Residual Neural Network for Filter Kernel Design in Filtered Back-projection for CT Image Reconstruction

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Abstract. Filtered back-projection (FBP) has been widely applied for computed tomography (CT) image reconstruction as a fundamental algorithm. Most of the filter kernels used in FBP are designed by analytic methods. Recently, the precision learning-based ramp filter (PL-Ramp) has been proposed to formulate FBP to directly learn the reconstruction filter. However, it is difficult to introduce regularization terms in this method, which essentially provides a massive solution space. Therefore, in this paper, we propose a neural network based on residual learning for filter kernel design in FBP, named resFBP. With such a neural network, it is possible for us to limit the solution space by introducing various regularization terms or methods to achieve better reconstruction quality on the test set. The experiment results demonstrate that both quality and reconstruction error of the proposed method has great superiority over FBP and also outperforms PL-Ramp when projection data are polluted by Poisson noise or Gaussian noise.

1 Introduction

Computed tomography (CT) is a technology to obtain internal information of an unknown object and has been extensively used in many areas, such as medical imaging and electron microscopy in materials science. Filtered back-projection (FBP), one of the most popular methods for CT image reconstruction, requires a large number of noise-free projections to yield accurate reconstructions. It is applied widely for its low computational cost and ease of implementation. However, in practice, noisy projections and projection discretization can make the image reconstructed by FBP suffer from severe artifacts. To suppress artifacts, the filter kernel designs for specific cases have been proposed to improve the quality of reconstruction images.

The methods for filter kernel design can be divided into two categories: (i) analytic design, (ii) data-driven learning. For analytic design, Ram-Lak filter [1] is mathematically optimized from the ramp filter for the discrete image and projection. Shepp-Logan filter [2], imposing a different noise assumption, is

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one common filter for FBP. To derive new filters, Wei et al. [3] propose a filter design methodology in the real space, and apply this methodology to deduce new filters as well as classic filters. New filters have been demonstrated to produce equivalent image quality in comparison to classic filters.

For data-driven methods, a novel scheme is proposed by Shi et al. [4] to design the reconstruction filters to replace the ramp filter. The reconstruction filters are optimized to drive the reconstruction matrix approach δ-matrix as close as possible with constraints. Wang et al. [5] propose an end-to-end network FBP-Net, combining the FBP algorithm with a denoiser neural network, to directly reconstruct positron emission tomography (PET) images from sinograms. The frequency filter is adaptively learned in the FBP part. Syben et al. [6] propose the precision learning-based ramp filter (denoted as PL-Ramp) to optimize discrete filter kernels by back-propagation, which solves the problem of manually designing filters. Experiments have proved that the initialized ramp filter can automatically approximate the hand-crafted Ram-Lak filter by training, and it greatly reduces the burden of manual design and allows the filter to be trained to adapt to more noise conditions.

Although PL-Ramp has been proved to have the ability to learn a discrete optimal reconstruction filter from the ramp filter, its performance on training noisy data is not as good as expected according to our experiments. Moreover, PL-Ramp does not have any regularization term to avoid over-fitting. To solve the problems mentioned above, in this paper, we propose a residual neural network to learn the filter in FBP, named resFBP. In detail, resFBP includes a residual fully connected neural network and a residual convolution neural network. Experiments on Poisson noise and Gaussian noise data demonstrate that our proposed method can better suppress the artifacts and has lower reconstruction root-mean-squared error (RMSE) than PL-Ramp.

2 Materials and methods

2.1 resFBP

The architecture of the proposed resFBP is illustrated in Fig. 1. The whole procedure can be described as following: the projection data first undergo Fourier transform F, and then are filtered in the frequency domain with the learned

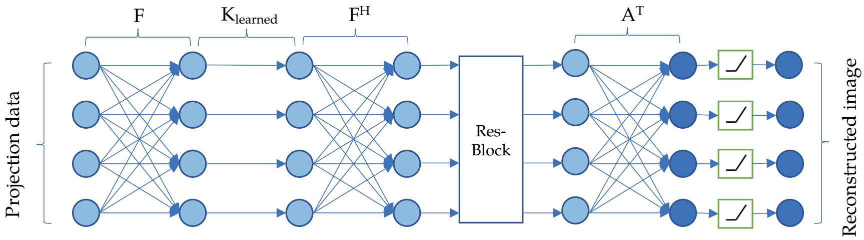

Fig. 1. The general architecture of resFBP.