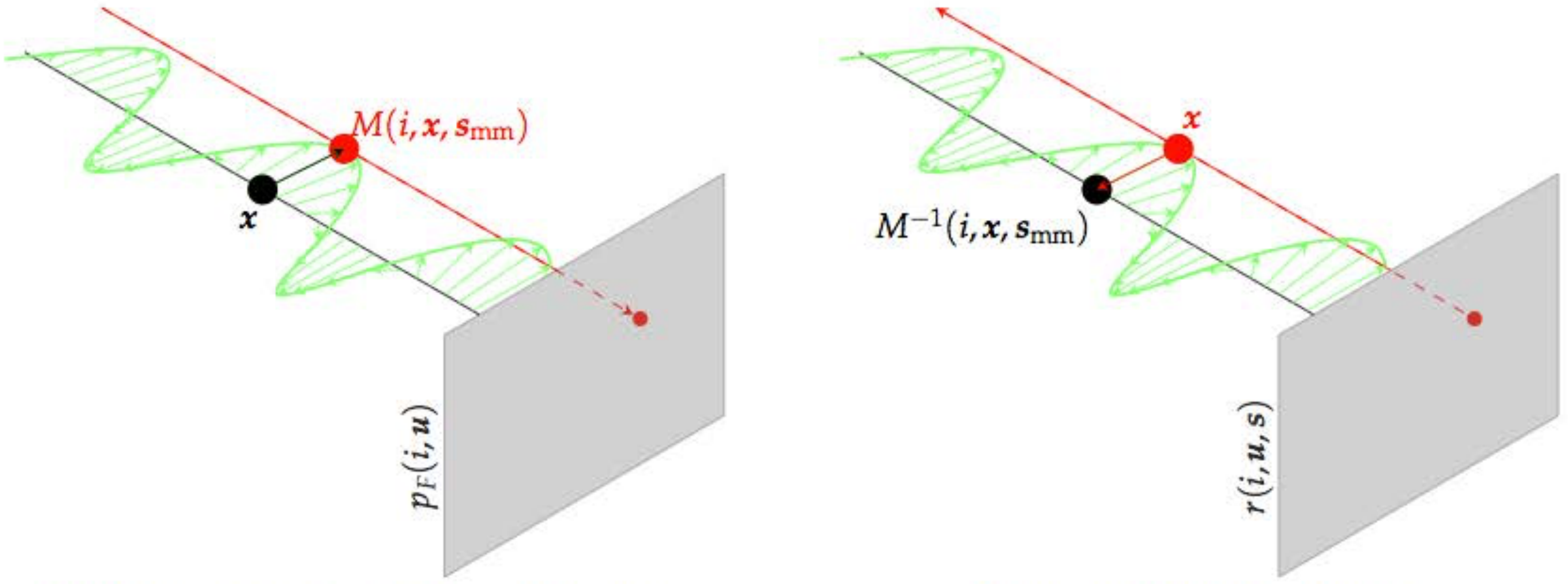


Figure 1: Volume deformation for different heart phases

ECG-Gated Motion Compensation

$$f(\boldsymbol{x}, \boldsymbol{s}) = \sum_{i=1+N_{\text{ign}}}^{N-N_{\text{ign}}} h_{\text{gfdk}}(j_i, \boldsymbol{x}, \boldsymbol{s}_{\text{mm}})$$

$$r(i, \boldsymbol{u}, \boldsymbol{s}) = \max_{\boldsymbol{x} \in L_{i,\boldsymbol{u}}} f\left(M^{-1}(i, \boldsymbol{x}, \boldsymbol{s}_{\text{mm}}), \boldsymbol{s}\right)$$



(a) Motion compensated reconstruction (b) Dynamic DRR generation

ECG-Gated Motion Compensation

Optimization problem:

$$\hat{\boldsymbol{s}}_{\text{mm}} = \underset{\boldsymbol{s}_{\text{mm}}}{\arg\min}\, \mathcal{L}(\boldsymbol{s}_{\text{mm}})$$

with

$$\mathcal{L}(\boldsymbol{s}_{\text{mm}}) = \frac{1}{\sum_{i=1}^{N} \lambda(i, \boldsymbol{s}_{\text{ga}})} \sum_{i=1}^{N} \lambda(i, \boldsymbol{s}_{\text{ga}}) \cdot q(i, \boldsymbol{s})$$

ECG-Gated Motion Compensation

- Parametrization of the motion:
  - Time dependent affine mapping with 12 DOF for each time sample
  - B-spline interpolation
- Eight heart beats
- 18 time samples
- 216 dimensional search space
- Function evaluation: 40 ms ($128 \times 128 \times 128$)
- Ca. 10,500 cost function evaluations
- Runtime: 7 min

