物理约束下的深度生成学习：

小样本影像数据分析的新路径？

Qiegen Liu

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物理约束下的深度生成学习：小样本影像数据分析的新路径？

1. 磁共振快速成像: From CS to AI

2. ISICDM报告-----

医学成像重建中的深度学习方式比较：有监督、无监督及自监督学习

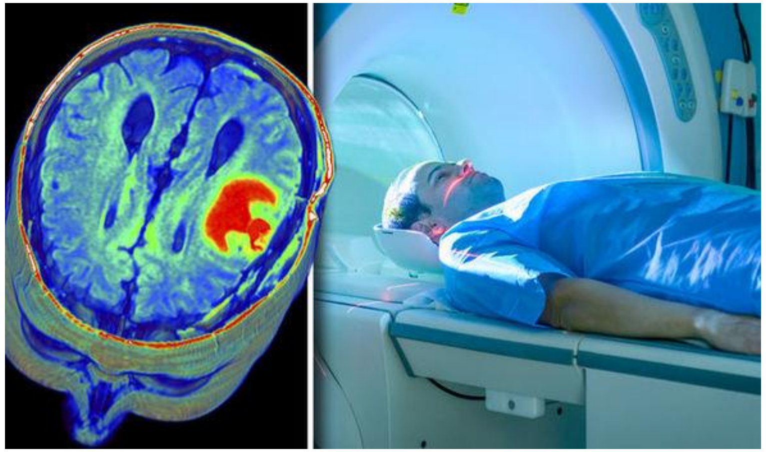
3. ISMRM报告-----在深度生成学习快速成像重建的工作

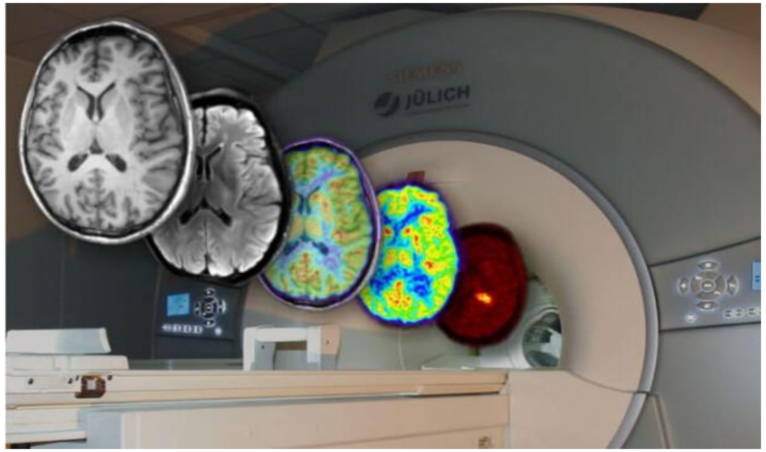
3.1 Examples of USL from DAE to DSM

3.2 Examples of DSM from image domain to k-space domain

4. 最新进展-----Hankel构造下的深度生成学习重建

Part 1-From CS to AI





Fast MRI Techniques:

