Motion Estimation in Coronary CT Angiography Images using Convolutional Neural Networks

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I INTRODUCTION

CCTA = Coronary Computed Tomography Angiography
Preferred non-invasive technique for detection of coronary artery disease

Problem: Cardiac Motion Artifacts

- May occur despite ECG-correlated acquisition and gated reconstruction
- Manifest in arc-shaped blurring and intensity undershoots
- Potentially limit or even preclude diagnosis or cause misinterpretations

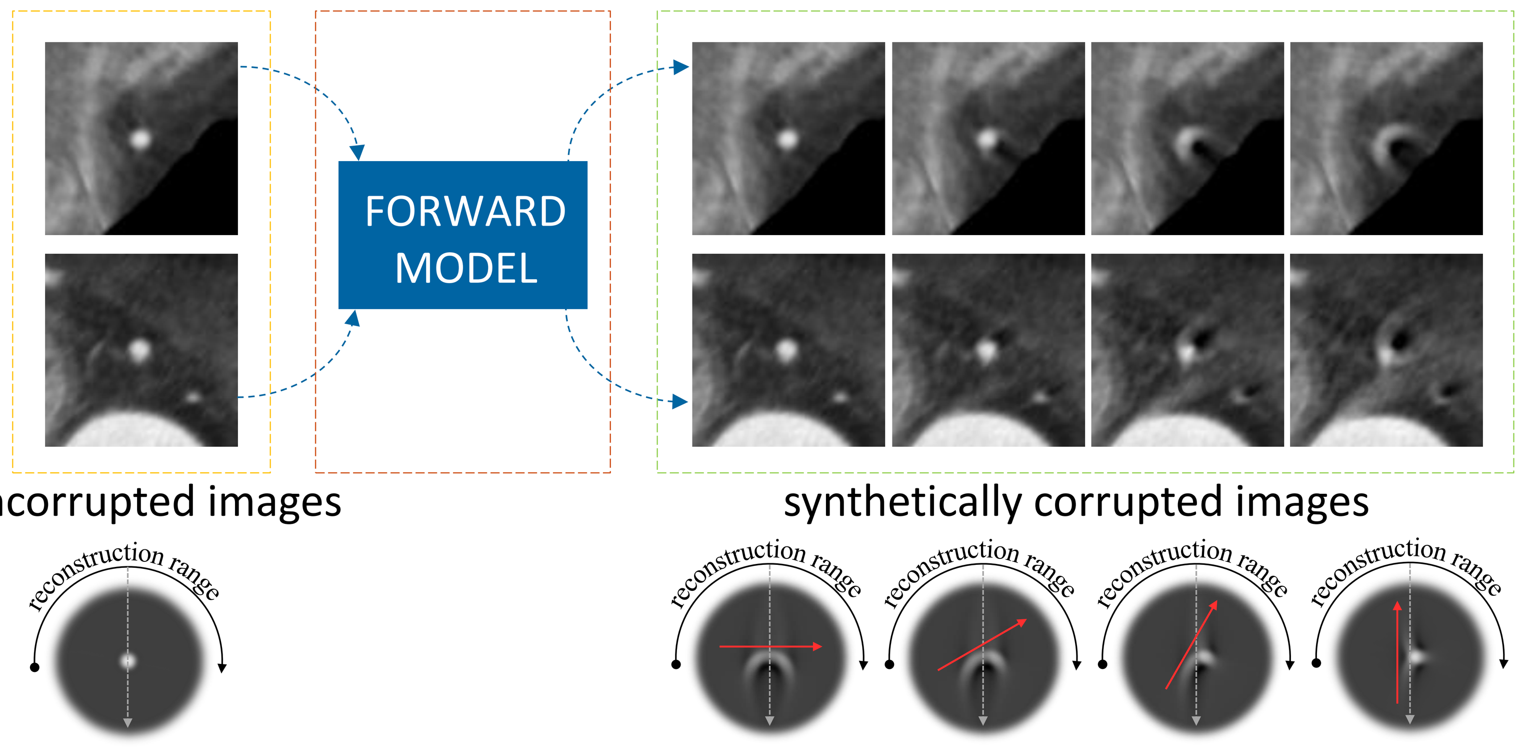
State of the art: Cardiac Motion Compensation