ECG-Gated Motion Compensation

(a) Standard

(b) Motion compensated

Figure 3: Coronary artery reconstruction

Topics

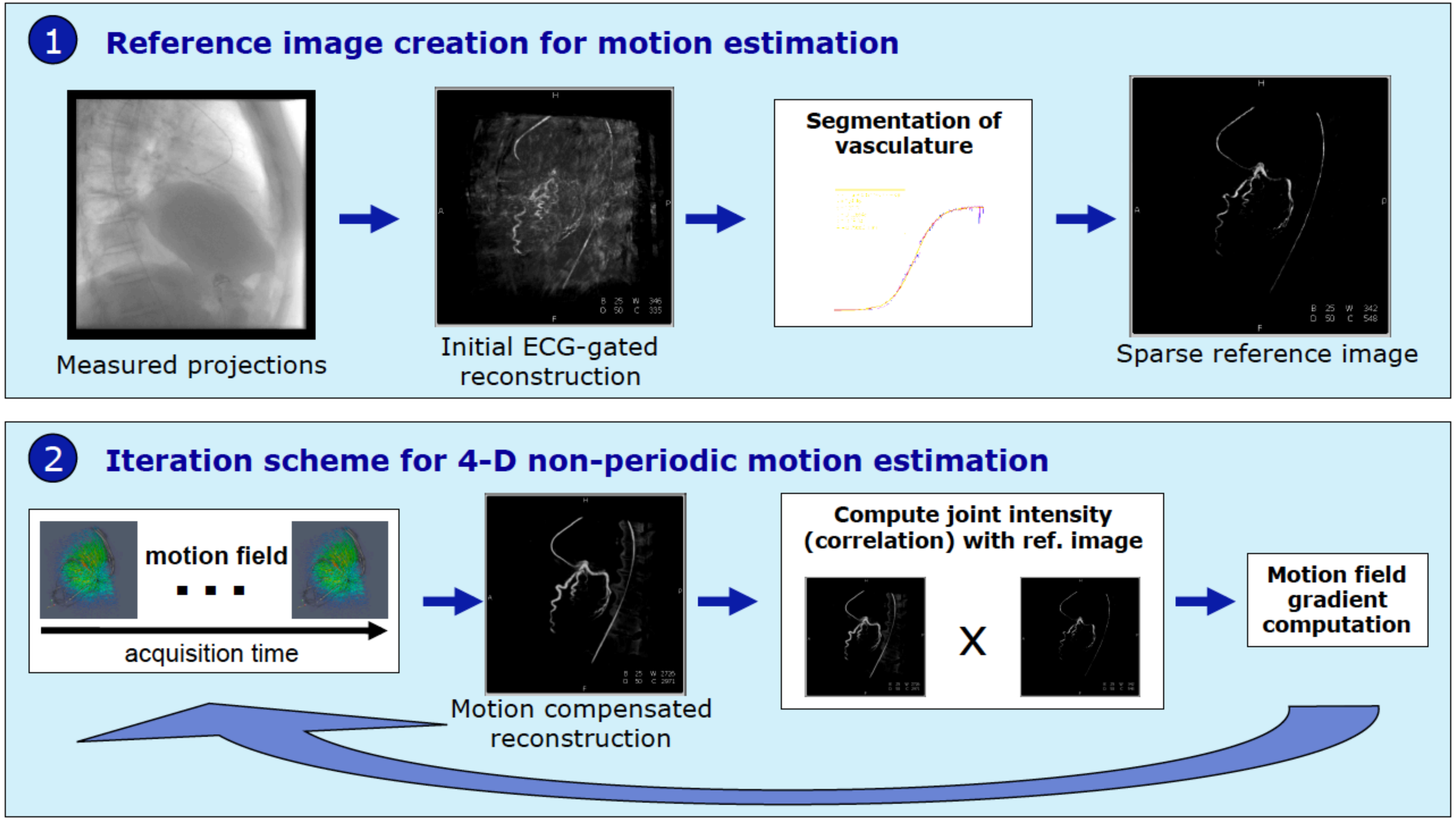
ECG-Gated Motion Compensation

Motion Compensated Reconstruction

Summary

- Take Home Messages
- Further Readings

Big Picture: Motion Compensated Reconstruction



Motion Compensated Reconstruction

- No ECG-gating at all
- Motion model based on B-splines
- Optimization problem:

$$\hat{\boldsymbol{s}}_{\mathrm{mm}} = \arg\min_{\boldsymbol{s}_{\mathrm{mm}}} \mathcal{L}(\boldsymbol{s}_{\mathrm{mm}})$$

  where

$$\mathcal{L}(\boldsymbol{s}_{\mathrm{mm}}) = \sum_{\boldsymbol{x}\in\Omega} \dot{q}(f_r(\boldsymbol{x}), f(\boldsymbol{x}, \boldsymbol{s}_{\mathrm{mm}}))$$

- Function evaluation time: 2.3 s
- Iterations: 100
- Runtime: less than 4 min

Clinical Results

CS

CA

Figure 5: Venous (CS) and arterial (CA) cardiac vasculature

Topics

ECG-Gated Motion Compensation

Motion Compensated Reconstruction

Summary

- Take Home Messages
- Further Readings

Take Home Messages

- ECG-gating under non-periodic motion can give unsatisfying results. Breathing or other patient motion has to be compensated for.
- A fully automatic algorithm for non-periodic motion estimation of cardiac vasculature can be built by using all available data in a 4-D spline model.

Further Readings

For more information on reconstruction in cardiac imaging, you can start here:

- Günter Lauritsch et al. “Towards Cardiac C-Arm Computed Tomography”. In: *IEEE Transactions on Medical Imaging* 25.7 (July 2006), pp. 922–934. DOI: 10.1109/TMI.2006.876166
- C. Schwemmer et al. “Residual Motion Compensation in ECG-gated Interventional Cardiac Vasculature Reconstruction”. In: *Physics in Medicine and Biology* 58.11 (2013), pp. 3717–3737. DOI: 10.1088/0031-9155/58/11/3717

Medical Image Processing for Interventional Applications

4-D Cardiac C-Arm CT – Temporal Inconsistency

Online Course – Unit 58

Andreas Maier, Oliver Taubmann, Frank Schebesch
Pattern Recognition Lab (CS 5)

Topics

Recap

Acquisition

Reconstruction

Temporal Inconsistency

Summary

Take Home Messages

Further Readings

Interventional 4-D (3-D+t) C-arm CT (Left Ventricle)

Goal: Functional analysis of cardiac motion

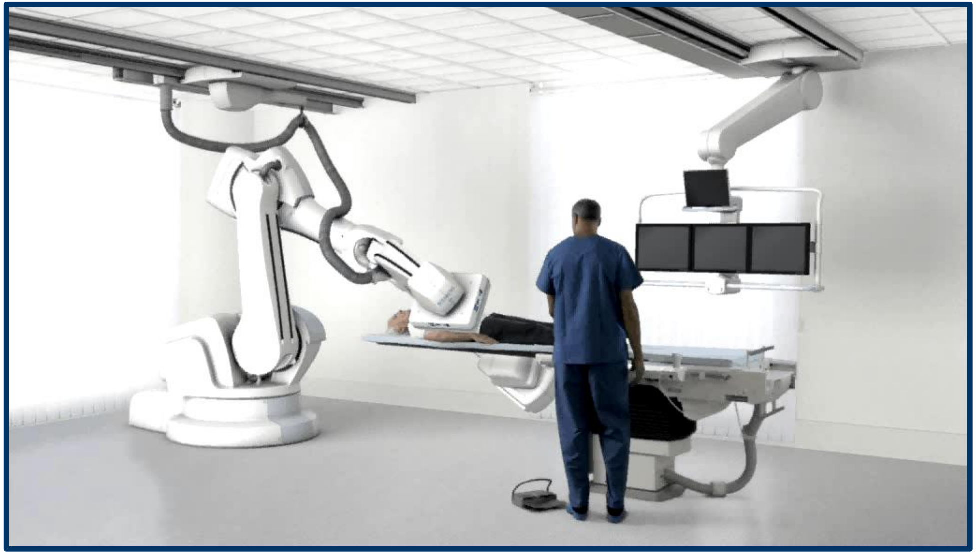


Figure 1: Artis zeego multi-axis C-arm system (Image courtesy of Siemens Healthcare GmbH, Forchheim, Germany)

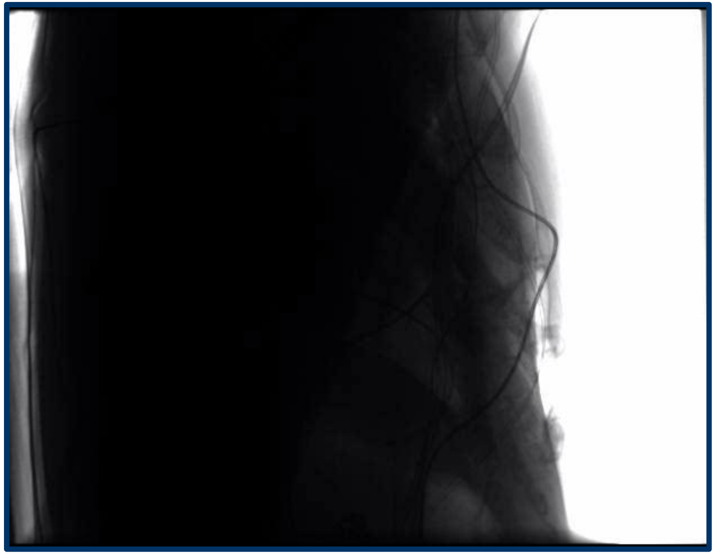


Figure 2: Rotational angiogram (Image courtesy of Dr. Bernd Abt, Centre of Cardiovascular Diseases, Rotenburg a. d. Fulda, Germany)

Acquisition Protocol (Artis zeego)

- Sweep of 14.5 s duration, 381 projection images

- Right ventricular pacing 115 bpm: $\sim$27 heart beats equals $\sim$27 distinct views per phase!

