AAPM DL-sparse-view CT Challenge

Team name: `robust-and-stable`

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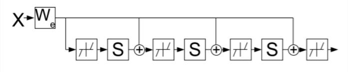
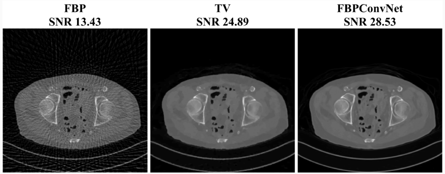
Grand Challenges: Deep Learning Sparse-View CT and DBTex

AAPM 63rd Annual Meeting
July 28, 2021

- **Since 2016:** Paradigm shift from sparsity-based regularization to deep learning
  - Post-processing networks [AAPM Low Dose CT Grand Challenge – McCollough 2016; Kang et al. 2017; Jin et al. 2017; Chen, Y. Zhang, Kalra, et al. 2017; Chen, Y. Zhang, W. Zhang, et al. 2017; ...]
  - Unrolled iterative schemes [Gregor & LeCun 2010; Yang et al. 2016; Adler & Öktem 2018; Hammernik, Klatzer, et al. 2018; Schlemper et al. 2019; Hammernik, Schlemper, et al. 2021; ...]
  - Pre-trained networks (GANs, plug-and-play, ...) [Bora et al. 2017; Romano et al. 2017; K. Zhang et al. 2017; Mukherjee et al. 2020; ...]
  - Learning the Invisible, Deep Image Prior, ... [Ulyanov et al. 2018; Bubba et al. 2019; ...]
- Defines **state of the art**, i.e., outperforms classical algorithms in terms of image quality and speed.



[Image from Gregor & LeCun 2010]



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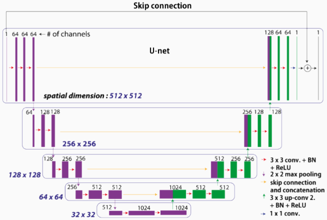

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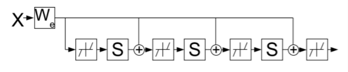
The gold-rush mood is over ...?



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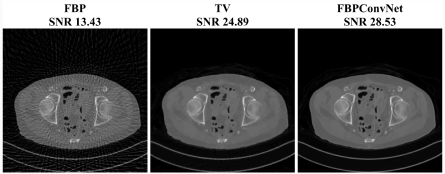

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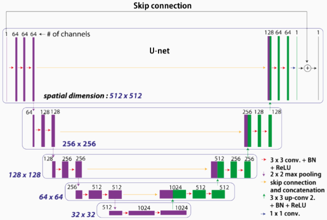

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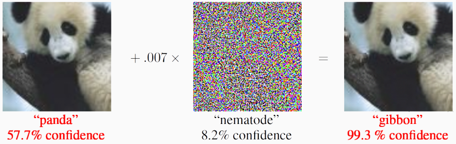
Which method performs best in practice? **Can I trust it?**

$$y = \mathcal{A}x_0 + e$$

- **Robustness:**

  How sensitive are DL-based reconstructions to perturbations in the input?

  [Huang et al. 2018; Antun et al. 2020; Raj et al. 2020; Genzel et al. 2020; ...]



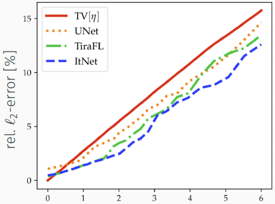
[Image from Goodfellow et al. 2015]

- **Accuracy:**

  Can DL-based methods solve the inverse problem?

  - Visual image quality vs. quant. error metrics [cf. Sidky et al. 2021]
  - Missing small features, hallucinations

  [e.g., see NYU fastMRI challenges – Zbontar et al. 2018; Knoll et al. 2020; Muckley et al. 2020]



rel. noise level [%] – adversarial

[Image from Genzel et al. 2020]

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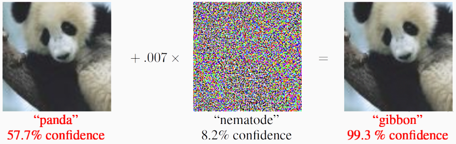

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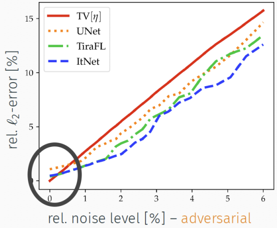


[Image from Genzel et al. 2020]

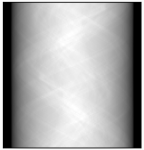
(Our) starting point for the AAPM sparse-view challenge ...

