Motion Estimation and Correction in Cardiac CT Angiography Images using Convolutional Neural Networks

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Abstract

Cardiac motion artifacts frequently reduce the interpretability of coronary computed tomography angiography (CCTA) images and potentially lead to misinterpretations or preclude the diagnosis of coronary artery disease (CAD). In this paper, a novel motion compensation approach dealing with Coronary Motion estimation by Patch Analysis in CT data (CoMPACT) is presented. First, the required data for supervised learning is generated by the Coronary Motion Forward Artifact model for CT data (CoMoFACT) which introduces simulated motion to 19 artifact-free clinical CT cases with step-and-shoot acquisition protocol. Second, convolutional neural networks (CNNs) are trained to estimate underlying 2D motion vectors from 2.5D image patches based on the coronary artifact appearance. In a phantom study with computersimulated vessels, CNNs predict the motion direction and the motion magnitude with average test accuracies of $13.37^{\circ} \pm 1.21^{\circ}$ and 0.77 ± 0.09 mm, respectively. On clinical data with simulated motion, average test accuracies of $34.85^{\circ} \pm 2.09^{\circ}$ and 1.86 ± 0.11 mm are achieved, whereby the precision of the motion direction prediction increases with the motion magnitude. The trained CNNs are integrated into an iterative motion compensation pipeline which includes distance-weighted motion vector extrapolation. Alternating motion estimation and compensation in twelve clinical cases with real cardiac motion artifacts leads to significantly reduced artifact levels, especially in image data with severe artifacts. In four observer studies, mean artifact levels of 3.08 ± 0.24 without MC and 2.28 ± 0.29 with CoMPACT MC are rated in a five point Likert scale.

Keywords: Coronary Computed Tomography Angiography, Motion Compensation, Deep Learning

1. Introduction

Non-invasive coronary computed tomography angiography (CCTA) has become a preferred technique for the detection and diagnosis of coronary artery disease (CAD) (Budoff et al., 2017; Foy et al., 2017; Camargo et al., 2017; Liu et al., 2017), but the temporal resolution of CCTA images is restricted by the angular range required for reconstruction and the system rotation time. Despite the application of dual source CT systems (Petersilka et al., 2008) and ECG-gated acquisition, cardiac motion frequently leads to artifacts in the reconstructed CT image volumes which hamper reliable evaluation (Ghekiere et al., 2017).

Several software-based solutions for motion artifact detection, quantification and reduction have been developed in the last few years. A selection of related papers is listed and compared in Table 1.

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Motion vector field (MVF) estimation and subsequent motion compensated reconstruction (MCR) are the key components of most motion compensation (MC) algorithms. A variety of MCR methods including motion compensated iterative reconstruction (Isola et al., 2010), motion compensated filtered back-projection (MC-FBP) (Schäfer et al., 2006; van Stevendaal et al., 2008) and backprojectthen-warp (BPW) strategies (Bhagalia et al., 2012; Brendel et al., 2014) are known. We assigned the algorithms in Table 1 into registration-based, PARbased (partial angle reconstruction), metric-based and image-based approaches.

Registration-based: Motion estimation by 3-D/3-D registration of multiple heart phases has shown great results in the reduction of moderate and severe motion artifacts (van Stevendaal et al., 2008; Isola et al., 2010; Bhagalia et al., 2012; Tang et al., 2012) but requires an extended temporal

Table 1: Literature survey in the research field of coronary motion artifacts in CCTA images. Papers are clustered into artifact reduction approaches, artifact detection/quantification approaches and approaches from our group which are based on synthetically motion-perturbed data generated with the *Coronary Motion Forward Artifact model for CT data* (CoMoFACT). In this manuscript, a method for *Coronary Motion estimation by Patch Analysis in CT data* (CoMPACT) is introduced.

Paper	Purpose			Approach				Data		Constraints		ints	Keywords		
Symbols H: hand-crafted D: data-driven Γ: required angular scan range	Artifact Detection	Artifact Quantification	Motion Estimation	Artifact Reduction	Registration-Based	PAR-Based	Metric-Based	Image-Based	Algorithm	Manually Labeled	Forward Model	Approximate Centerline	$\Gamma = 180^{\circ} + Fan Angle$	$\Gamma > 180^{\circ} + Fan Angle$	Abbreviations PAR partial angle reconstruction MC-FBP motion compensated filtered back-projection MC-IR motion compensated iterative reconstruction BPW backproject-then-warp ME motion estimation TRIM temporal resolution improvement method MAM motion artifact measure
van Stevendaal et al. (2008)			\checkmark	\checkmark	\checkmark				H					\checkmark	model-based surface reg.; MC-FBP
Isola et al. (2010)			\checkmark	\checkmark	\checkmark				H					\checkmark	multi-phase elatic image reg.; MC-IR
Bhagalia et al. (2012)			\checkmark	\checkmark	\checkmark				H			\checkmark		\checkmark	centerline reg.; subphasic warp and add; BPW
Tang et al. (2012)			\checkmark	\checkmark	✓				H					\checkmark	multi-phase image reg.; alternating ME and MC-FBP
Grass et al. (2016)			\checkmark	\checkmark	✓	\checkmark			H					\checkmark	vesselness filtering; opposite PAR reg.
Kim et al. (2018)			\checkmark	\checkmark	\checkmark	\checkmark	\checkmark		H					\checkmark	linear PAR reg.; metric-based MVF refinement
Schöndube et al. (2011)				\checkmark		\checkmark			H				\checkmark		iterative PAR; histogram constraint; TRIM
Rohkohl et al. (2013)			\checkmark	\checkmark			\checkmark		Н			\checkmark	\checkmark		iterative MAM optimization
Hahn et al. (2017)			\checkmark	\checkmark		\checkmark	\checkmark		H			\checkmark	\checkmark		PAR; MAM optimization; BPW
Jung et al. (2018)				\checkmark				\checkmark	D		\checkmark	\checkmark	\checkmark		cross-phase style transfer; image-to-image translation
Šprem et al. (2017)	\checkmark				[\checkmark	D	 ✓ 		 Image: A start of the start of	\checkmark		coronary artery calcification; deep learning
Ma et al. (2018)	\checkmark	\checkmark						\checkmark	Н			\checkmark	\checkmark		fold overlap ratio; low-intensity region score
Elss et al. (2018b)	\checkmark	Ι			Γ		[\checkmark	D		\checkmark	\checkmark	\checkmark	Γ	CoMoFACT; deep learning
Elss et al. (2018a)			√					√	D		\checkmark	\checkmark	\checkmark		CoMoFACT; deep learning
Lossau et al. (2019)	\checkmark	\checkmark						\checkmark	D		\checkmark	\checkmark	\checkmark		CoMoFACT; deep learning
This manuscript			\checkmark	\checkmark				\checkmark	D		\checkmark	\checkmark	\checkmark		CoMoFACT; deep learning; CoMPACT