- Key components: motion vector field (MVF) estimation and subsequent motion compensated filtered back-projection (MC-FBP) [1,2]
- MVF estimation via 3D/3D registration of multiple heart phases [3,4]
- MVF estimation via iterative minimization of handcrafted artifact measures [5]

Can we perform motion estimation from a single reconstructed CT image based on the coronary artifact appearance?

- Goal: single-phase, image-based 2D motion vector estimation
- Constraint: constant linear motion in the axial plane

II DATA GENERATION

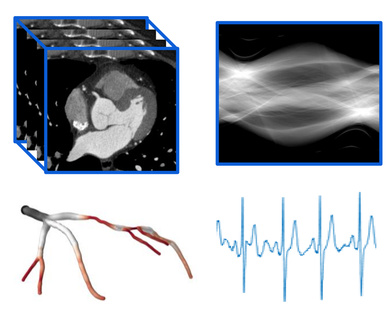


Main idea: Forward model [6, 7] introduces artificial motion to high quality CT cases to generate the required input and label data for supervised learning

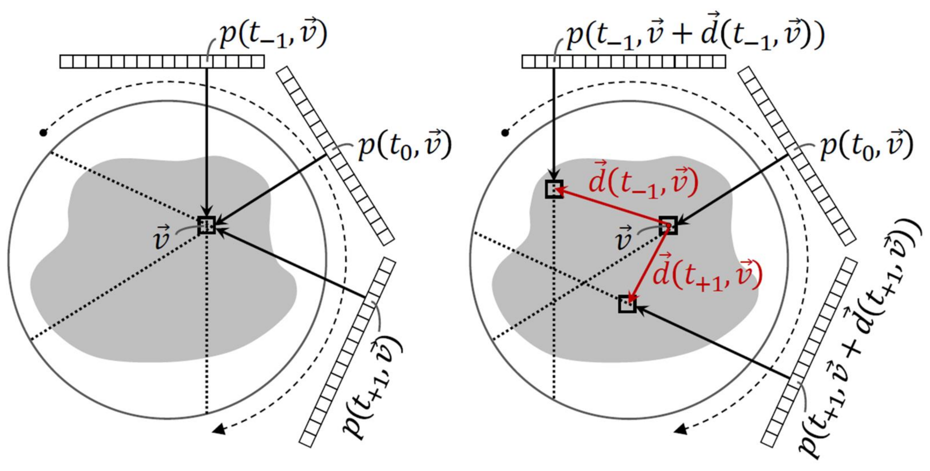
Reference Data

- Step-and-shoot cardiac CT data sets with excellent image quality
- Coronary artery tree including centerline and lumen contour
- Corresponding ECG-triggered raw projection data