- Systemic contrast injection (91 ml total, pulmonary artery):

  Bolus gets “stretched out” over time by lung vessels → more homogeneous contrast

Recap: Gated Reconstruction

Retrospective electrocardiography (ECG) gating (Desjardins and Kazerooni, 2004)

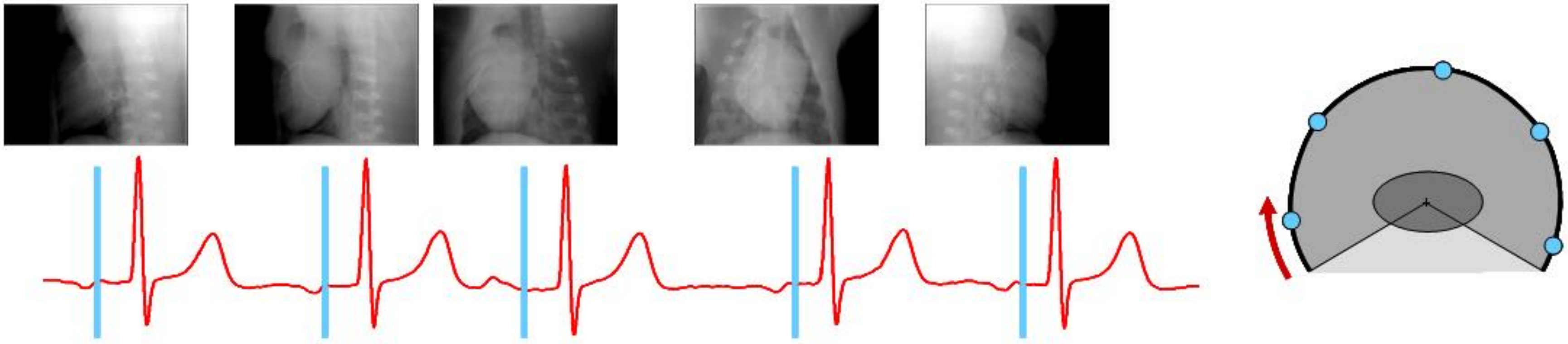


Figure 3: Projection images from a C-arm sweep belonging to the same relative heart phase

Recap: Motion Compensation

- Image quality of gated reconstructions insufficient

  → Artifacts due to angular undersampling

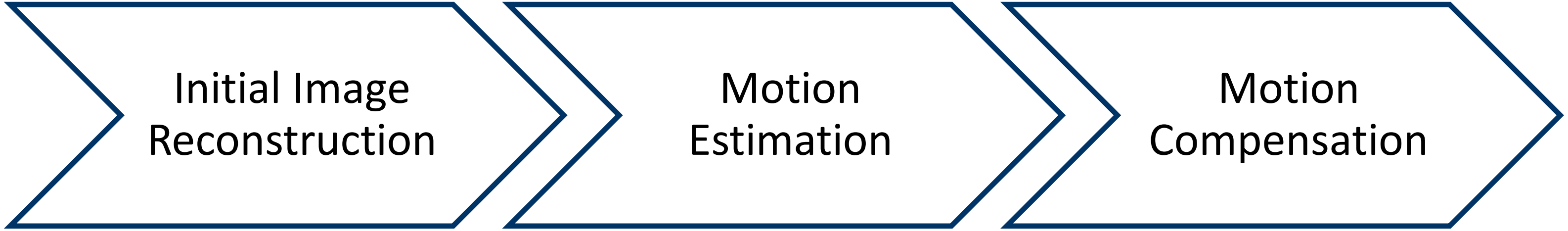
- Approach: Motion compensated reconstruction (Müller et al., 2014)
  - Estimate motion from initial reconstruction
  - Final reconstruction from all data

Recap: Motion Compensation

- Image quality of gated reconstructions insufficient

  → Artifacts due to angular undersampling

- Approach: Motion compensated reconstruction (Müller et al., 2014)
  - Estimate motion from initial reconstruction
  - Final reconstruction from all data



Initial Image Reconstruction

- Severe artifacts in clinical patient data
- Can be reduced by conventional approaches:
  - Removal of high-density objects
  - Specialized streak reduction (Mc Kinnon and Bates, 1981)
  - Denoising (e.g. joint bilateral filter)

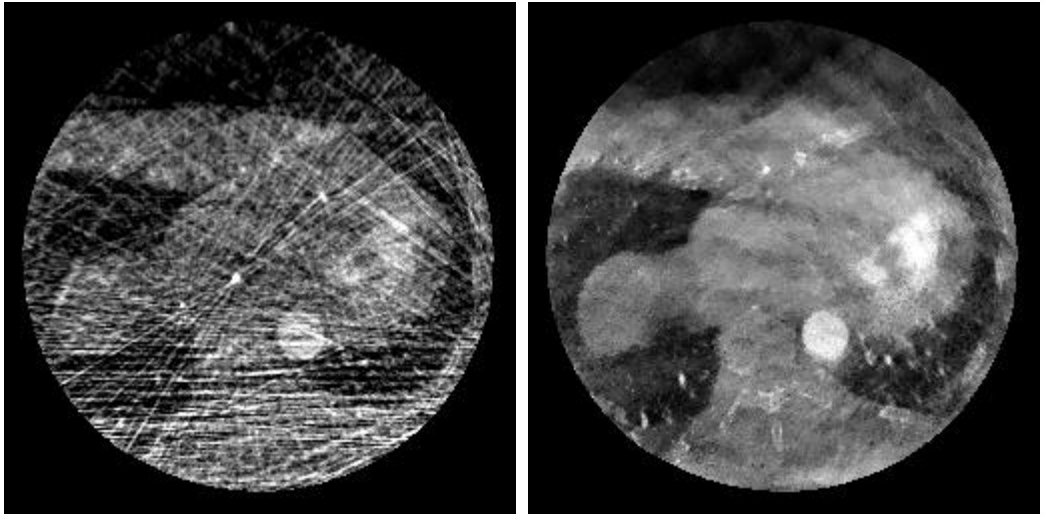


Figure 4: Axial views of ECG-gated reconstructions from clinical data, without (left) and with (right) artifact reduction (Data courtesy of Dr. Abt, Centre of Cardiovascular Diseases, Rotenburg a. d. Fulda)