scan range which corresponds to increased radiation doses. In (Grass et al., 2016) a series of CT image volumes with reduced angular range of 75° is reconstructed at the angular positions -120° , -60° , $+60^{\circ}$ and $+120^{\circ}$ around a selected center phase. The resulting partial angle volumes are post-processed by first combining high frequencies from the partial scans with low frequencies from a central full scan and subsequent vessel feature enhancement according to (Wiemker et al., 2013). Elastic image registration of diametrically opposed partial scans as described by Kim et al. (2015)yields dense MVFs which are integrated into MC-FBP. By this procedure, Grass et al. (2016) reduced the required angular scan range to 315° plus fan angle of the reconstruction field of view.

PAR-based: The increased temporal resolution of PARs are exploited in several MC methods (Grass et al., 2016; Hahn et al., 2017; Kim et al., 2018). Schöndube et al. (2011) introduced the temporal resolution improvement method based on an iterative PAR with an additional histogram constraint.

Metric-based: An initial metric-based approach dealing with MVF estimation by iterative minimization of handcrafted motion artifact measures (MAM) has been presented by Rohkohl et al. (2013). This method was extended in

(Hahn et al., 2017) by introducing a novel motion model parametrization and application of estimated MVFs to PARs. Kim et al. (2018) proposed a combination of these approaches by first estimating linear motion using registration of PARs and subsequent MVF refinement by information potential minimization.

Image-based: Image-to-image translation using deep residual convolutional neural networks (CNNs) allows for artifact suppression without consideration of the corresponding projection data (Jung et al., 2018). However, these approaches are essentially restricted by the information content of the motion perturbed input patches.

So far, most MC approaches are rule-based, i.e. they exploit hand-crafted features for MVF determination. Machine learning holds the promise to solve tasks of any complexity (Hornik et al., 1989), but requires either appropriate manually labeled or synthesized data. Forward models may help to circumvent time-consuming and possibly noiseaffected hand-labeling processes with the benefit of reproducibility. Coronary motion artifacts do manifest in typical patterns containing intensity undershoots and arc-shaped blurring due to the CT reconstruction geometry which can be realistically simulated by the *Coronary Motion Forward Arti-*



Figure 1: Constant linear motion is introduced to phantom vessel trees using the CoMoFACT. Depending on the relation of motion direction, reconstruction direction and coronary orientation, motion artifacts of different appearance occur. In case of motion in direction of the coronary artery, artifacts are hardly visible due to blurring within the vessel (left box, bottom row). The forward projected coronary artery mask depicted in the center is split into two scanning shots. Patch-based motion prediction models have to be robust regarding related stack transition artifacts.

fact model for CT data (CoMoFACT) from Elss et al. (2018b) and Lossau et al. (2019). This preliminary work has demonstrated that CNNs trained on synthesized data are applicable for motion artifact recognition and quantification in clinical practice, i.e. CNNs are capable of identifying coronary motion artifact patterns. Phantom studies furthermore revealed that the relation between angular reconstruction range and motion direction is crucial for the artifact appearance (Elss et al., 2018a).

This paper addresses the question of how well motion estimation can be performed from a single reconstructed CT image patch based on the coronary artifact appearance. Furthermore, potential and limitations of single-phase, image-based motion estimation using CNNs for MC in clinical practice are investigated. An initial feasibility study for axial motion estimation in coronary artery segments which are aligned along the scanners z-axis has been presented in (Elss et al., 2018a). Building on this work, the Coronary Motion estimation by Patch Analysis in CT data (CoMPACT) method is introduced here. We extended the model from Elss et al. (2018a) for application on coronary artery segments with arbitrary orientations and adapted the network architecture, accordingly. Furthermore, learned motion vector prediction networks are integrated into a novel iterative motion compensation pipeline which enables reduction of severe artifacts in dose efficient short scan data. The following steps are applied to build and test the proposed motion compensation method, whereby the main contributions of this work are 2. and 3., i.e. the deeplearning-based motion estimation approach and the motion compensation pipeline:

- 1. The CoMoFACT presented by Lossau et al. (2019) enables introduction of simulated and hence controlled motion to artifact-free cardiac CT data. By restricting the trajectories of the CoMoFACT to constant linear motion in the axial plane, 19 000 pairs of motion perturbed image patches and underlying 2D motion vectors are generated from 19 clinical cases with excellent image quality (see Section 3.1).
- 2. Based on the synthetically motion perturbed data, CNNs are trained to estimate underlying 2D motion vectors from 2.5D image patches. First, a phantom study is performed as starting point for motion vector estimation in a wellcontrolled scenario without variation in background intensities, contrast agent density or noise level. Finally, CNNs are trained for the more difficult task of motion vector estimation on clinical data (see Section 3.2).
- 3. The trained CNNs are integrated into an iterative motion compensation pipeline which uses alternating MVF estimation and MC-FBP. The MVF estimation step includes distanceweighted extrapolation of motion vectors predicted along the approximate coronary centerlines (see Section 3.3).
- 4. CoMPACT MC is tested on twelve clinical cases with real artifacts and compared to the registration-based MC approach from Grass et al. (2016) in order to evaluate generalization capabilities of the trained CNNs regarding non-synthetic artifacts and the feasibility of patch-based motion estimation in clinical practice (see Section 4.2).

2. Material

The CoMoFACT from Lossau et al. (2019) uses artifact-free CCTA cases with step-and-shoot acquisition protocol as reference point for the motion introduction process. In addition to the reconstructed CT image volumes which determine the *no motion* state, the corresponding coronary artery trees and the raw projection data are required. The restriction to step-and-shoot cases offers the advantage to generate artifacts in a well-controlled situation without table movement or multi-cycle reconstruction. Phantom as well as patient data studies are performed. Section 2.1 details collection and pre-processing of the clinical reference data. The design of the computer-simulated vessels is described in Section 2.2. Twelve additional clinical cases with real motion-perturbation are collected in order to test the transferability to non-synthetic artifacts (see Section 2.3).

2.1. Clinical reference data without artifacts

Slice-by-slice visual inspection is performed to gather contrast-enhanced cardiac CT data sets which exhibit no coronary motion artifacts in the reconstructed CT image volume. In total, 19 prospectively ECG-triggered clinical data sets from different patients are collected. A 256-slice CT scanner (Brilliance iCT, Philips Healthcare, Cleveland, OH, USA) with a gantry rotation speed of 0.272 sec per turn was used for the acquisition of these reference cases. The mean heart rates HR_{mean} ranged from 45.2 bpm to 68.9 bpm. Cardiac CT image volumes are reconstructed at the mid-diastolic quiescent phase by aperture-weighted cardiac reconstruction (AWCR) (van Stevendaal et al., 2007). The center of the cardiac gating window hereafter called the reference cardiac phase r is chosen between 70% and 80% R-R interval, respectively. The coronary artery tree of each case is segmented using the Comprehensive Cardiac Analysis Software (IntelliSpace Portal 9.0, Philips Healthcare, Cleveland, OH, USA) delivering a set of centerline points $\vec{c} \in C$ with associated information on the lumen contour. Centerline points with a minimum vessel diameter of 1.5 millimeters are utilized for data generation.

2.2. Phantom reference data without artifacts

From each clinical reference case, one binary phantom mask is extracted which contains the segmented lumen contour of the entire vessel tree (see Figure 1). Ray-driven forward projection (Bippus et al., 2011) and subsequent high-pass filtering delivers the projection data required for application of the CoMoFACT. The projection geometry, the ECG-data and the coronary centerline points are adopted from the corresponding clinical data set.

The phantom study allows one to identify the limits of deep-learning-based motion estimation in a well-controlled scenario without variation in background intensities, contrast agent density or noise level and focuses on variations in the vessel structure comprising different orientations, curvatures, radii and bifurcations.

2.3. Clinical test data with real artifacts

Twelve additional clinical cases which belong to different patients and exhibit real motion artifacts at the coronary arteries are collected for testing purposes. Acquisition is performed by a Brilliance iCT scanner using the same scan protocol as in the reference data. The mean heart rates of the patients HR_{mean} ranged from 57.9 bpm to 83.0 bpm.

3. Methods

CNNs are trained for motion vector estimation in coronary image patches. The required data for supervised learning is generated using an adapted version of the CoMoFACT for simulated motion introduction. Subsection 3.1 details the data generation process including synthetic motion vector field (MVF) creation and patch sampling. Data augmentation and data separation strategies as well as the supervised learning setups are described in Section 3.2. Finally, the trained CNNs are integrated into an iterative motion compensation pipeline which includes distance-weighted extrapolation of the predicted motion vectors (see Section 3.3).

3.1. Data generation

The CoMoFACT from Lossau et al. (2019) enables the generation of CT image data with simulated and hence controlled motion at the coronary arteries. It is based on motion compensated filtered back-projection (MC-FBP) (Schäfer et al., 2006) taking artifact-free CT images and synthetic MVFs as input. In the MC-FBP, the attenuation coefficient $\mu(\vec{\nu})$ of each voxel $\vec{\nu} \in \Omega$ in the field of view $\Omega \subset \mathbb{R}^3$ is calculated by:

$$\mu(\vec{\nu}) = \int_{t_{\text{start}}}^{t_{\text{end}}} w_{\text{AWCR}}(t, \vec{\nu} + \vec{d}(t, \vec{\nu})) \ p_{\text{filt}}(t, \vec{\nu} + \vec{d}(t, \vec{\nu})) \ \mathrm{d}t$$

$$\tag{1}$$

As part of the filtered back-projection, lineintegrals in p_{filt} are already re-binned to parallel beam geometry and high-pass filtered with a ramp filter. The projection data $p_{\text{filt}}(t, \vec{\nu})$ indicates the filtered line-integral which passes through the voxel $\vec{\nu}$ at time point t. It is multiplied by a weighting function w_{AWCR} which includes angular weighting for gated reconstruction, pi-partner and aperture weighting for normalization of redundant and oblique rays according to (van Stevendaal et al., 2007). As illustrated in Figure 2, line integrals are spatially corrected with respect to the estimated voxel displacement $\vec{d}(t, \vec{\nu})$ at each time point t within the acquisition period $[t_{\scriptscriptstyle\rm start},t_{\scriptscriptstyle\rm end}].$ Application of the MC-FBP on CT data with excellent quality using synthetic MVFs reverses the usual effect of motion compensation. Inconsistent projection data is created and motion artifacts are induced in the reconstructed CT image volume.