➢ Phantom case + 12 clinical cases



Motion Introduction



usual back-projection MC-FBP

Constant Linear Motion Model

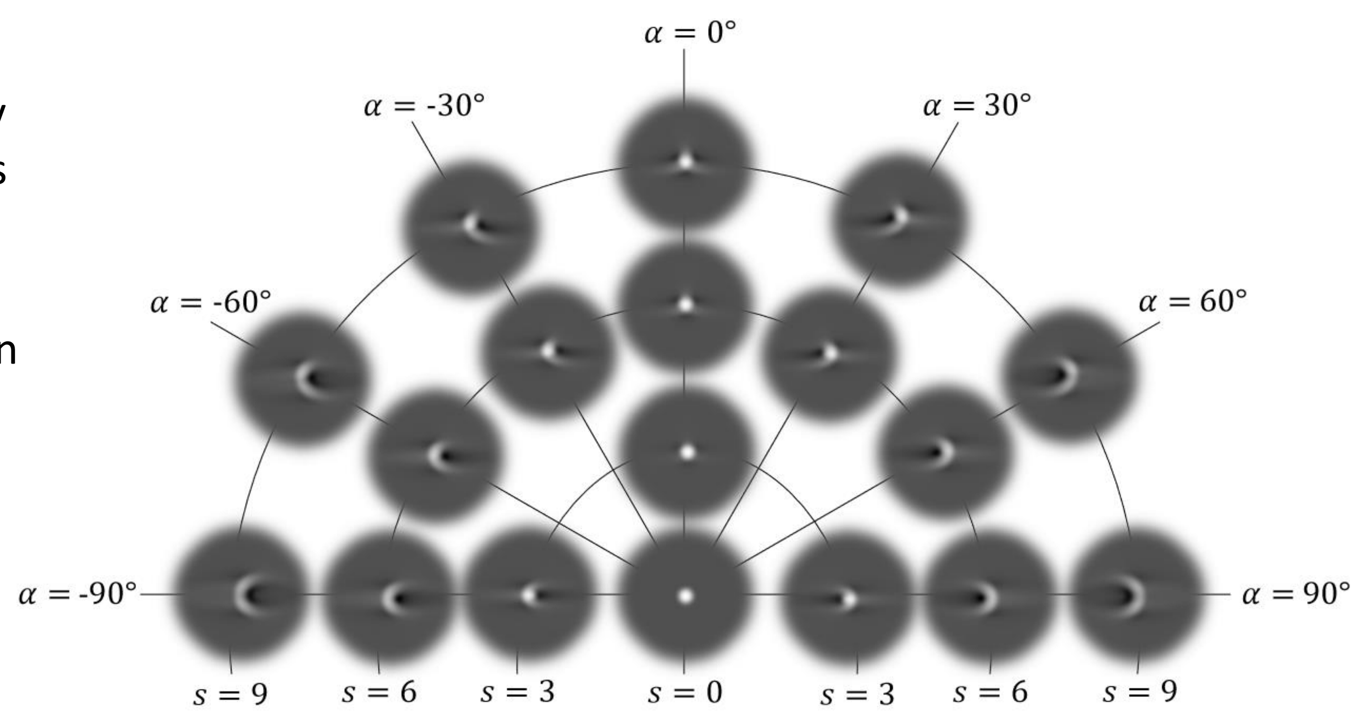
$$\vec{d}_{\vec{c}}(t_{cc},\vec{v}) = s \cdot m_{\vec{c}}(\vec{v}) \cdot \vec{\delta}_{\vec{c}}(t_{cc},\alpha)$$

Uniformly sampled control parameters:

- $s \in [0,10]$
determines displacement width
- $\alpha \in (-180°, 180°]$
determines motion direction relative to the reconstruction range

Patch Sampling

- axial coronary cross-sections
- orientation along mean reconstruction direction
- size 80 x 80 pixels
- resolution 0.4 x 0.4 mm²/pixel