- ✓ **MR physics (1970’s)**

  Pulse sequence design

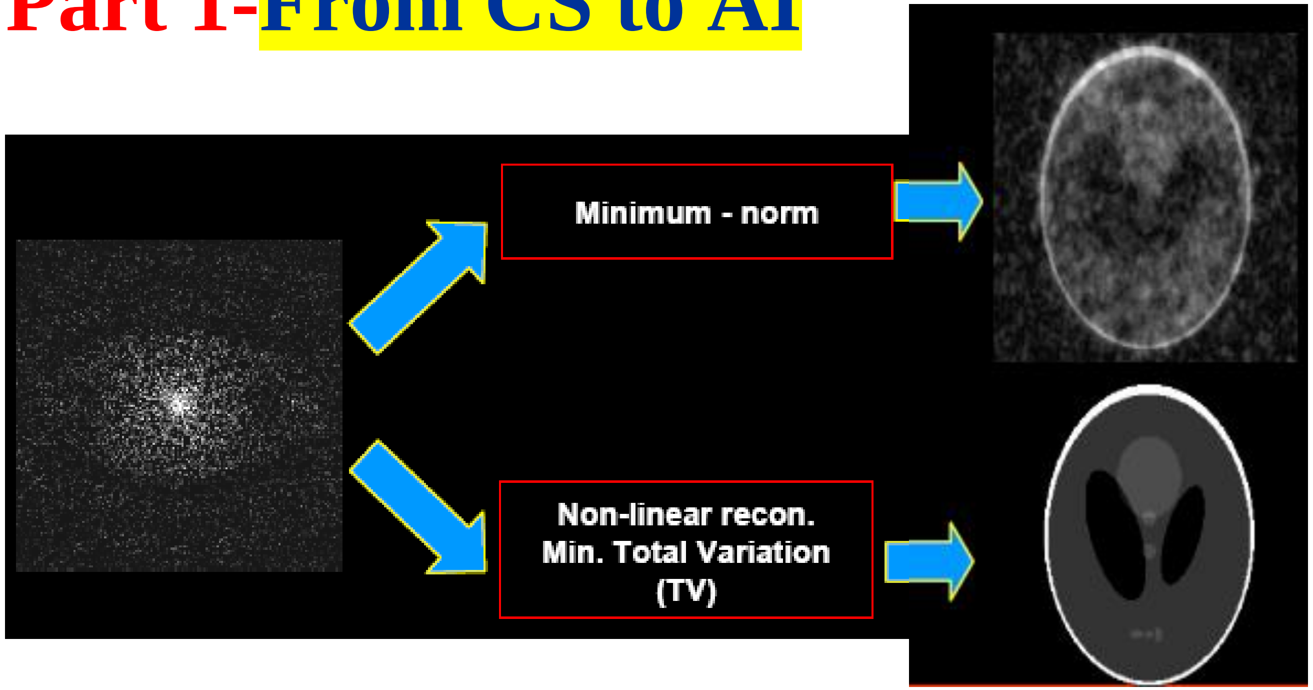
- ✓ **Hardware (2000’s)**

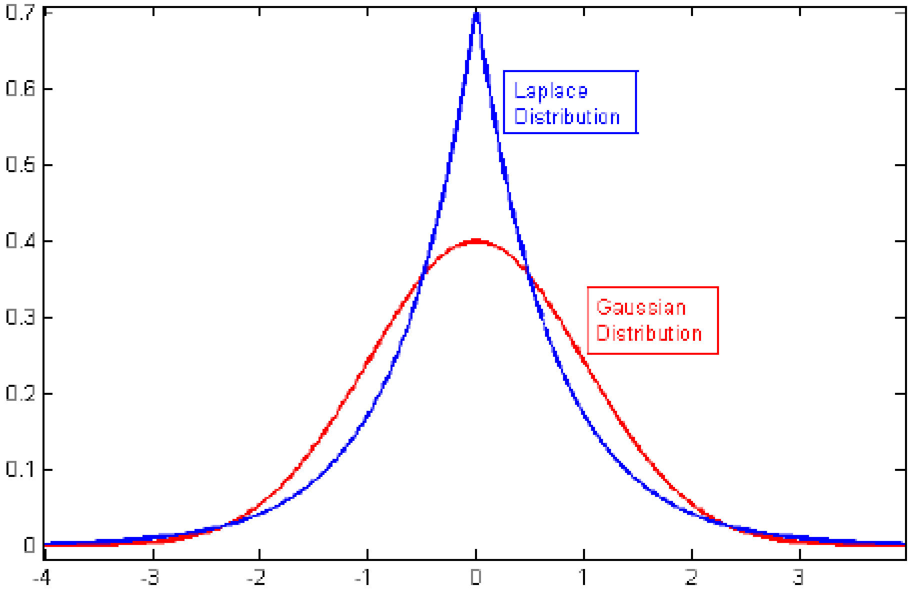
  Parallel imaging with phased array coils

