Abstract: Gradient-based Geometry Learning for Fan-beam CT Reconstruction

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Incorporating computed tomography (CT) reconstruction operators into differentiable pipelines has proven beneficial in many applications. Such approaches usually focus on the projection data and keep the acquisition geometry fixed. However, precise knowledge of the acquisition geometry is essential for high quality reconstruction results. Here, the differentiable formulation of fan-beam CT reconstruction is extended to the acquisition geometry. The CT reconstruction operation is analytically derived with respect to the acquisition geometry. This allows to propagate gradient information from a loss function on the reconstructed image into the geometry parameters. As a proof-of-concept experiment, this idea is applied to rigid motion compensation. The cost function is parameterized by a trained neural network which regresses an image quality metric from the motion-affected reconstruction alone. Since this regressed quality index and the geometry parameters are connected in a differentiable manner, optimization can be performed using standard gradient-based optimization procedures. Oppositely, all previous approaches rely on gradient-free optimization in this context. The proposed motion compensation algorithm improves the structural similarity index measure (SSIM) from 0.848 for the initial motion-affected reconstruction to 0.946 after compensation. It also generalizes to real fan-beam sinograms which are rebinned from a helical trajectory where the SSIM increases from 0.639 to 0.742. Furthermore, we can show that the number of target function evaluations is decreased by several orders of magnitude compared to gradient-free optimization. Using the proposed method, we are the first to optimize an autofocus-inspired algorithm based on analytical gradients. Next to motion compensation, we see further use cases of our differentiable method for scanner calibration or hybrid techniques employing deep models. The GPU-accelerated source code for geometry-differentiable CT backprojection in fan-beam and cone-beam geometries is publicly available at `https://github.com/mareikethies/geometry_gradients_CT` [1].

References

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