Figure 2: In voxel-driven MC-FBP, line integrals are spatially adapted with respect to the input MVF $\vec{d}(t, \vec{\nu})$ which contains the voxel displacements between a reference time t_0 and the time t_i each specific projection was acquired.

Synthetic MVF: In principle, arbitrary motion trajectories can be simulated using this approach by adjusting the synthetic MVF. For simplicity, we restrict the model to constant linear motion. Therefore, minor adaptations of the simulated MVF from Lossau et al. (2019) are performed. In our CoMoFACT variant, the displacement $\vec{d_{c}}: [0\%, 100\%) \times \Omega \to \mathbb{R}^3$ of each voxel $\vec{\nu}$ at time point $t_{cc} \in [0\%, 100\%)$ in millimeters is calculated by:

$$\vec{d}_{\vec{c}}(t_{cc},\vec{\nu}) = s \cdot m_{\vec{c}}(\vec{\nu}) \cdot \vec{\delta}_{\vec{c}}(t_{cc},\alpha) \tag{2}$$

As described in Lossau et al. (2019), t_{cc} is measured in percent cardiac cycle, $s \in \mathbb{R}_+$ denotes the target motion strength and $m_{\vec{c}} \colon \Omega \to [0, 1]$ indicates a weighting mask which limits the motion

to the area of the currently processed centerline point $\vec{c} \in \Omega$. The motion direction is determined by $\vec{\delta_{\vec{c}}}$: [0%, 100%) × (-180°, 180°] which is adapted to:

$$\vec{\delta}_{\vec{c}}(t_{cc}, \alpha) = \frac{60 \text{bpm}}{\text{HR}_{\text{mean}}} \cdot \frac{\vec{\rho}_{\vec{c}}(\alpha)}{\|\vec{\rho}_{\vec{c}}(\alpha)\|_2}$$
(3)
$$\cdot \begin{cases} -0.5 & \text{if } t_{cc} < r - 10\% \\ \frac{(t_{cc} - r)}{20\%} & \text{if } r - 10\% \le t_{cc} \le r + 10\% \\ +0.5 & \text{if } t_{cc} > r + 10\% \end{cases}$$
(4)

The parameter HR_{mean} denotes the patient's average heart rate during acquisition and r is the reference cardiac phase during AWCR. The motion direction determined by $\vec{\rho}_{\vec{c}}(\alpha)$ is limited to the axial plane, i.e. the z-component is set to zero. The x- and y-components of $\vec{\rho}_{\vec{c}}(\alpha)$ are defined in such a way that α corresponds to the angle between mean reconstruction direction of the currently processed centerline point \vec{c} and the motion direction (see Figure 3). The mean reconstruction direction is defined by the gantry rotation angle γ_{mean} at the reference heart phase r and is constant for each voxel reconstructed by the same circular scanning shoot. It has to be noted, that the system rotation direction is consistent for all cases. This is important, since the reverse rotational directions would lead to a flipping of the artifact shapes.

Lossau et al. (2019) investigated the feasibility of motion artifact recognition and quantification by utilizing the parameter s for target value assignment. As an extension of this work, our forward model has one additional (angular) degree of freedom α , i.e. each MVF is now defined by the parameter tuple (s, α) . The target motion strength s scales the length of each displacement vector in the MVF and therefore determines the motion magnitude. On the basis of the velocity measurements at the coronary arteries by Vembar et al. (2003), the target motion strength s is limited to the interval [0, 10] in all experiments. The newly introduced angle parameter $\alpha \in (-180^\circ, 180^\circ]$ determines the in-plane motion direction. Both parameters s and α are randomly sampled from uniform distributions in the following experiments. The corresponding Cartesian coordinates $x = s \cos(\alpha)$ and $y = s \sin(\alpha)$ define the ground-truth labels for the supervised learning task.

Patch sampling: The extended CoMoFACT enables the generation of multiple motion-perturbed CT image volumes with controlled motion level and



Figure 3: The x-y plane of an example centerline point is illustrated in phantom (top) and clinical (bottom) mode for varying parameter settings (s, α) . For better visualization, the patches of size 60×60 pixels are illustrated as circles. Depending on the motion angle α , distinct blurring artifacts occur. Orthogonal motion ($\alpha = \pm 90^{\circ}$) leads to the most severe banana-shaped artifacts while parallel motion ($\alpha = 0^{\circ}$ or $\alpha = 180^{\circ}$) causes bird-shaped blurring. In the clinical data, visibility of blurring artifacts and intensity undershoots are strongly influenced by surrounding background intensities, i.e. artifact types are visually more difficult to distinguish.

motion direction at a specific coronary centerline point \vec{c} . For each centerline point \vec{c} and parameter setting (s, α) , one 2.5D image patch $I^{2.5D}$ is sampled as input data for supervised learning. As illustrated in Figure 3, γ_{mean} defines the relation between the static patient coordinate system and the rotated patch coordinate system. Each 2.5D patch contains three orthogonal image slices of size 60×60



Figure 4: The orthogonal planes of each 2.5D input patch are processed separately in an individual path. Information about in-plane artifact pattern are finally fused in a dense layer with two output neurons to predict \hat{x} and \hat{y} . The network comprises 523 346 learned weights.

pixels with an image resolution of $0.4 \times 0.4 \text{ mm}^2$ per pixel, the so-called x-y plane, x-z plane and yz plane. The centerline point \vec{c} defines the patch center and the patch orientation is contingent on the angular reconstruction range. The z-axis corresponds to the scanner's z-axis, while the x-y plane is spanned by two orthogonal vectors which are constructed with respect to the mean reconstruction direction of the centerline point, i.e. a rotation of the coordinate system by γ_{mean} about the z-axis is performed. By this procedure, the information about the angular reconstruction range is embedded in the patch orientation.