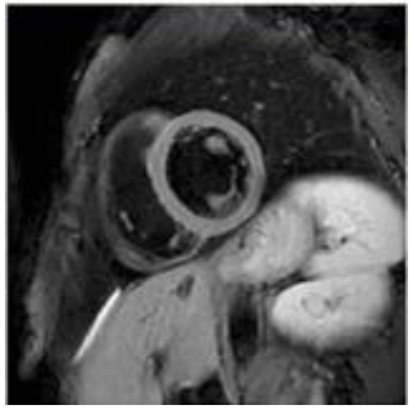
- ✓ **Partial K-space reconstruction** (past two decades)

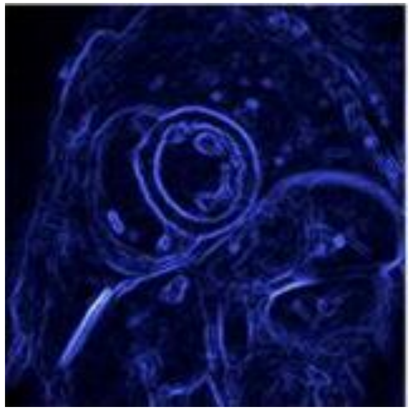
  Modeling using priori knowledge, etc.

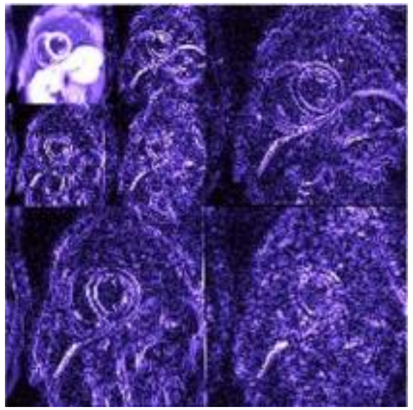
Part 1-From CS to AI