Topics

Recap

Acquisition

Reconstruction

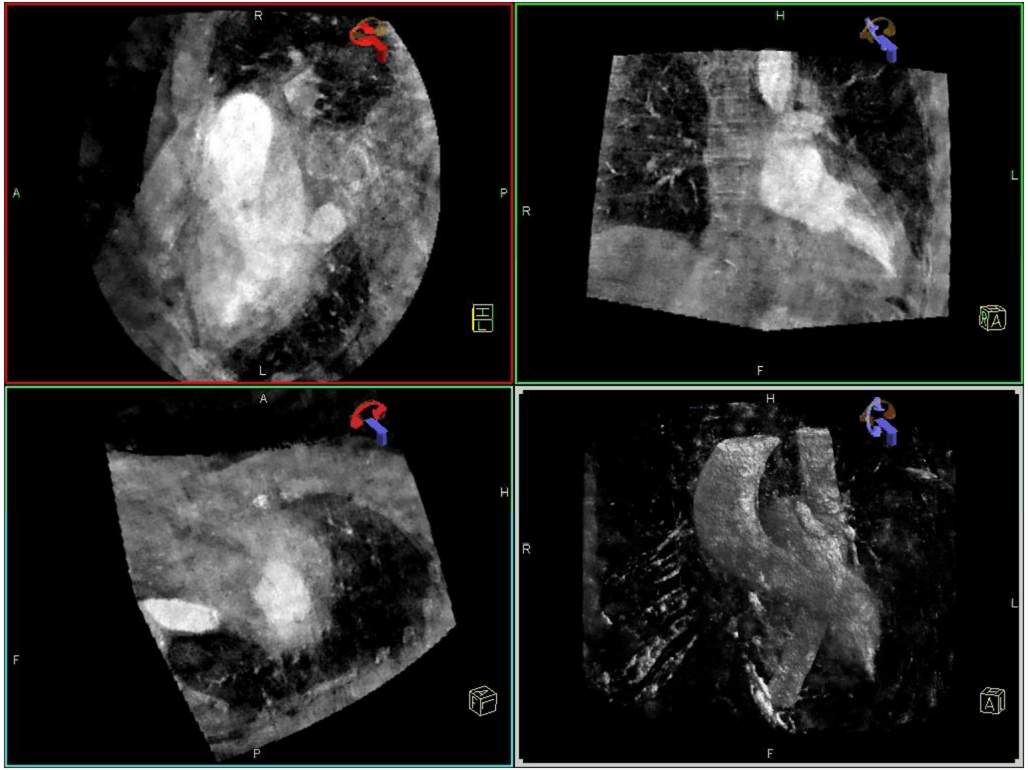
Temporal Inconsistency

Summary

Take Home Messages

Further Readings

Temporal Inconsistency



Temporal Inconsistency

Remaining artifacts appear to “jump” over time:

- undesired flickering impression,
- tough challenge for non-rigid motion estimation.

→ **How to deal with it?**

Temporal Inconsistency

Temporal regularization/smoothing:

- Temporal TV regularization in algebraic reconstruction (Mory et al., 2014)
- Motion estimation using 4-D B-Splines (implicit smoothing) (Metz et al., 2011)
- Adaptive Gaussian smoothing based on a motion map (next unit)
- Bilateral smoothing in iterative motion estimation/compensation (next unit)

Topics

Recap

- Acquisition
- Reconstruction

Temporal Inconsistency

Summary

- Take Home Messages
- Further Readings

Take Home Messages

- Motion artifacts are a problem especially in cardiac imaging, since the heart moves constantly.
- Temporal flickering degrades image quality. It can be reduced with some methods, two discussed in the next unit.

Further Readings

- Benoit Desjardins and Ella A. Kazerooni. "ECG-Gated Cardiac CT". In: *American Journal of Roentgenology* 182.4 (Apr. 2004), pp. 993–1010. DOI: 10.2214/ajr.182.4.1820993
- K. Müller et al. "Image Artefact Propagation in Motion Estimation and Reconstruction in Interventional Cardiac C-arm CT". In: *Physics in Medicine and Biology* 59.12 (2014), pp. 3121–3138. DOI: 10.1088/0031-9155/59/12/3121
- G. C. Mc Kinnon and R. H. T. Bates. "Towards Imaging the Beating Heart Usefully with a Conventional CT Scanner". In: *IEEE Transactions on Biomedical Engineering* BME-28.2 (Feb. 1981), pp. 123–127. DOI: 10.1109/TBME.1981.324785
- Cyril Mory et al. "Cardiac C-arm Computed Tomography Using a 3D+time ROI Reconstruction Method with Spatial and Temporal Regularization". In: *Medical Physics* 41.2 (Feb. 2014), pp. 021903-1–12. DOI: 10.1118/1.4860215
- C.T. Metz et al. "Nonrigid Registration of Dynamic Medical Imaging Data Using nD+t B-Splines and a Groupwise Optimization Approach". In: *Medical Image Analysis* 15.2 (Apr. 2011), pp. 238–249. DOI: 10.1016/j.media.2010.10.003

Medical Image Processing for Interventional Applications

4-D Cardiac C-Arm CT – Temporal Smoothing

Online Course – Unit 59

Andreas Maier, Oliver Taubmann, Frank Schebesch
Pattern Recognition Lab (CS 5)

virtuelle hochschule bayern

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Topics

Heart Rate Informed 3-D Motion Detection for Adaptive Temporal Smoothing

Bilateral Filtering in Iterative Motion Estimation and Compensation

Summary

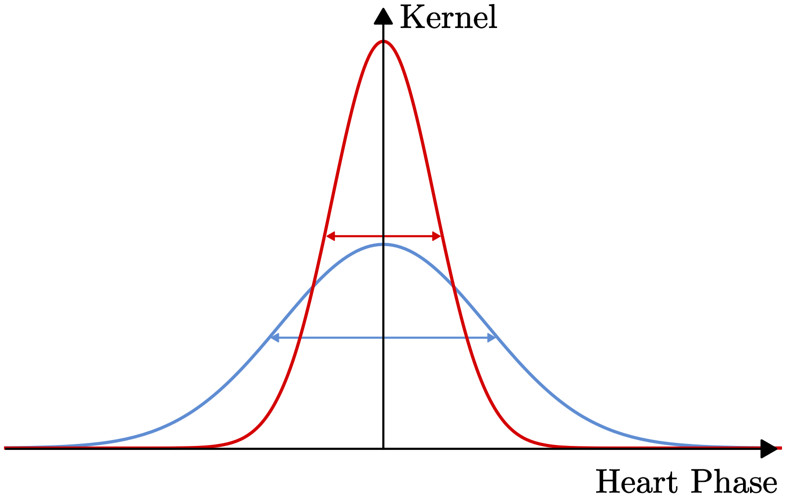
- Take Home Messages
- Further Readings

Adaptive Temporal Smoothing

- Perform Gaussian smoothing in temporal domain:

$$\boldsymbol{I}_s^t(\boldsymbol{x}) = \sum_{t'=0}^{N_{\text{phases}}} \boldsymbol{I}^{t'}(\boldsymbol{x}) \cdot \frac{1}{\sigma(\boldsymbol{x})\sqrt{2\pi}} \exp\left(-\frac{\text{dist}^2(t,t')}{2\sigma^2(\boldsymbol{x})}\right).$$

- Choose $\sigma(\boldsymbol{x})$ dependent on the amount of cardiac motion $\boldsymbol{M}_w(\boldsymbol{x})$.



$$\sigma(\boldsymbol{x}_i) \leq \sigma(\boldsymbol{x}_j) \Leftrightarrow \boldsymbol{M}_{\mathrm{w}}(\boldsymbol{x}_i) \geq \boldsymbol{M}_{\mathrm{w}}(\boldsymbol{x}_j)$$

Figure 1: Smoothing strength is selected w.r.t. cardiac motion

Heart Rate Informed 3-D Motion Detection

- Center piece of the method

- Key ideas:
  1. Projections show heart motion, but no artifacts correlated with it.
  2. High temporal resolution (many individual heart beats)
  3. Frequency (heart rate!) is known from the ECG.