In both studies, phantom and patient data, the CoMoFACT with subsequent patch sampling is applied 1000 times per reference case, thus, delivering a total amount of 19 000 samples as database for supervised learning. The artifact appearance with respect to the relation between motion direction and vessel orientation is illustrated in Figure 1. Figure 3 shows distinct blurring artifacts depending on angular reconstruction range and motion direction.

3.2. Supervised Learning

Based on the synthetically motion perturbed data, CNNs are trained for patch-based motion estimation. The networks take one image patch $I^{2.5D}$ as input and deliver the predicted predominant motion vector (\hat{x}, \hat{y}) as output. Due to the patch similarity of adjacent centerline points, the data is casewise separated for training, validation and testing with a ratio of 11 : 4 : 4 to avoid a bias. By this procedure, robustness of the trained networks is evaluated with regard to unknown variations in the vessel geometry and background intensity.

Data augmentation: The data basis during network training is extended by online data augmentation. Inherent symmetry properties of motion artifacts are exploited for random mirroring of each axis in the input patches. The target labels x, y are adapted accordingly. This procedure increases the amount of vessel geometry variations in the phantom study and background variations in the patient data study. Additionally, translation is performed as label-preserving augmentation strategy. The patch center is randomly shifted in a range of [-10, 10] voxels in x, y and z direction in order to build translation invariance into the networks. This allows deviation between extracted and actual centerline positions. During testing and validation, no mirroring and no translation is performed.

Learning setup: Multiple patch sampling strategies (2D, 2.5D and 3D), network architectures and hyperparameter settings were tested by extensive cross-validation. Best generalization capabilities are achieved by the CNN visualized in Figure 4 which is employed in all subsequent experiments. The x-y plane, the x-z plane and the y-z plane are processed separately in an eight-layer ResNet (He et al., 2016). No weight sharing between the paths is performed since each plane exhibits individual, characteristic motion artifact pattern. The outputs of the global average pooling are concatenated and information are merged in a final dense layer with linear activation function and two output neurons to predict \hat{x} and \hat{y} .

The learning process is driven by the squared error $l = (x - \hat{x})^2 + (y - \hat{y})^2$. The stochastic gradient descent solver Adam (Kingma, Diederik and Ba, Jimmy) with an initial learning rate of 0.01, a minibatch size of 32 and a momentum of 0.8 is used for network optimization. Training is performed over 45 epochs while the learning rate halves after every 15^{th} epoch. L2 regularization with a weight of 0.001 is used. Network training from scratch is performed on the phantom and the clinical data, separately. Furthermore, weight initialization based on previous phantom studies and subsequent fine-tuning on clinical data is investigated. This is motivated by the recent success of transfer learning approaches (Long et al., 2015; Zeiler and Fergus, 2014) and comparable with learning to recognize digits before learning to read house numbers.

Bagging approach: Three ensembles of five CNNs each are learned using the aforementioned network design and hyper-parameter setting by the following bagging approach:

- 1. Four validation cases and four test cases are randomly sampled.
- 2. Network training is performed based on the remaining eleven clinical cases.
- 3. After every epoch of the learning process the generalization capability is examined by means of the validation set.
- 4. The model with the lowest mean euclidean error $\bar{\epsilon}_{x,y}$ on the validation set during 45 epochs of training is selected for calculation of the test metrics.
- 5. Steps 1.-4. are performed five times in total.
- 6. Mean and standard deviation of each test metric over the five splits are calculated.
- 7. Steps 5.-6. are performed for the phantom data and the clinical data with and without network initialization based on the learned weights from the phantom study (using the same separations in training, validation and testing for comparability).

3.3. Motion compensation pipeline

CNNs trained on the clinical database become the main component of the following motion compensation pipeline. A cardiac CT image volume with corresponding set of approximate centerline positions $C \subset \mathbb{R}^3$ and the raw projection data are required as input. By patch sampling and subsequent application of the trained CNNs, a set of motion vectors $\hat{d}_{\vec{c}} \in \mathbb{R}^3$ for $\vec{c} \in C$ is predicted along the centerline. The estimated motion vectors $(\hat{x}, \hat{y}, 0)$ are back rotated in $\hat{\vec{d}}_{\vec{c}}$ by $-\gamma_{\text{mean}}$ about the z-axis and specify the displacement in the static patient coordinate system. For MC-FBP, these sparse motion information are transformed into a dense motion vector field $\hat{\vec{d}}(t_{cc}, \vec{\nu}) \colon [0\%, 100\%) \times \Omega \to \mathbb{R}^3$ by distance-weighted extrapolation (see Figure 5). The estimated voxel displacements are calculated by:

$$\hat{\vec{d}}(t_{cc}, \vec{\nu}) = m_C(\vec{\nu}) \frac{60 \text{bpm}}{\text{HR}_{\text{mean}}}
\cdot \begin{cases} 0 & \text{if } \vec{\nu} \notin \Theta_\tau(C) \\ \sum_{\vec{c} \in C: \ \vec{c} \in \Theta_\tau(\{\vec{\nu}\})} w(\vec{\nu}, \vec{c}) \hat{\vec{d}_c} & \text{if } \vec{\nu} \in \Theta_\tau(C) \\ \\ \cdot \begin{cases} 0.5 & \text{if } t_{cc} < r - 10\% \\ \frac{(r - t_{cc})}{20\%} & \text{if } r - 10\% \le t_{cc} \le r + 10\% \\ -0.5 & \text{if } t_{cc} > r + 10\% \end{cases}$$
(5)

$$w(\vec{\nu}, \vec{c}) = \frac{g(\vec{c} - \vec{\nu})}{\sum_{\vec{c}_i \in C : \ \vec{c}_i \in \Theta_\tau(\{\vec{\nu}\})} g(\vec{c}_i - \vec{\nu})}$$
(6)