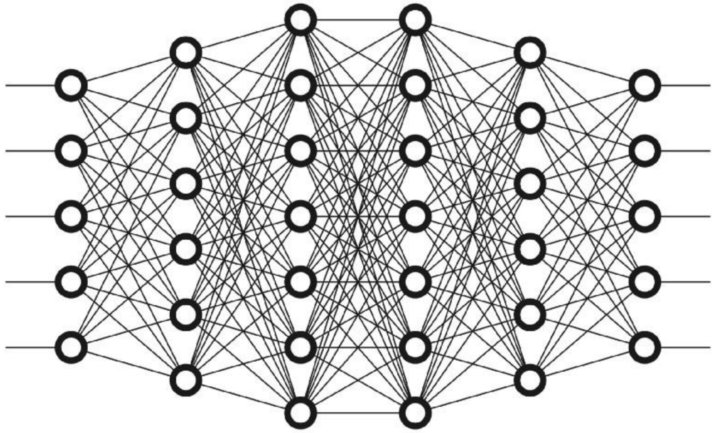










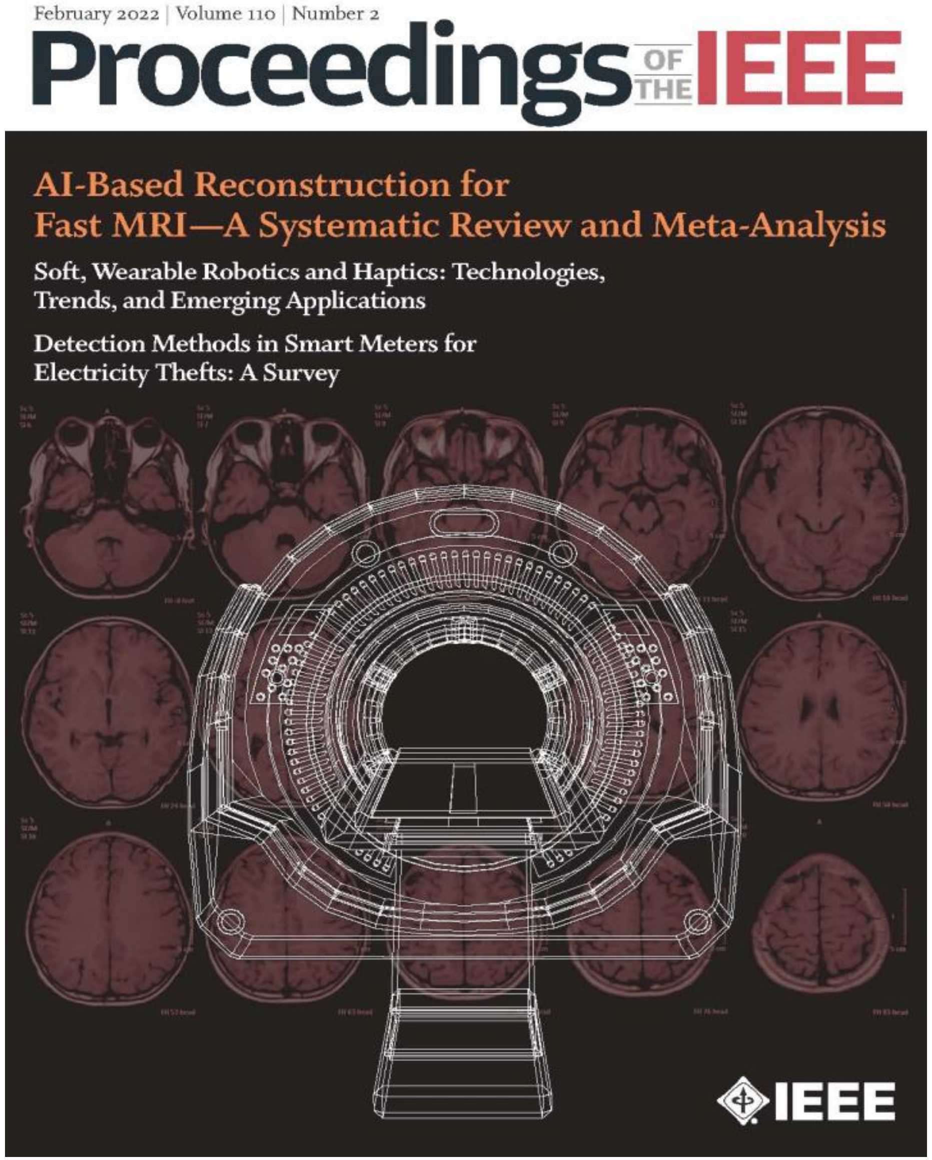


Sparse in Gradient

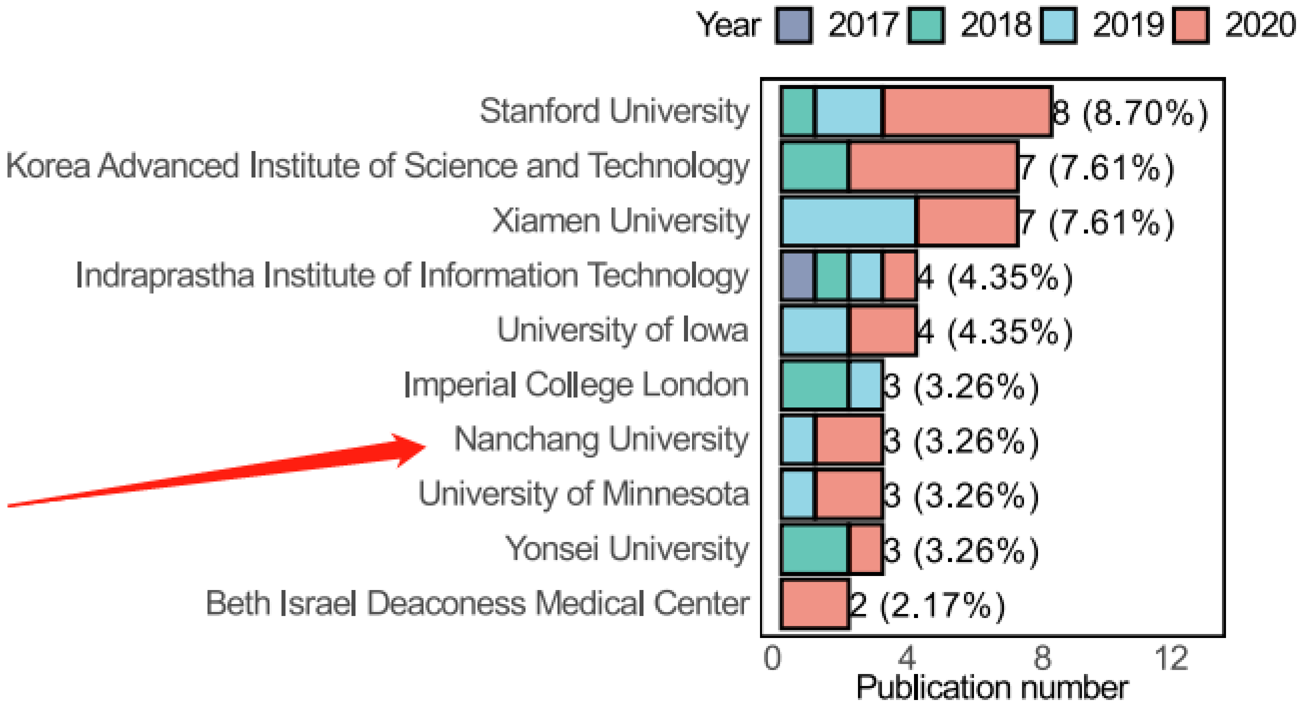
Sparse in Wavelet

From compressed sensing (CS) to Artificial intelligence (AI)