Heart Rate Informed 3-D Motion Detection

Approach:

1. "Follow" $\boldsymbol{x}$ over the whole sweep.
2. Consider line integrals as temporal profile.
3. Perform frequency analysis and compute power spectrum.
4. Obtain energy $\boldsymbol{M}(\boldsymbol{x})$ associated with the heart rate.

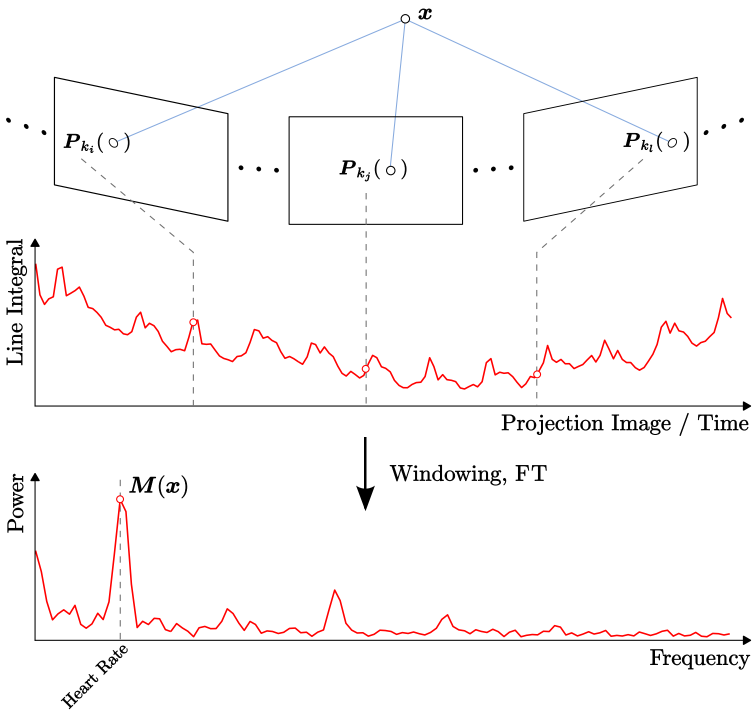


Figure 2: Overview of the motion detection approach

Motion Maps

Spatial distribution of heart rate energy visualized:

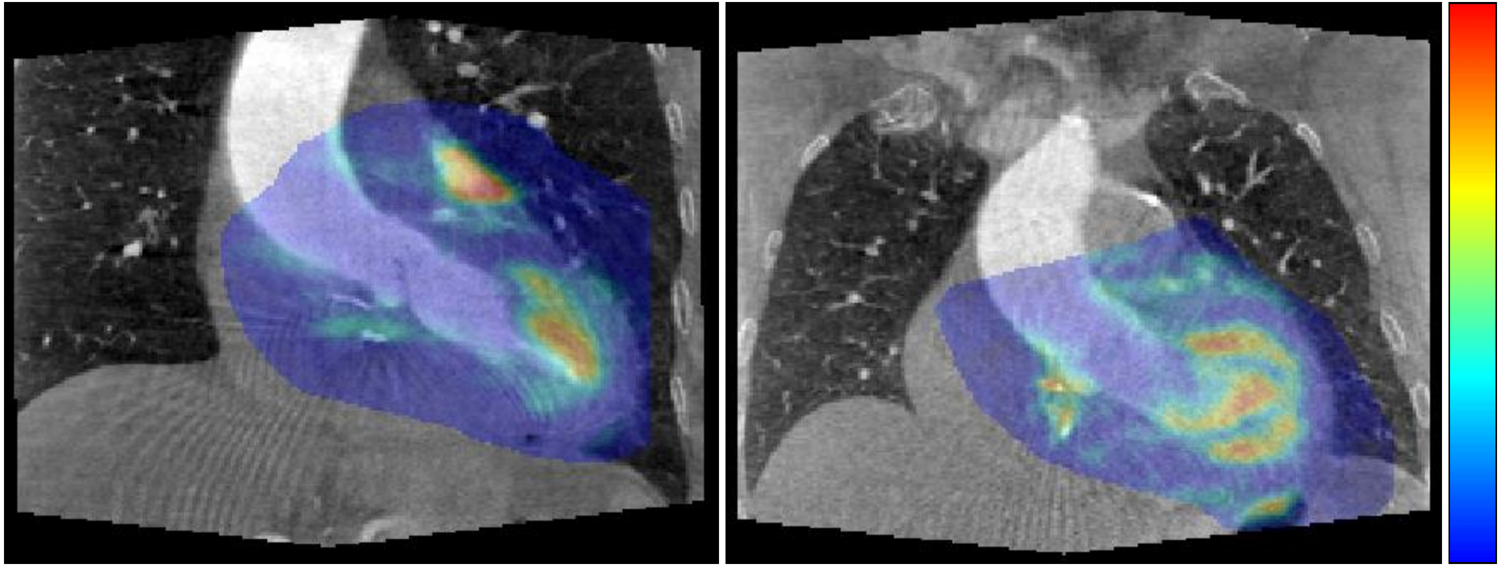
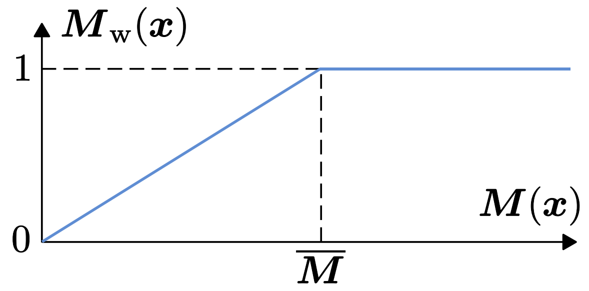


Figure 3: Color-coded visualizations of detected cardiac motion inside considered ROI for patients 1 and 2. Overlayed on reconstruction from all data for orientation. Warmer hues correspond to larger motion.