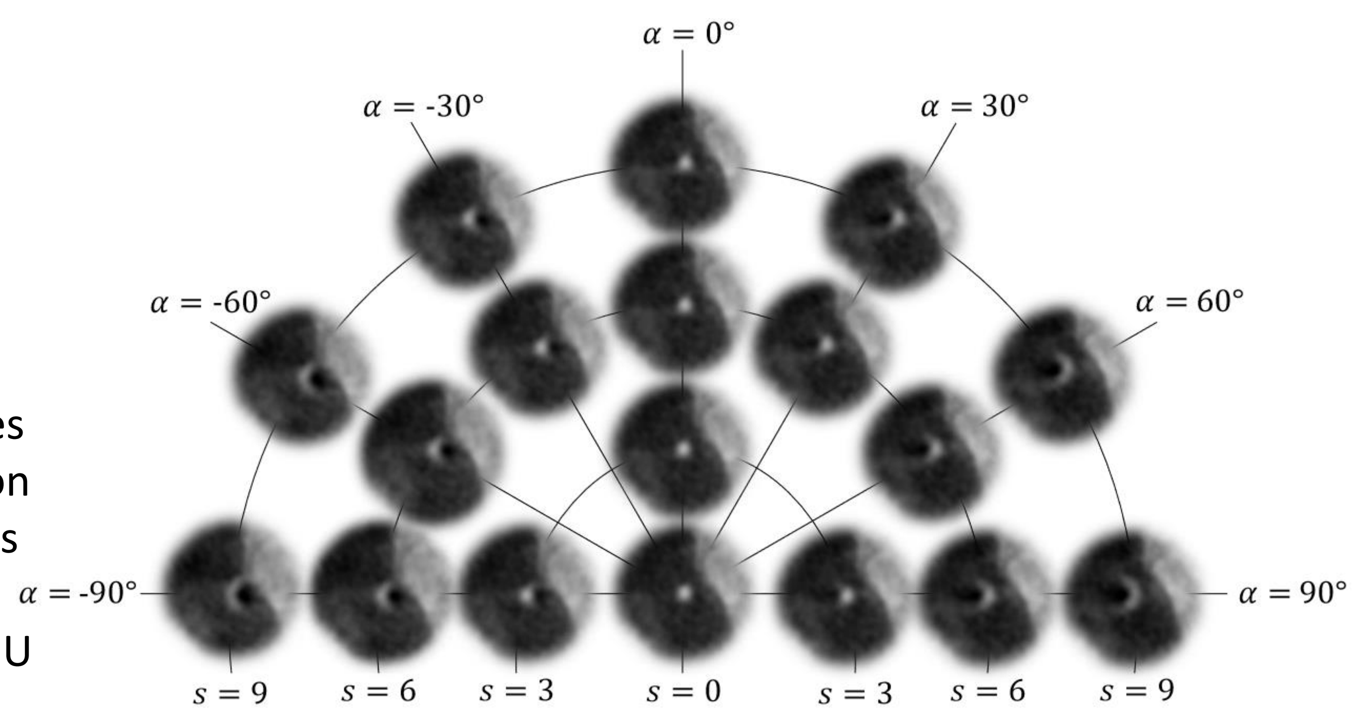


Phantom Study

- 6 000 samples
- vessel radius 0.8-1.6mm

Clinical Study

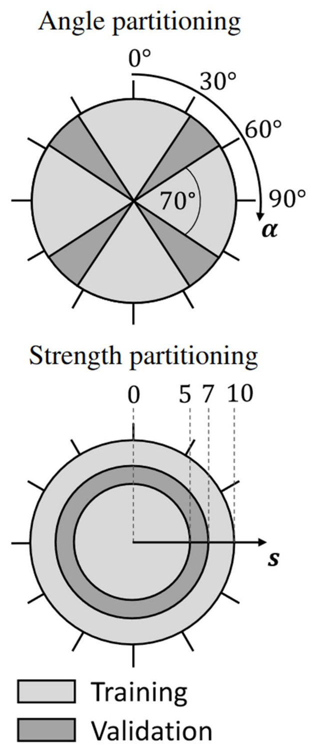
- 24 000 samples
- max. inclination of 45° to z-axis
- level 200 HU window 700 HU



III SUPERVISED LEARNING

Network Input: (60 x 60) axial cross-sectional image patches
Network Output: underlying 2D motion vector in cartesian coordinates $x = s\cos(\alpha),\ y = s\sin(\alpha)$

- Data Separation
  - Phantom study: angle partitioning and strength partitioning
  - Clinical study: case-wise separation (10 Training, 2 Validation)
- Data Augmentation
  - Cropping: (80 x 80) to (60 x 60)
  - Mirroring: horizontal and vertical
- Learning Setup:
  - Loss: squared error $l = (x-\hat{x})^2 + (y-\hat{y})^2$
  - Network: 20-layer ResNet