Hypothesis: High accuracy only if the forward model is explicitly incorporated into the reconstruction mapping.

- $\mathcal{A}$ = sparse-view fanbeam CT-operator (unknown!)

x_0 (image signal)

$$\xrightarrow{\mathcal{A}} \qquad \xleftarrow[?]{}$$



y_0 (sinogram)

Our Approach (1/2)

Hypothesis: High accuracy only if the forward model is explicitly incorporated into the reconstruction mapping.

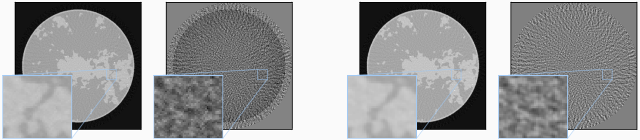
- $\mathcal{A}$ = sparse-view fanbeam CT-operator (unknown!)
- Step 1: Fully **data-driven operator identification** based on a generic, parameterized forward model $\mathcal{A}[\theta]$.

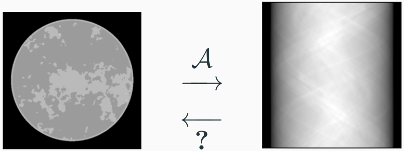
$$\min_{\theta} \sum_i \|\mathcal{A}[\theta](x_0^i) - y_0^i\|_2^2$$

(DL-style: coordinate descent with backpropagation/autodiff in PyTorch)

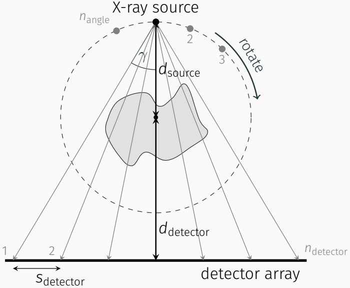
Challenge FBP (RMSE = 5.96e-03)

Our FBP (RMSE = 3.73e-03)



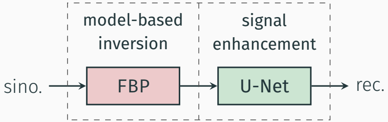


x_0 (image signal) y_0 (sinogram)



Our Approach (2/2)

- Step 2: **Pre-train a U-Net** as FBP-post-processor.
  - ⤳ our computational backbone [Jin et al. 2017; Kang et al. 2017; ...]



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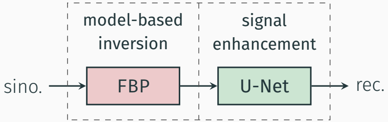
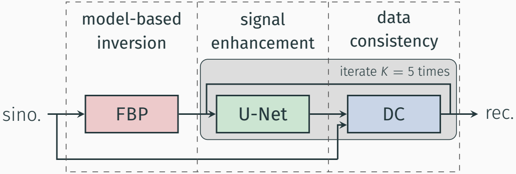


- Step 3: **Construct an iterative scheme.**
  - ⇝ loop over NN- and data-consistency blocks

[Aggarwal et al. 2018; Schlemper et al. 2019; Hammernik, Schlemper, et al. 2021; ...]



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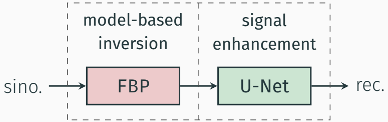

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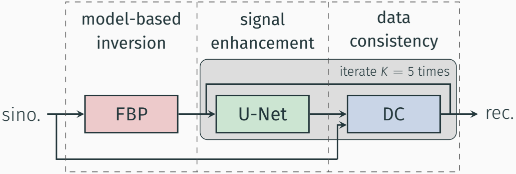
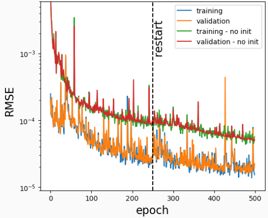


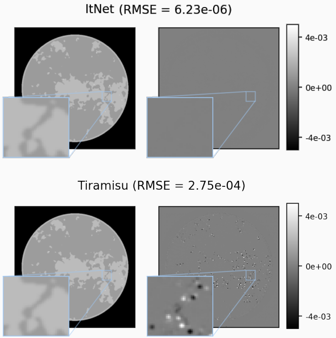
- What's new?
  - Pre-trained U-Net as backbone is very effective
  - Data-consistency layer uses filtered backprojection
    ⇝ $\mathrm{DC}(x, y) = x - \lambda_k \cdot \mathrm{FBP}(\mathcal{A}x - y)$

(A lot more tricks & tuning: post-training, weight sharing, ensembling, group normalization, memory channels, restarting)