Heart Rate Informed 3-D Motion Detection

- Remove outliers and denoise:
  - Median filter (3 x 3)
  - Blur filter (1.5 mm std. dev.)
- Normalization:



- Linear interpolation of $\sigma(\boldsymbol{x})$:

$$\sigma(\boldsymbol{x}) = \sigma_{\min} \cdot \boldsymbol{M}_w(\boldsymbol{x}) + \sigma_{\max} \cdot \left(1 - \boldsymbol{M}_w(\boldsymbol{x})\right)$$

Results: Experimental Setup

1. Generate initial images with and without temporal smoothing.

2. Perform motion estimation and compensation on both.

3. Compare final images (same projections, different motion).

Results (Axial)

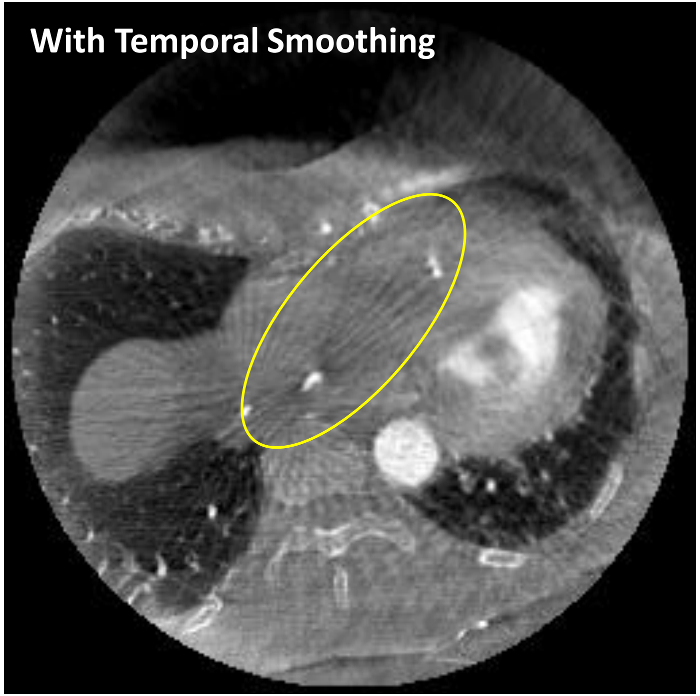


Figure 5: Reconstructions for patient 1, animation of 10 phases in the cardiac cycle

Results (Long Axis)

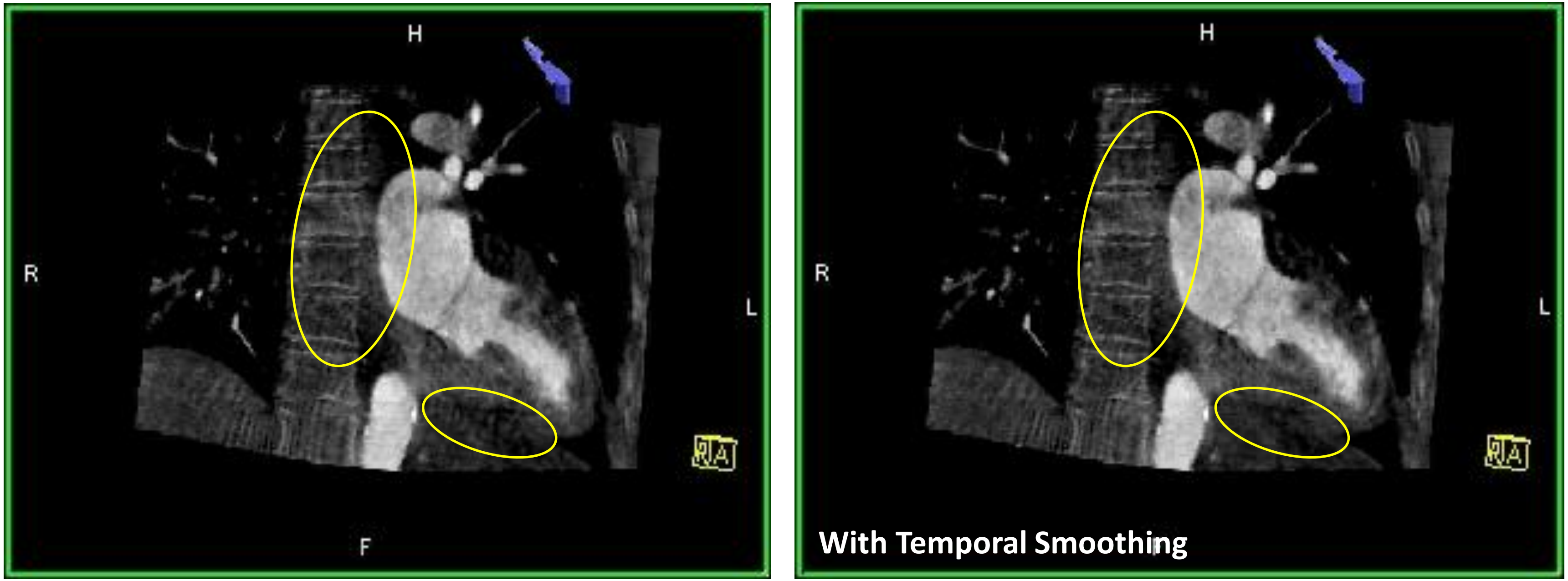
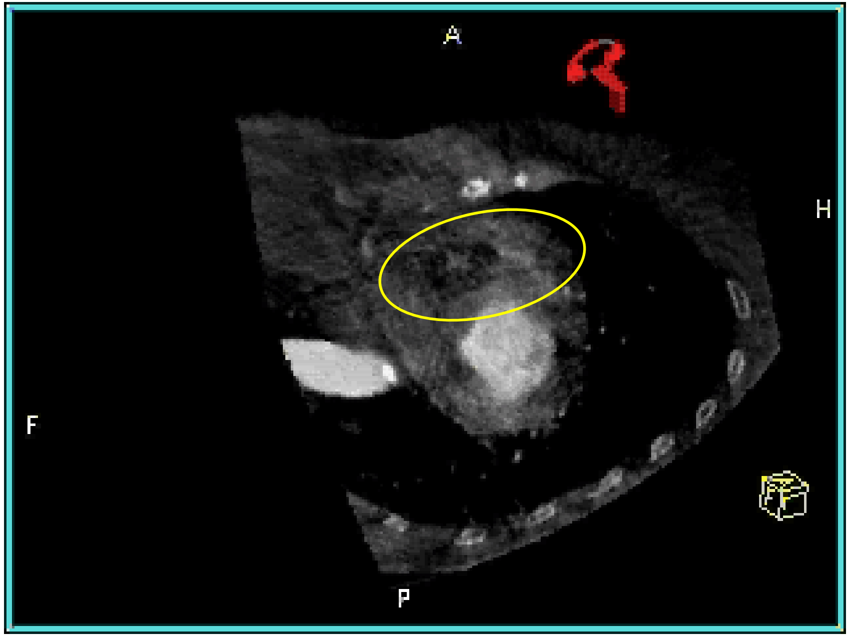


Figure 6: Reconstructions for patient 1, animation of 10 phases in the cardiac cycle

Results (Short Axis)



