I INTRODUCTION

CCTA = Coronary Computed Tomography Angiography

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 artery 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

Constant Linear Motion Model
\[ \hat{d}(x, y, t) = \hat{d}(t) \cdot \hat{d}(t, a) \]

Uniformly sampled control parameters:
- \( a \in [0, 10] \) determines displacement width
- \( \alpha \in (-180^\circ, 180^\circ) \) 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 mm/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 3D motion vector in cartesian coordinates

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 \( l = (x - \hat{x})^2 + (y - \hat{y})^2 \)
- \( \epsilon_{xp} = \min(\vert a - \hat{a} \vert, 360^\circ - \vert a - \hat{a} \vert) \)
- \( \epsilon_{s} = \left| a - \hat{a} \right| \)

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

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

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

- 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.

IV EXPERIMENTS AND RESULTS

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

<table>
<thead>
<tr>
<th>Data</th>
<th>Phantom (angle partitioning)</th>
<th>Phantom (strength partitioning)</th>
<th>Clinical</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r ) error</td>
<td>( \epsilon_{xp} )</td>
<td>( \epsilon_{s} )</td>
<td>( \epsilon_{s} )</td>
</tr>
<tr>
<td>( 0.088 \pm 0.078 )</td>
<td>( 0.997 \pm 3.981^\circ )</td>
<td>( 0.602 \pm 0.002 )</td>
<td></td>
</tr>
<tr>
<td>( 0.068 \pm 0.061 )</td>
<td>( 0.559 \pm 0.459^\circ )</td>
<td>( 0.052 \pm 0.042 )</td>
<td></td>
</tr>
</tbody>
</table>

- See Table 1 for quantitative evaluation results in the phantom and the clinical study.

REFERENCES