	Baselines		Our Network Variants		Comparison Networks	
	Chall. **FBP**	Our **FBP**	**U-Net**	ItNet	**Tiramisu**	**LPD**
RMSE	5.72e-3	3.40e-3	3.50e-4	**6.37e-6**	2.24e-4	1.24e-4

[Jégou et al. 2017; Adler & Öktem 2018]



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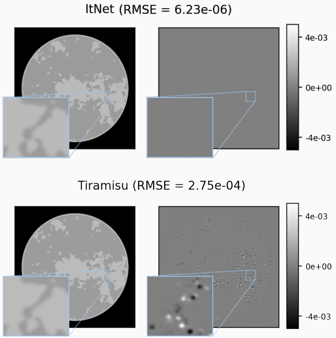
[Jégou et al. 2017; Adler & Öktem 2018]

Our main take-aways

- Near-exact image recovery by DL-techniques is possible.
- Using model-based knowledge is very effective.
- Deep-learning-based geometry-identification is possible.
  $\rightsquigarrow$ unsupervised by consistency conditions?
- Simple and well-trained methods over mathy pixie-dust.



Thank You!

Code available: `https://github.com/jmaces/aapm-ct-challenge/`

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M. Genzel, J. Macdonald, and M. März. "Solving Inverse Problems With Deep Neural Networks – Robustness Included?" arXiv:2011.04268. 2020.

Bibliography I

J. Adler and O. Öktem. "Learned primal-dual reconstruction". *IEEE Trans. Med. Imag.* 37.6 (2018), 1322–1332.

H. K. Aggarwal, M. P. Mani, and M. Jacob. "MoDL: Model-based deep learning architecture for inverse problems". *IEEE Trans. Med. Imag.* 38.2 (2018), 394–405.

V. Antun, F. Renna, C. Poon, B. Adcock, and A. C. Hansen. "On instabilities of deep learning in image reconstruction and the potential costs of AI". *Proc. Natl. Acad. Sci.* 117.48 (2020), 30088–30095.

A. Bora, A. Jalal, E. Price, and A. G. Dimakis. "Compressed Sensing using Generative Models". *Proceedings of the 34th International Conference on Machine Learning (ICML).* 2017, 537–546.

T. A. Bubba, G. Kutyniok, M. Lassas, M. März, W. Samek, S. Siltanen, and V. Srinivasan. "Learning the invisible: A hybrid deep learning-shearlet framework for limited angle computed tomography". *Inverse Probl.* 35.6 (2019), 064002.

H. Chen, Y. Zhang, M. K. Kalra, F. Lin, Y. Chen, P. Liao, J. Zhou, and G. Wang. "Low-dose CT with a residual encoder-decoder convolutional neural network". *IEEE Trans. Med. Imag.* 36.12 (2017), 2524–2535.

H. Chen, Y. Zhang, W. Zhang, P. Liao, K. Li, J. Zhou, and G. Wang. "Low-dose CT via convolutional neural network". *Biomed. Opt. Express* 8.2 (2017), 679–694.

M. Genzel, J. Macdonald, and M. März. "Solving Inverse Problems With Deep Neural Networks – Robustness Included?" arXiv:2011.04268. 2020.

I. J. Goodfellow, J. Shlens, and C. Szegedy. "Explaining and Harnessing Adversarial Examples". Preprint arXiv:1412.6572. 2015.

Bibliography II

K. Gregor and Y. LeCun. “Learning Fast Approximations of Sparse Coding”. *Proceedings of the 27th International Conference on International Conference on Machine Learning (ICML)*. 2010, 399–406.

K. Hammernik, T. Klatzer, E. Kobler, M. P. Recht, D. K. Sodickson, T. Pock, and F. Knoll. “Learning a variational network for reconstruction of accelerated MRI data”. *Magn. Reson. Med.* 79.6 (2018), 3055–3071.

K. Hammernik, J. Schlemper, C. Qin, J. Duan, R. M. Summers, and D. Rueckert. “Systematic evaluation of iterative deep neural networks for fast parallel MRI reconstruction with sensitivity-weighted coil combination”. *Magn. Reson. Med.* (2021), available online: `https://doi.org/10.1002/mrm.28827`.

Y. Huang, T. Würfl, K. Breininger, L. Liu, G. Lauritsch, and A. Maier. “Some Investigations on Robustness of Deep Learning in Limited Angle Tomography”. *Medical Image Computing and Computer Assisted Intervention (MICCAI)*. 2018, 145–153.