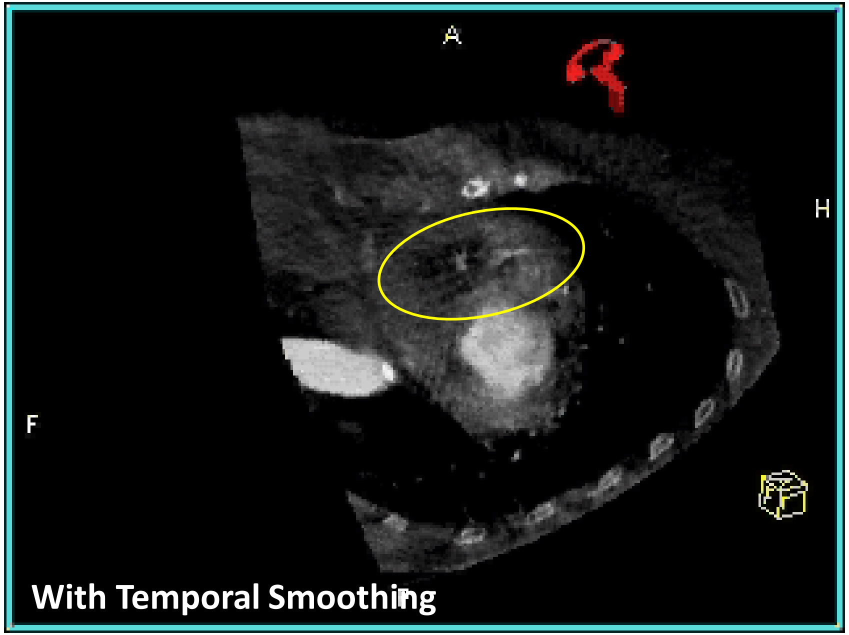
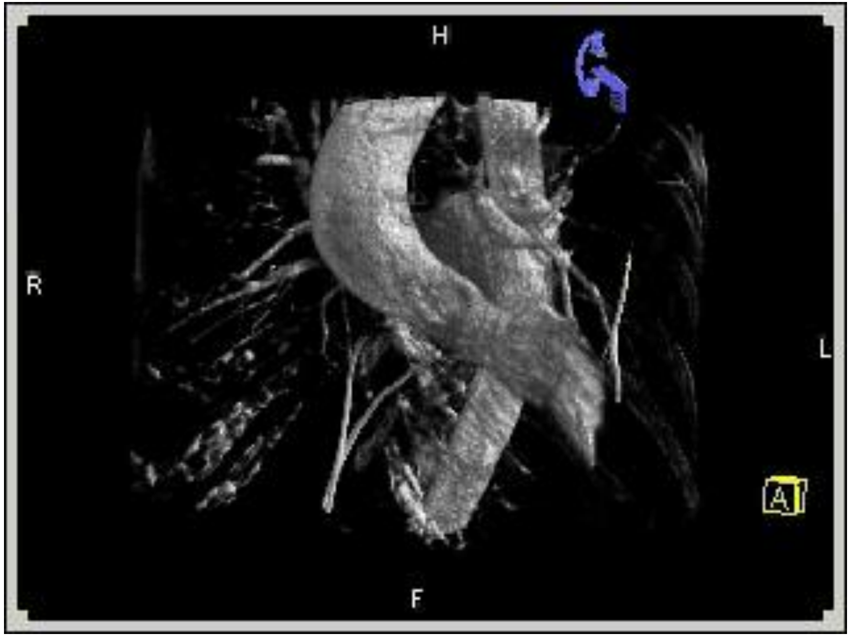


Figure 7: Reconstructions for patient 1, animation of 10 phases in the cardiac cycle

Results (VRT)



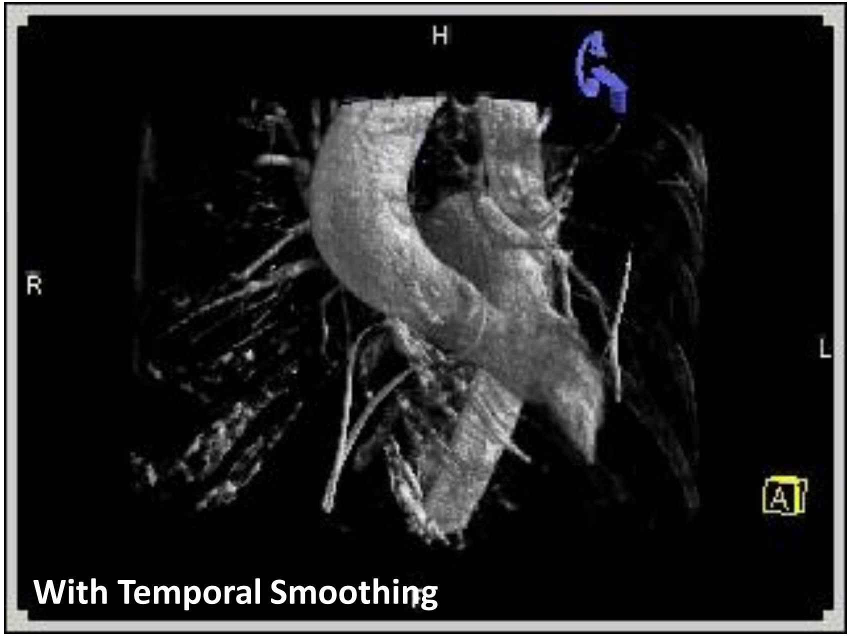


Figure 8: Reconstructions for patient 1, animation of 10 phases in the cardiac cycle

Topics

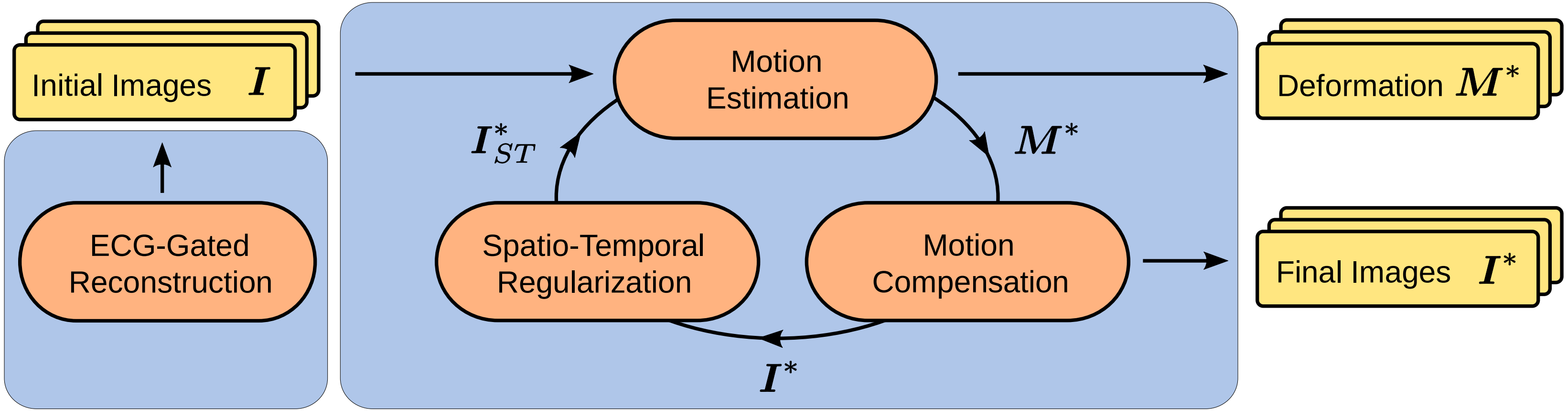
Heart Rate Informed 3-D Motion Detection for Adaptive Temporal Smoothing