IV EXPERIMENTS AND RESULTS

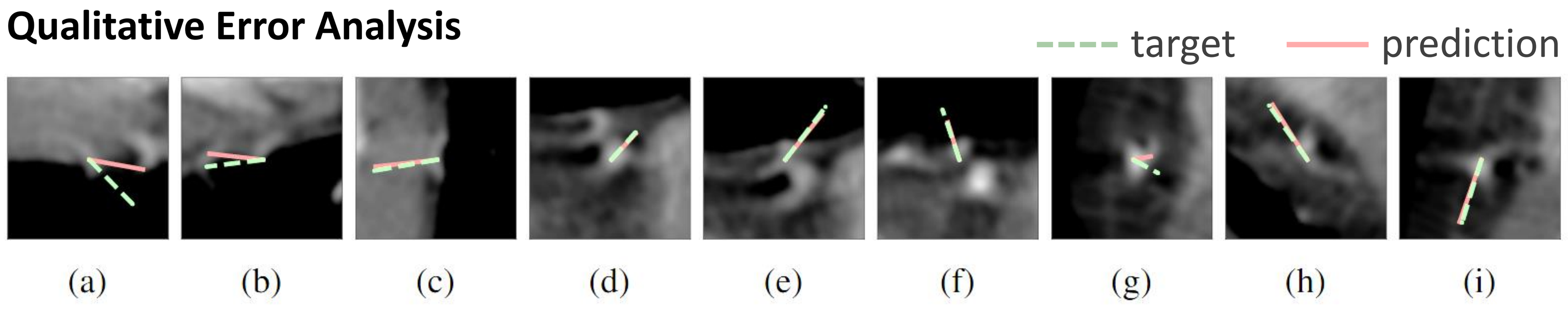
Table 1: Quantitative comparison of the validation results in the phantom and the clinical study.

Data	(x,y) error: $\varepsilon_{x,y}$	α error: ε_α	s error: ε_s
Phantom (angle partitioning)	0.088 ± 0.078	$1.084° \pm 3.861°$	0.062 ± 0.062
Phantom (strength partitioning)	0.086 ± 0.051	$0.559° \pm 0.450°$	0.053 ± 0.042
Clinical	1.497 ± 1.200	$20.659° \pm 30.985°$	0.942 ± 0.924

$$\varepsilon_{x,y} = \sqrt{(x-\hat{x})^2 + (y-\hat{y})^2}, \qquad \varepsilon_\alpha = \min(|\alpha - \hat{\alpha}|, 360° - |\alpha - \hat{\alpha}|), \qquad \varepsilon_s = |s - \hat{s}|$$

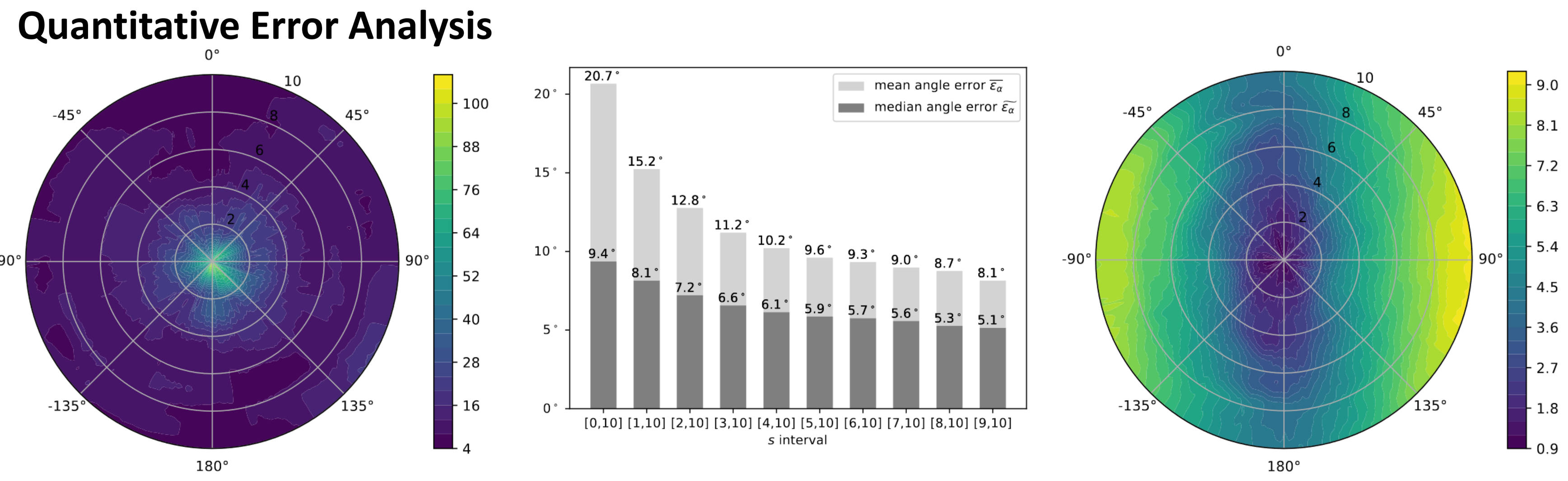
➢ accurate prediction substantially more difficult in clinical cases, due to variations in noise level, background intensities, vessel structure and contrast agent density