Part 1-From CS to AI

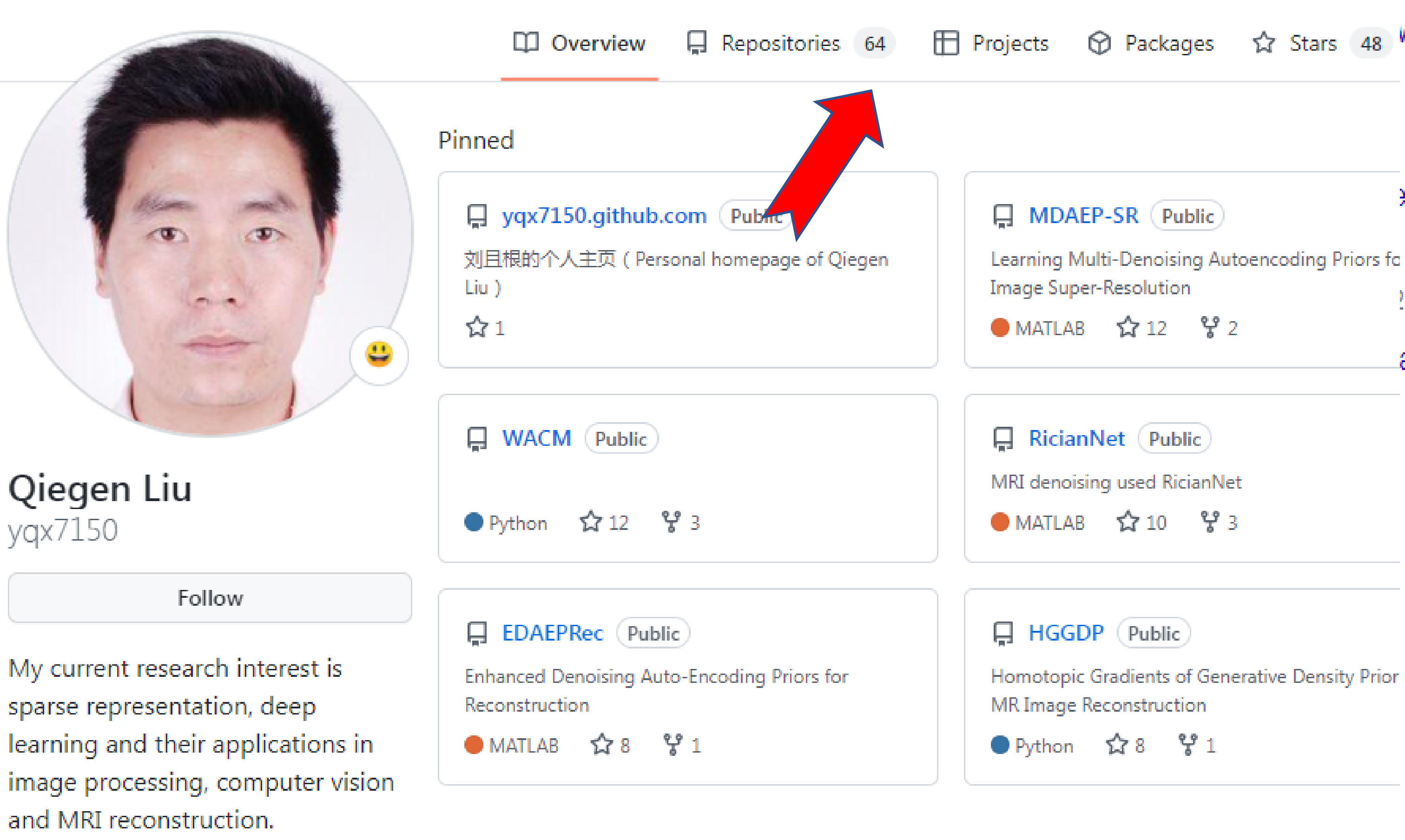


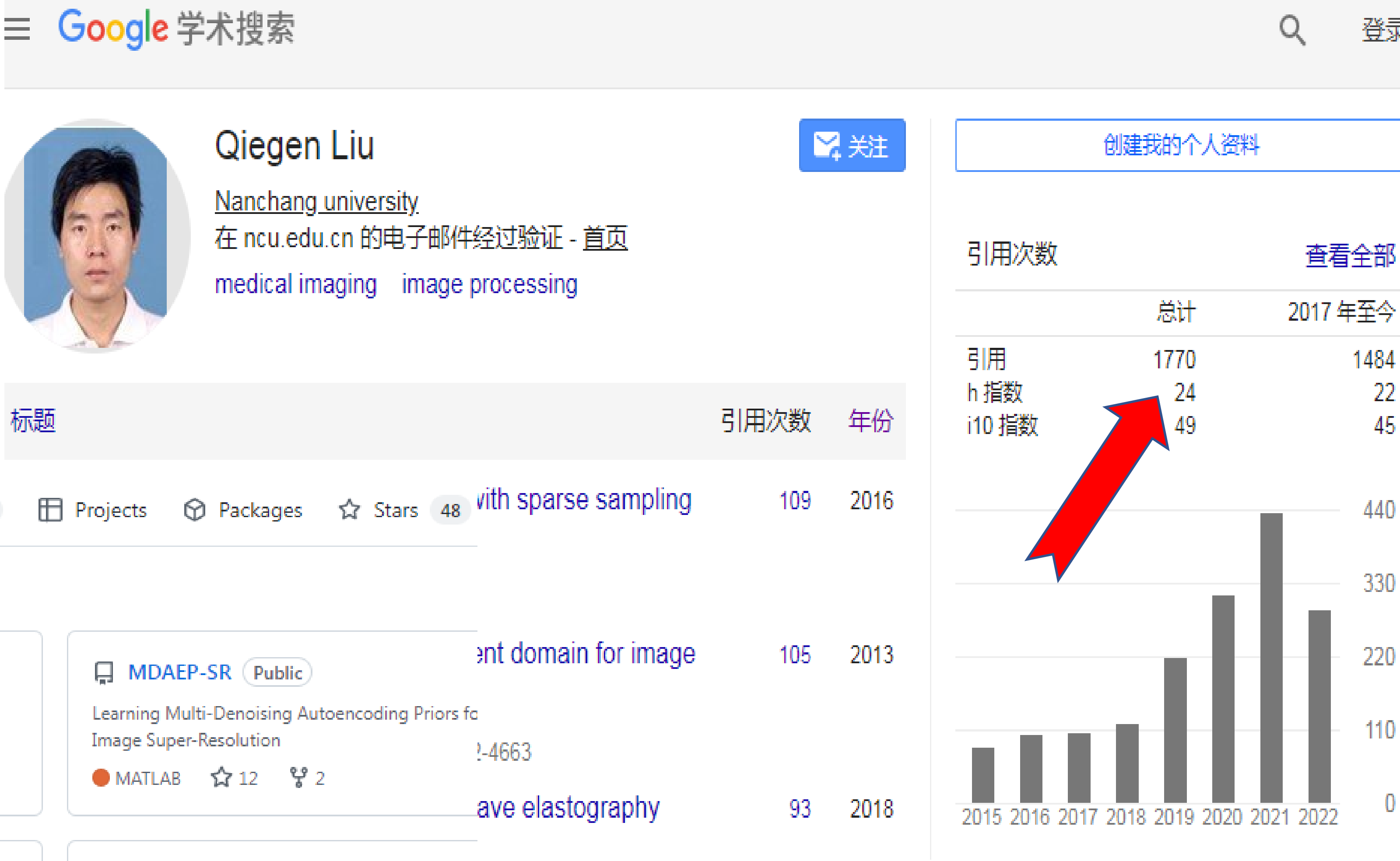
AI-Based Reconstruction for Fast MRI—A Systematic Review and Meta-Analysis



