Deep Autofocus with Cone-Beam CT Consistency Constraint

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Abstract. High quality reconstruction with interventional C-arm cone-beam computed tomography (CBCT) requires exact geometry information. If the geometry information is corrupted, e. g., by unexpected patient or system movement, the measured signal is misplaced in the back-projection operation. With prolonged acquisition times of interventional C-arm CBCT the likelihood of rigid patient motion increases. To adapt the backprojection operation accordingly, a motion estimation strategy is necessary. Recently, a novel learning-based approach was proposed, capable of compensating motions within the acquisition plane. We extend this method by a CBCT consistency constraint, which was proven to be efficient for motions perpendicular to the acquisition plane. By the synergistic combination of these two measures, in and out-plane motion is well detectable, achieving an average artifact suppression of 93 %. This outperforms the entropy-based state-of-the-art autofocus measure which achieves on average an artifact suppression of 54 %.

1 Introduction

Cone-beam computed tomography (CBCT) using interventional C-arm systems has gained strong interest since an update of the guidelines of the American Stroke Association favoring mechanical thrombectomy [1, 2]. The procedure needs to be guided by an interventional C-arm system capable of 3-D imaging with soft tissue image quality comparable to helical CT [3]. This allows to perform diagnostic stroke imaging before therapy directly on the C-arm system without prior patient transfers to CT or MRI. This one-stop procedure improves the time-to-therapy [4], but 3-D image acquisition is challenging due to the prolonged acquisition time compared to helical CT. Rigid patient head motion is more likely to occur, which leads to motion artifacts in the reconstructed slice images. Thus, a robust patient motion compensation technique is highly demanded.

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Rigid patient motion in CBCT can be compensated by adapting the projection matrices, which represent the acquisition trajectory. This compensated trajectory is denoted as the motion free trajectory. Multiple methods for rigid motion estimation in transmission imaging have been proposed, which can be clustered in three categories: (1) image-based autofocus [5, 6], (2) registration-based [7] and (3) consistency-based [8, 9]. Within those categories, learning-based approaches have been presented that detect anatomical landmarks for registration [10, 11] or assess the reconstruction quality to guide an image-based autofocus [12]. The latter approach demonstrates promising initial results, capable of competing with the state of the art, but the motion estimation is restricted to in-plane motion [12].

As a counterpart, consistency-based methods are merely sensitive to in-plane motion, as they evaluate their consistency by the comparison of epipolar lines. For circular trajectories, epipolar lines are dominantly parallel to the acquisition plane allowing precise detection of out-plane motion. This pose consistency conditions a synergetic constraint for the deep autofocus approach presented in Preuhs et al. [12].

We propose an extension of this learning-based autofocus approach which is constrained by the epipolar consistency conditions (ECC) derived from Grangeat's theorem [13].

2 Motion estimation and compensation framework

2.1 Autofocus

Autofocus frameworks iteratively find a motion trajectory $\mathcal{M}$ by optimizing an image-quality metric (IQM) evaluated on intermediate reconstructions which are updated according to the current estimated motion trajectory. The motion trajectory defines a transformation for each acquired projection i representing the view-dependent patient orientation $\boldsymbol{M}_i \in \mathbb{SE}(3)$. $\mathcal{M}$ is used, together with the offline-calibrated trajectory $\mathcal{T}$, for the backprojection operation in the Feldkamp-Davis-Kress (FDK) reconstruction algorithm [14]. If the image-quality metric saturates, the method outputs a motion compensated reconstruction as illustrated in Fig. 1.

We use a data driven IQM which is computed by a convolutional neural network (CNN) trained to regress the reprojection error (RPE) from the observable motion artifacts within a reconstructed slice image. To account for out-plane motion, the autofocus framework is further constrained using the ECC based on Grangeat's theorem [13, 15]. Thus, in inference, we estimate the motion free trajectory $\hat{\mathcal{M}}$ by iteratively minimizing

$$\hat{\mathcal{M}} = \underset{\mathcal{M}}{\operatorname{argmin}} \ \ \mathrm{CNN}(\mathrm{FDK}(\mathcal{M})) + \lambda \cdot \mathrm{ECC}(\mathcal{M}) \tag{1}$$

with $\mathrm{CNN}(\mathrm{FDK}(\mathcal{M}))$ denoting the network output (Sec. 2.2) for an intermediate reconstruction and $\mathrm{ECC}(\mathcal{M})$ the consistency constraint (Sec. 2.3), both for a current motion estimate $\mathcal{M}$. The regularization weight λ is choosen such that both metrics are within the same range.