Qualitative Error Analysis



➢ prediction less accurate in case of non-visible coronary blurrings at the heart wall (a-c) and low level artifacts (g)

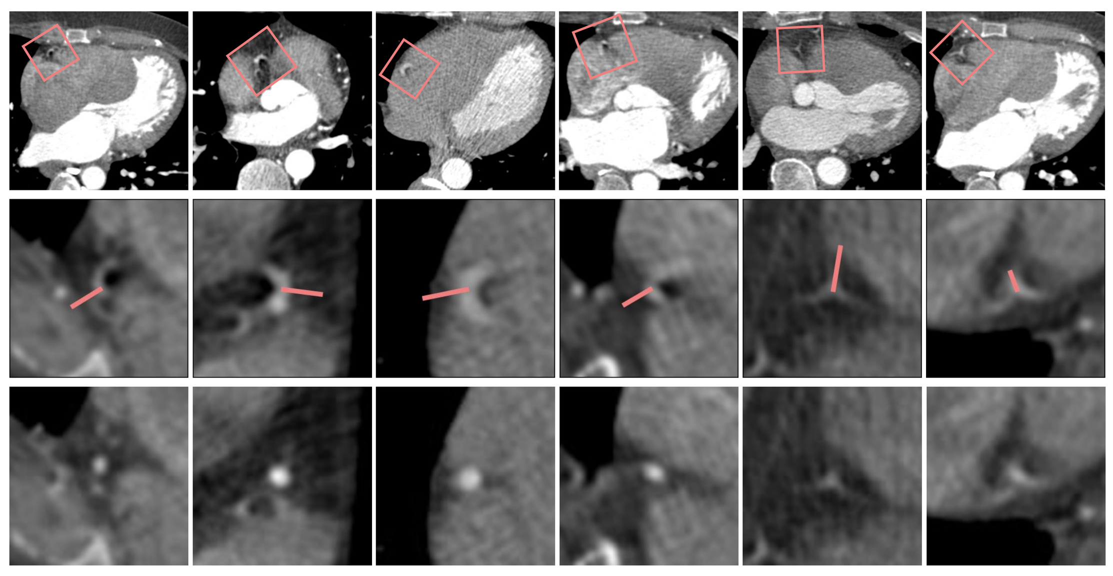
Quantitative Error Analysis



Polar contour plot of the angle error ε_α — Bar plot of mean and median angle error ε_α — Polar contour plot of the predicted artifact level

➢ most accurate prediction of the motion direction for patches with severe artifacts

Motion Compensation Experiment



1. Patch sampling
2. Motion vector estimation
3. Motion compensated reconstruction

➢ reasonable motion vector estimation in six test cases with real motion artifacts
➢ artifact reduction archived by subsequent MC-FBP in four of six test cases

Conclusion: Convolutional Neural Networks are remarkably successful in solving the ill-posed problem of image-based motion estimation. Model extension to 3D motion trajectories will be a part of future research.

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