S. Jégou, M. Drozdzal, D. Vazquez, A. Romero, and Y. Bengio. “The one hundred layers tiramisu: Fully convolutional densenets for semantic segmentation”. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2017, 11–19.

K. H. Jin, M. T. McCann, E. Froustey, and M. Unser. “Deep convolutional neural network for inverse problems in imaging”. *IEEE Trans. Image Process.* 26.9 (2017), 4509–4522.

E. Kang, J. Min, and J. C. Ye. “A deep convolutional neural network using directional wavelets for low-dose X-ray CT reconstruction”. *Med. Phys.* 44.10 (2017), e360–e375.

F. Knoll, J. Zbontar, A. Sriram, M. J. Muckley, M. Bruno, A. Defazio, M. Parente, K. J. Geras, J. Katsnelson, H. Chandarana, Z. Zhang, M. Drozdzalv, A. Romero, M. Rabbat, P. Vincent, J. Pinkerton, D. Wang, N. Yakubova, E. Owens, C. L. Zitnick, M. P. Recht, D. K. Sodickson, and Y. W. Lui. “fastMRI: A Publicly Available Raw k-Space and DICOM Dataset of Knee Images for Accelerated MR Image Reconstruction Using Machine Learning”. *Radiology Artif. Intell.* 2.1 (2020), e190007.

C. McCollough. “TU-FG-207A-04: Overview of the Low Dose CT Grand Challenge”. *Med. Phys.* 43.6Part35 (2016), 3759–3760.

M. J. Muckley, B. Riemenschneider, A. Radmanesh, S. Kim, G. Jeong, J. Ko, Y. Jun, H. Shin, D. Hwang, M. Mostapha, S. Arberet, D. Nickel, Z. Ramzi, P. Ciuciu, J.-L. Starck, J. Teuwen, D. Karkalousos, C. Zhang, A. Sriram, Z. Huang, N. Yakubova, Y. Lui, and F. Knoll. “State-of-the-Art Machine Learning MRI Reconstruction in 2020: Results of the Second fastMRI Challenge”. arXiv:2012.06318. 2020.

S. Mukherjee, S. Dittmer, Z. Shumaylov, S. Lunz, O. Öktem, and C.-B. Schönlieb. “Learned convex regularizers for inverse problems”. arXiv:2008.02839. 2020.

A. Raj, Y. Bresler, and B. Li. “Improving Robustness of Deep-Learning-Based Image Reconstruction”. *Proceedings of the 37th International Conference on Machine Learning (ICML).* 2020, 7932–7942.

Y. Romano, M. Elad, and P. Milanfar. “The Little Engine That Could: Regularization by Denoising (RED)”. *SIAM J. Imag. Sci.* 10.4 (2017), 1804–1844.

O. Ronneberger, P. Fischer, and T. Brox. “U-Net: Convolutional Networks for Biomedical Image Segmentation”. *Medical Image Computing and Computer Assisted Intervention (MICCAI).* 2015, 234–241.

J. Schlemper, I. Oksuz, J. R. Clough, J. Duan, A. P. King, J. A. Schnabel, J. V. Hajnal, and D. Rueckert. “dAUTOMAP: decomposing AUTOMAP to achieve scalability and enhance performance”. arXiv:1909.10995. 2019.

E. Sidky, I. Lorente, J. G. Brankov, and X. Pan. “Do CNNs solve the CT inverse problem?” *IEEE Trans. Biomed. Eng.* 68.6 (2021), 1799–1810.

D. Ulyanov, A. Vedaldi, and V. Lempitsky. “Deep image prior”. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).* 2018, 9446–9454.

Bibliography IV

Y. Yang, J. Sun, H. Li, and Z. Xu. “Deep ADMM-Net for Compressive Sensing MRI”. *Advances in Neural Information Processing Systems 29*. 2016, 10–18.

J. Zbontar, F. Knoll, A. Sriram, T. Murrell, Z. Huang, M. J. Muckley, A. Defazio, R. Stern, P. Johnson, M. Bruno, M. Parente, K. J. Geras, J. Katsnelson, H. Chandarana, Z. Zhang, M. Drozdzal, A. Romero, M. Rabbat, P. Vincent, N. Yakubova, J. Pinkerton, D. Wang, E. Owens, C. L. Zitnick, M. P. Recht, D. K. Sodickson, and Y. W. Lui. “fastMRI: An Open Dataset and Benchmarks for Accelerated MRI”. arXiv:1811.08839. 2018.

K. Zhang, W. Zuo, S. Gu, and L. Zhang. “Learning deep CNN denoiser prior for image restoration”. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2017, 3929–3938.