The bounding volume of a set $A \subset \mathbb{R}^3$ is defined as $\Theta_{\tau}(A) = \{ \vec{\nu} \mid \exists \vec{v} \in A \colon \| \vec{\nu} - \vec{v} \| < \tau \}$. The distance weighting is performed using a 3D Gaussian kernel $g(\vec{c} - \vec{\nu}) = \exp(-\|\vec{c} - \vec{\nu}\|^2 / (2\sigma^2)) / \sqrt{2\pi\sigma^2}^3$ with $\sigma = 8$ (in millimeters). Beside MV extrapolation, the distance weighting also leads to MVF smoothing. The weighting mask $m_C : \mathbb{R}^3 \mapsto [0, 1]$ is generated by dilation of each centerline point in C with a kernel radius of 15 mm and subsequent uniform filtering with a kernel radius of 6.2 mm according to Lossau et al. (2019). In order to yield a smooth transition to zero, the bounding volume radius τ is set to 21.2 mm in the following experiments. The MVF extrapolation in equation (5) is performed shot-wise, i.e. for each circular acquisition, as motion across different scanning shots is usually not smooth.

Iterative MC: In order to increase the robustness of the MV estimation, an ensemble of five CNNs (see bagging approach in Section 3.2) is utilized for gradual approximation in an iterative fashion. An additional input parameter k_{max} is introduced which indicates the number of alternating MV estimation and MC-FBP steps. Algorithm 1 provides the pseudo code of the iterative CoMPACT MC pipeline.

As an extension, alternative stopping criteria in-



Figure 5: For each voxel $\vec{\nu} \in \Theta_{\tau}(C)$ in the centerline bounding volume highlighted in gray, a motion vector is calculated by scattered data extrapolation. Distance weighting of adjacent centerline points $\vec{c} \in \Theta_{\tau}(\{\vec{\nu}\})$ is performed according to the equations (5) and (6).

Input: image volume I_0^{Ω} , raw projection data p, approximate centerline C, number iterations k_{\max}

Output: improved image volume
$$I_{k_{\text{max}}}^{\mathcal{M}}$$

set
$$d_{\vec{c}} = 0$$
 for $\vec{c} \in C$;
for $k = 1, 2, ..., k_{max}$ do
for $\vec{c} \in C$ do
 $\begin{vmatrix} I^{2.5D} = \text{sample} \left(I_{k-1}^{\Omega}, \vec{c}\right); \\ \hat{d}_{\vec{c}} & += \text{ensemble} \left(I^{2.5D}\right); \\ \text{end} \\ \text{calculate } \hat{\vec{d}}(t_{cc}, \vec{\nu}) \text{ according to } (5); \\ I_k^{\Omega} = \text{MC-FBP} \left(p, \hat{\vec{d}}(t_{cc}, \vec{\nu})\right); \\ \text{end} \\ \end{cases}$

Algorithm 1: Iterative MC in CCTA images using patch-based motion estimation.

stead of a fixed number of iterations are conceivable. Termination with respect to the convergence behavior or exploitation of the artifact level quantification networks from Lossau et al. (2019) are possible solutions. The proposed CoMPACT MC pipeline can be either applied on the full coronary artery tree, on individual segments or on a single centerline point. In case of |C| = 1 and accurate motion estimation, the dense MVF $d(t_{cc}, \vec{\nu})$ equals to $d_{\vec{c}}^{-1}(t_{cc}, \vec{\nu})$. The duration and the robustness regarding outliers can be regulated by the density of centerline points.

4. Experiments and Results

The Microsoft Cognitive Toolkit (CNTK v2.5+, Microsoft Research, Redmond, WA, USA) is used as deep learning framework. In Section 4.1, networks accuracies are analyzed based on synthetic motion artifacts. Qualitative performance evaluation of the proposed CoMPACT MC pipeline based on real motion artifacts, observer studies and a runtime analysis are provided in Section 4.2.

4.1. Quantitative analysis on synthetic artifacts

The following error metrics are introduced for network evaluation:

$$\begin{aligned} \epsilon_{x,y} &= \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2}, \\ \epsilon_\circ &= |\circ - \hat{\circ}|, \text{ for } \circ \in \{s, x, y\}, \\ \epsilon_\alpha &= \min(|\alpha - \hat{\alpha}|, 360^\circ - |\alpha - \hat{\alpha}|) \end{aligned}$$

Table 2 summarizes the results on the testing subsets. As expected, more accurate MV prediction is achieved during the phantom study. Finetuning shows a slight advantage over network optimization from scratch. However, during qualitative performance evaluation of the proposed CoM-PACT MC pipeline based on real motion artifacts, networks trained from scratch yield better results than fine-tuned ones. The fine-tuned networks deliver too conservative in clinical practice, i.e. they seldom venture predictions far from the mean $\vec{0}$ also in the presence of severe artifacts. This could be explained by possible overfitting on the synthetic artifacts. For this reason, the following quantitative error analysis and qualitative experiments are performed based on the bagging ensemble of the five networks trained on the clinical data without fine-tuning.