Bilateral Filtering in Iterative Motion Estimation and Compensation

Summary

- Take Home Messages
- Further Readings

Idea



- Motion compensated images have better SNR
- Allow for stronger edge-preserving smoothing
- In turn, smoother images make motion estimation more robust
- Joint improvement of images and motion estimate by iteratively filtering, estimating and compensating for motion

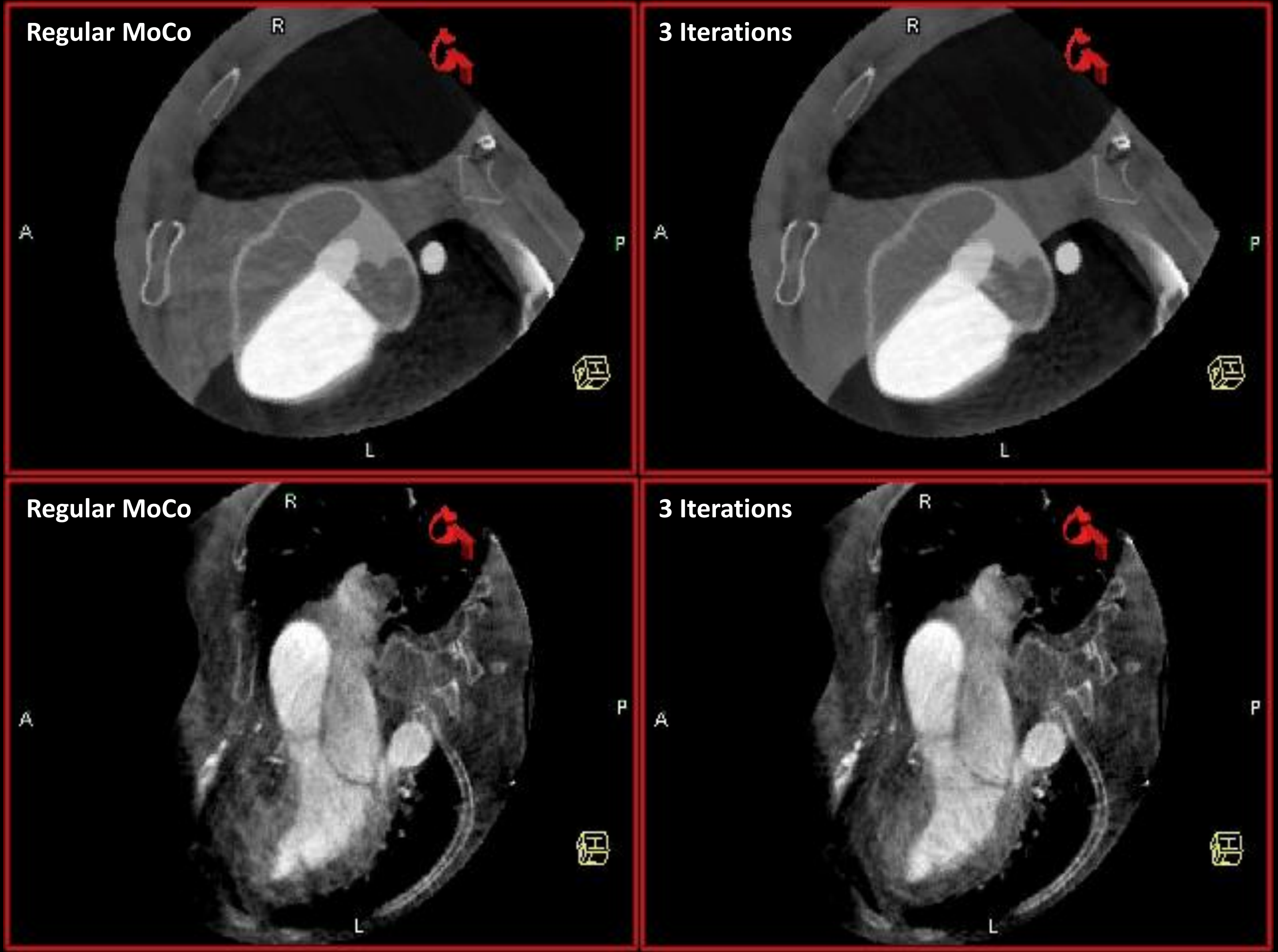
Filtering Step

Spatial and temporal bilateral filtering:

$$\boldsymbol{I}_S^t(\boldsymbol{x}) = \sum_{\boldsymbol{x}' \in N(\boldsymbol{x})} \frac{\boldsymbol{I}^t(\boldsymbol{x}')}{w_S} \cdot \exp\left(-\frac{\|\boldsymbol{x}-\boldsymbol{x}'\|_2^2}{2\sigma_S^2} - \frac{(\boldsymbol{I}^t(\boldsymbol{x}) - \boldsymbol{I}^t(\boldsymbol{x}'))^2}{2\sigma_I^2}\right)$$

$$\boldsymbol{I}_{ST}^t(\boldsymbol{x}) = \sum_{t' \in \mathcal{N}_{\mathrm{ph}}} \frac{\boldsymbol{I}_S^{t'}(\boldsymbol{x})}{w_T} \cdot \exp\left(-\frac{\mathrm{dist}^2(t,t')}{2\sigma_T^2} - \frac{\left(\boldsymbol{I}^t(\boldsymbol{x}) - \boldsymbol{I}^{t'}(\boldsymbol{x})\right)^2}{2\sigma_I^2}\right)$$

- $\sigma_S, \sigma_T, \sigma_I$: standard deviations in spatial, temporal and intensity domain
- w_S, w_T: normalization factors
- $\mathrm{dist}(t,t')$: distance of phases in the cardiac cycle


Regular MoCo
R
A
P
L
3 Iterations
R
A
P
L
Regular MoCo
R
A
P
L
3 Iterations
R
A
P
L

Topics

Heart Rate Informed 3-D Motion Detection for Adaptive Temporal Smoothing

Bilateral Filtering in Iterative Motion Estimation and Compensation

Summary

- Take Home Messages
- Further Readings

Take Home Messages

Two methods for improving temporal consistency:

1. **3-D Motion Detection**
   Frequency analysis of acquired projection images over time
   → **Adaptive Temporal Smoothing**
   Based on spatial distribution of detected motion magnitudes

2. **Motion Estimation** → **Motion Compensation**

   Spatio-Temporal Regularization
   Bilateral filtering in spatial and temporal domain

Further Readings

- Oliver Taubmann et al. “Keeping the Pace: Heart Rate Informed 3-D Motion Detection for Adaptive Temporal Smoothing”. In: *The 13th International Meeting on Fully Three-Dimensional Image Reconstruction in Radiology and Nuclear Medicine*. Ed. by Michael King, Stephen Glick, and Klaus Mueller. Newport, Rhode Island, USA, 2015, pp. 530–533
- Oliver Taubmann et al. “Estimate, Compensate, Iterate: Joint Motion Estimation and Compensation in 4-D Cardiac C-arm Computed Tomography”. In: *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part II*. ed. by Nassir Navab et al. Vol. 9350. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2015, pp. 579–586. DOI: 10.1007/978-3-319-24571-3_69