A Benchmark for Deep Learning Reconstruction Methods for Low-Dose Computed Tomography

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Motivation

- Learned methods in imaging boost reconstruction quality
- Often only limited amount of paired data available

Contributions

1. Compare different classical and deep learning approaches for CT reconstruction in low-dose scenarios
2. Investigate the influence of the number of training and validation samples on the performance of learned models
3. Explore ways to use the Deep Image Prior (DIP) for CT reconstruction

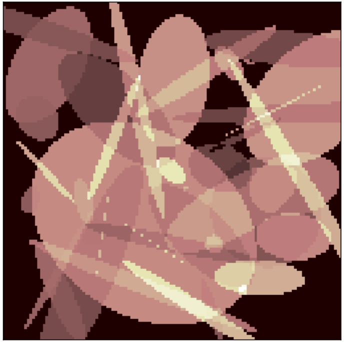
Reduction Strategies

- 1.5% of all cancers in the U.S. might relate to current CT usage [4]
- Low-dose CT can lead to challenges for the reconstruction models
- We include two common reduction strategies in our study:
  1. **Sparse angle**: undersampled
     → Synthetic Ellipses Dataset
  2. **Low photon count**: Poisson noise
     → LoDoPaB-CT Dataset [8]
- Both datasets are easily accessible through our python library DIV$\alpha\ell$[1]

[1] pypi.org/project/dival

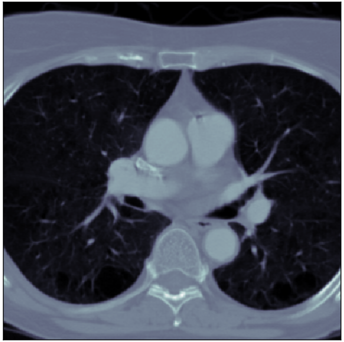
Synthetic Ellipses Dataset

- Random ellipse phantoms
- Around 40 000 images in total
- Sparse angle setup
- Undersampled & Gaussian noise



LoDoPaB-CT Dataset

- Thoracic CT scans from the LIDC/IDRI database [3]
- Over 800 patients and 40 000 scan slices
- Low photon count setting
- Poisson noise



Definition DIP [7]

For fixed input z and neural network φ with parameters θ solve

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \|A\varphi(\theta, z) - y^\delta\|^2, \quad \hat{x} = \varphi(\hat{\theta}, z)$$

- No ground truth and training data needed
- Optimize using gradient descent with early stopping
- Regularization is a combination of early stopping and the architecture

Our Approaches for CT

1. **Deep Image Prior + Regularization**
   - Add an additional regularization term $\mathcal{R}$ with weighting factor $\alpha \in \mathbb{R}^+$

$$\hat{\theta} = \underset{\theta \in \Theta}{\arg\min} \|A\varphi(\theta, z) - y^\delta\|^2 + \alpha\mathcal{R}\left(\varphi(\theta, z)\right)$$

   - Choose Total Variation (TV) $\mathcal{R}(\cdot) = \|\nabla \cdot\|_1$ for sparse gradients [9]

2. **Start with an initial reconstruction**
   - Choose z as output of another reconstruction algorithm
   - Can lead to better reconstructions and fewer optimization steps
   - DIP can adapt the initial algorithm to a new setting without retraining

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Compared Methods

Methods without training

- Filtered Backprojection (FBP)
- Total Variation (TV)
- Deep Image Prior (DIP) + TV

Learned iterative schemes

- Learned Gradient Descent (LearnedGD) [2]
- Learned Primal-Dual (LearnedPD) [1]

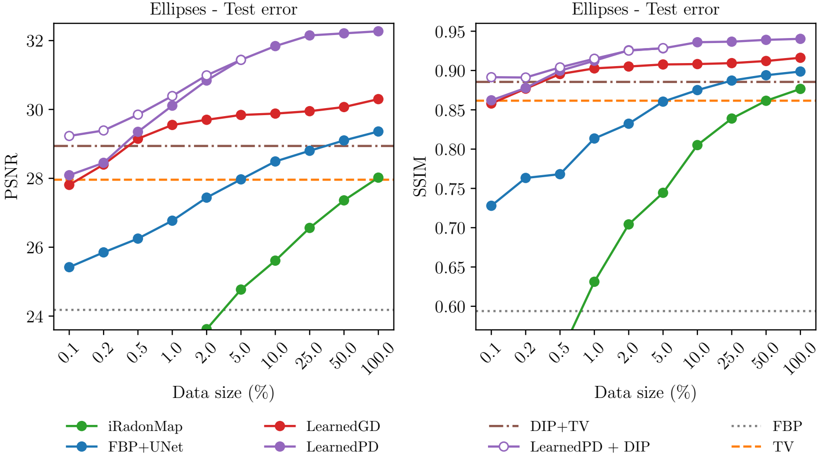
Fully-learned inversion

- iRadonMap [5]

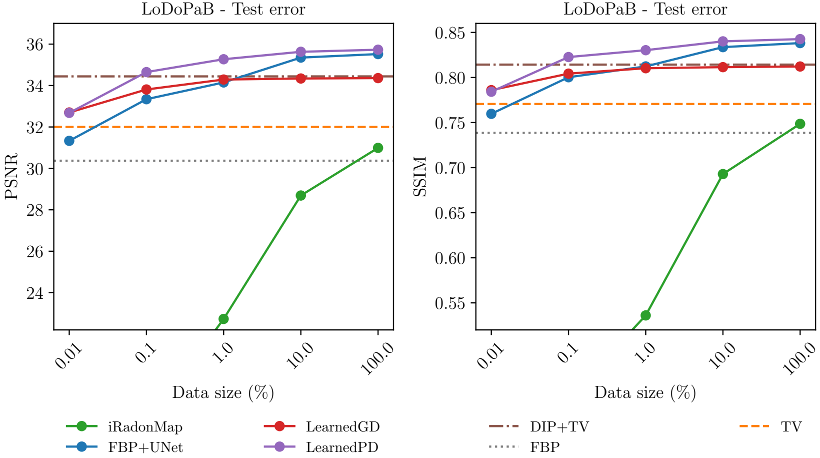
Post-processing

- FBP + U-Net [6]
- LearnedPD + DIP

Ellipses Dataset



LoDoPaB-CT Dataset



Additional Information

Thanks for your Attention!

Follow the link below or scan the QR code for additional information

dival.math.uni-bremen.de/isbi2020_ct_dip_dl

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