Figure 6 illustrates the correlation between the accuracy of the predicted motion direction and the introduced motion strength s. High angle errors ϵ_{α} correlate with low s values, i.e. most accurate prediction of the motion direction is feasible for image patches with severe motion artifacts. Figure 7 shows the mean confusion matrix of the target motion strength s. The CNNs in the network ensemble frequently deliver too conservative predictions. Especially high motion levels tend to be underestimated. This network behavior supports the iterative MC scheme. Furthermore, a weakness in the differentiation of low motion levels $s \in [0, 3]$ is observable, which is also difficult for a human observer (see Figure 3).

Table 2: Error metrics on the test cases with synthetic artifacts during the phantom study and the patient data study with and without fine-tuning (FT). The baseline corresponds to the mean ground truth MV ($\hat{d}_{\vec{c}} = \vec{0}$) determined in the CoMoFACT.

	$\epsilon_{x,y}$	ϵ_s	ϵ_x	ϵ_y	ϵ_{lpha}
Baseline	5.00	5.00	3.24	3.24	NaN^*
Phantom	1.10 ± 0.12	0.77 ± 0.09	0.72 ± 0.05	0.66 ± 0.11	$13.37^\circ\pm1.21^\circ$
Clinical (no FT)	2.92 ± 0.13	1.89 ± 0.07	1.75 ± 0.10	1.96 ± 0.07	$35.66^{\circ} \pm 1.57^{\circ}$
Clinical (with FT)	2.87 ± 0.16	1.86 ± 0.11	1.71 ± 0.08	1.93 ± 0.13	$34.85^{\circ} \pm 2.09^{\circ}$

* The angle error ϵ_{α} is 90.00° for arbitrary constant $\vec{d}_{\vec{c}} \neq \vec{0}$



Figure 6: Bar plot of mean and median angle error evaluated for subsets determined by the selected s ranges.

4.2. Qualitative analysis on real artifacts

Local MC: In the first experiment, we investigate how well motion estimation and subsequent compensation can be done from a single 2.5D image patch, i.e. in case of |C| = 1. Centerline points for 24 test patches are manually selected from the twelve clinical test cases described in Section 2.3 at vessel segments of varying position, orientation and artifact level. In Figure 8, the corresponding x-y planes of size 60×60 pixels are visualized before and after $k \in \{1, 3, 10\}$ iterations of CoMPACT MC. For comparison, the registration-based MC approach from Grass et al. (2016) is considered which exploits the entire 3D image field of view (FOV).

The CoMPACT MC shows gradual improvement of the image quality in a multitude of test cases (e.g. in Figure 8c,h,i,k) and sensible convergence properties (except for Figure 8m). Is has to be noted, that the registration-based approach also fails in the patch of Figure 8m. Indeed, our pipeline has an advantage over the registration-based approach in several patches, like for instance in Figure 8d,p,t. The networks are robust regarding slight shifts between patch center and vessel position (see Figure 8b,e). The main weakness of our method is the



Figure 7: Confusion matrix of the target motion strength s.

restricted motion model complexity. We assume constant linear motion in the axial plane which is spatially constant in a local neighborhood. In some cases, these assumptions do not seem to be fulfilled, e.g. in the presence of more complex motion trajectories like turning motion (see Figure 8v) and spatially varying predominant motion directions (see Figure 8i,m,q). Nevertheless, the CoMPACT MC is remarkably successful in view of the little information content obtained from a single 2.5D image patch.

Global MC: In the second experiment, we investigate how well motion estimation and subsequent compensation can be done in clinical practice by application on the whole coronary artery tree. The simultaneous consideration of various centerline points also allows for spatially irregular predominant motion directions. Figure 9 shows the multiplanar reformats of four vessels without MC, after 10 iterations of CoMPACT MC and after registration-based MC. In Figure 9a,c,d, the corre-



Figure 8: The x-y planes of 24 image patches belonging to twelve different patients are visualized before (org) and after $k \in \{1, 3, 10\}$ steps of CoMPACT MC. For comparison, the registration-based MC (reg) is considered. Significantly reduced artifact levels are observable in the majority of the test patches.

sponding centerlines were extracted from the output image volume of the registration-based MC using the Comprehensive Cardiac Analysis Software.

The centerline in Figure 9b was determined based on the original image volume as the registrationbased approach leads to increased artifact levels





(b)



Figure 9: The multiplanar reformats of four vessels belonging to different patients and branches of the right coronary artery (RCA) are visualized before (org) and after k = 10 iterations of CoMPACT MC. Corresponding cross-sectional image patches which are perpendicular to the extracted centerline are given below for visual inspection. Furthermore, registration-based MC (reg) is considered for comparison. Both MC approaches, the registration-based and the proposed CoMPACT MC, lead to significant reduction of moderate and severe artifacts along the vessel.

in the distal vessel segment. Significantly reduced artifact levels after CoMPACT MC are observable in all cases, also in the presence of noise (see Figure 9a) or bifurcations (see Figure 9d). In Figure 9c, moderate artifacts in the proximal RCA are removed while the artifact-free mid and distal vessel segments captured by the second scanning shot remain unchanged.

Observer studies: Four separate observer studies were performed to rate cross-sectional image patches before MC, after k = 10 iterations of CoMPACT MC and after registration-based MC. Eight cross-sectional image patches are equidistantly sampled along the RCA (as illustrated in Figure 9) from eleven test cases resulting in a total number of $4 \cdot 3 \cdot 8 \cdot 11 = 1056$ labeled patches. The twelfth clinical test case was omitted as stack transition artifacts preclude the automatic coronary artery tree segmentation by means of the Comprehensive Cardiac Analysis Software. Rating is performed in a five point Likert scale (1: excellent, 2: good, 3: mixed, 4: strong artifact, 5: nondiagnostic). Vessel segments are presented in random order without indication of the underlying algorithm (org/k = 10/reg) to the readers. It has to be noted that the readers were no radiologists, but research scientists with high level of expertise in reading cardiac CT images. The resulting annotations are summarized in Figure 10. Mean observer scores of 3.08 ± 0.24 , 2.28 ± 0.29 and 2.42 ± 0.23 are achieved on image volumes without MC, after k = 10 iterations of CoMPACT MC and after registration-based MC. The performed experiments demonstrate the generalization capabilities of the trained neural networks on non-synthetic motion artifacts and a reasonable convergence behavior of the iterative MC scheme.



Figure 10: Cross-sectional image patches before and after MC are rated by four human observers in a five point Likert scale (from 1: excellent to 5: non-diagnostic).

Run-time analysis: Table 3 provides the results of a five-fold run-time analysis performed on a NVIDIA GeForce GTX 1080 Ti. In case of k = 1, patch sampling is performed with respect to the mean reconstruction direction and voxel positions are cached for faster sampling in subsequent iterations (k > 1). Motion vector prediction by means of the networks, i.e. ensemble application, is the most time-efficient processing step, whereas MVF extrapolation and MC-FBP are quite timeconsuming in the current implementation. Acceleration is possible by parallel processing of the individual scanning shots and restriction of the reconstruction region during MC-FBP to the cached voxel positions required for patch sampling. Furthermore, the run-time is controllable by adjusting the number of iteration steps k_{max} and the centerline point density along the vessel.

Table 3: Mean duration of the CoMPACT MC pipeline in case of |C| = 1000 and a FOV of size $512 \times 512 \times 300$ voxels.

Processing S	Duration [secs]			
Patch Sampling	k = 1	62.10 ± 3.61		
	k > 1	11.54 ± 0.27		
Ensemble Applic	4.86 ± 0.03			
MVF Extrapolat	172.17 ± 0.87			
MC-FBP	116.16 ± 0.16			
Total $(k_{\text{max}} = 10$	3196.44 ± 139.39			

5. Discussion

We proposed the first single-phase motion estimation approach which works solely on reconstructed image data. The designed motion model which comprises linear trajectories in the axial plane, reveals potential and limitations of imagebased motion estimation. Despite severe simplification of the actual, more complex heart motion, significant artifact reduction is achieved on clinical test data. More complex trajectories (e.g. turning motion) could be determined by performing constant linear motion estimation at multiple time points. Areas around the ostia exhibit 3D velocities with a noticeable contribution from the zcomponent. In contrast, mid- and distal RCA and mid-LCX segments have a dominant axial component and velocities in these segments are typically higher (Wang et al., 1999; Vembar et al., 2003). The introduced procedure of data generation by the CoMoFACT and subsequent supervised learning is, in principle, extendable to arbitrary non-linear 3D motion trajectories. However, the information content of the reconstructed image volumes is a limiting factors in model extension to more complex motion, i.e. motion along the z-axis. Furthermore, performed experiments on network fine-tuning from phantom to clinical data reveal the problem of potential overfitting to synthetic artifacts.

For application of the proposed CoMPACT MC pipeline, the approximate locations of the coronary arteries have to be known. In case of incomplete or incorrect fully automatic centerline segmentation due to severe motion artifacts, semi-automatic approaches which enable user-interaction have to be considered. This requirement constitutes the main disadvantage of patch-based MC in comparison to registration-based MC. Both approaches lead to significantly reduced artifact levels in the CCTA images. CoMPACT requires the minimal angular range of 180 degrees in parallel rebinned geometry while the registration-based MC demands 315 degrees for the partial image reconstructions. Furthermore, CoMPACT shows very promising results despite minimal spatial information which enables fast local processing of a few centerline points and their neighborhood.

Patch-based motion estimation offers a lot of potential for further research. Additional prediction of network uncertainty and integration into the distance-weighted MVF extrapolation might be useful in patches with little information content, i.e. in case of low contrast enhancement. So far, the proposed CoMPACT method is merely based on 19 clinical data sets. In general, CCTA images are acquired with a wide variety of scanner types, imaging protocols and reconstruction algorithms. In order to increase the network's robustness, collection of more data and network fine-tuning is required. The transferability of the proposed CoMPACT MC pipeline to other scanner types and imaging protocols should be investigated.

The methodology of first introducing simulated motion to clinical cases with excellent quality and subsequent supervised learning of motion estimation models based on the artifact appearance is, in principle, not restricted to contrast-enhanced coronary arteries. By providing a set of reference cases without motion artifacts, patch-based motion estimation and compensation is on-site trainable for data of arbitrary contrast protocol and other parts of the human anatomy. Possible examples are motion artifact reduction at the aortic valve or correction of calcium scores in non-contrast CT. The information content of the reconstructed image patches and overfitting to synthetic artifacts are again potentially limiting factors.

6. Conclusions

Typical coronary artifact patterns are introduced in phantom and clinical data by a forward model which simulates linear, axial motion. The generated image data is used for subsequent supervised learning of CNNs for estimation of underlying motion vectors which are integrated into an iterative motion compensation pipeline. Despite variations in noise level, background intensity and contrast agent density, CNNs are remarkably successful in patchbased MV estimation on clinical data. The proposed CoMPACT MC method furthermore generalizes to non-synthetic artifacts and deep-learningbased motion estimation is particularly suitable for MC in clinical cases with severe artifacts.

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