Part 1-From CS to AI

https://github.com/yqx7150





https://scholar.google.com/citations?user=T00zMvIAAAAJ&hl=zh-CN

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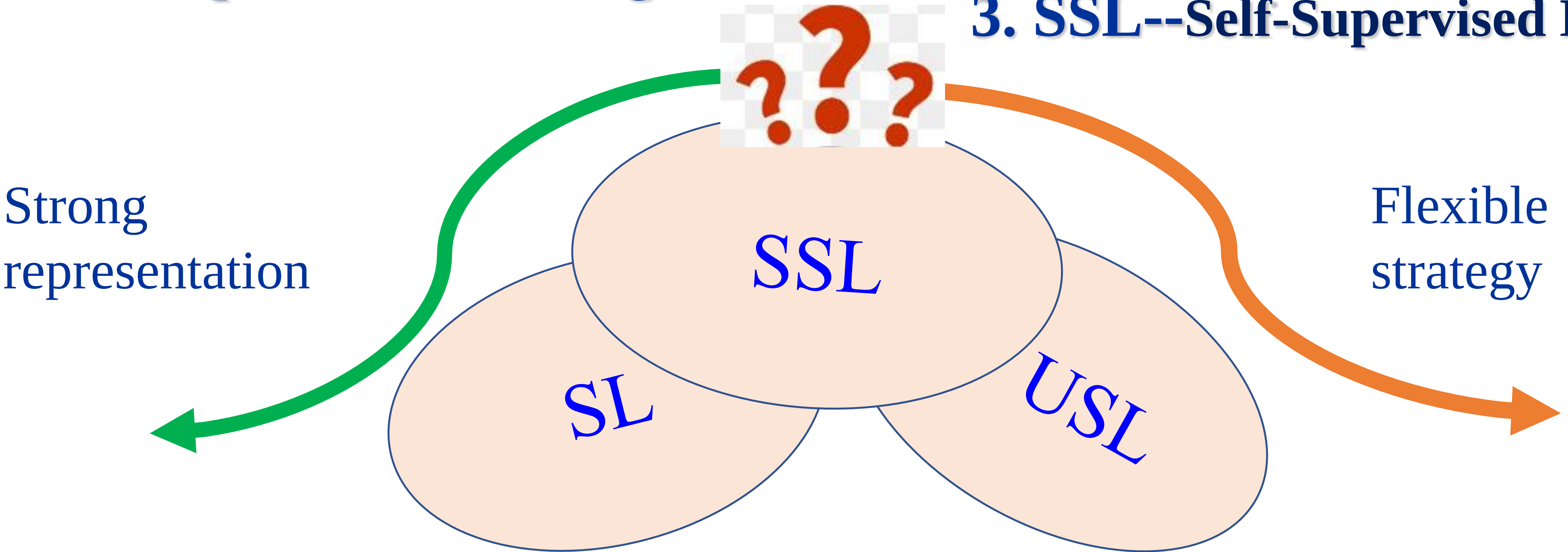
Comparison of deep learning methods in medical imaging: Supervised, unsupervised and self-supervised learning

Motivation:

The Purpose of Learning ?

1. **SL--Supervised Learning**
2. **USL–UnSupervised Learning**
3. **SSL--Self-Supervised Learning**



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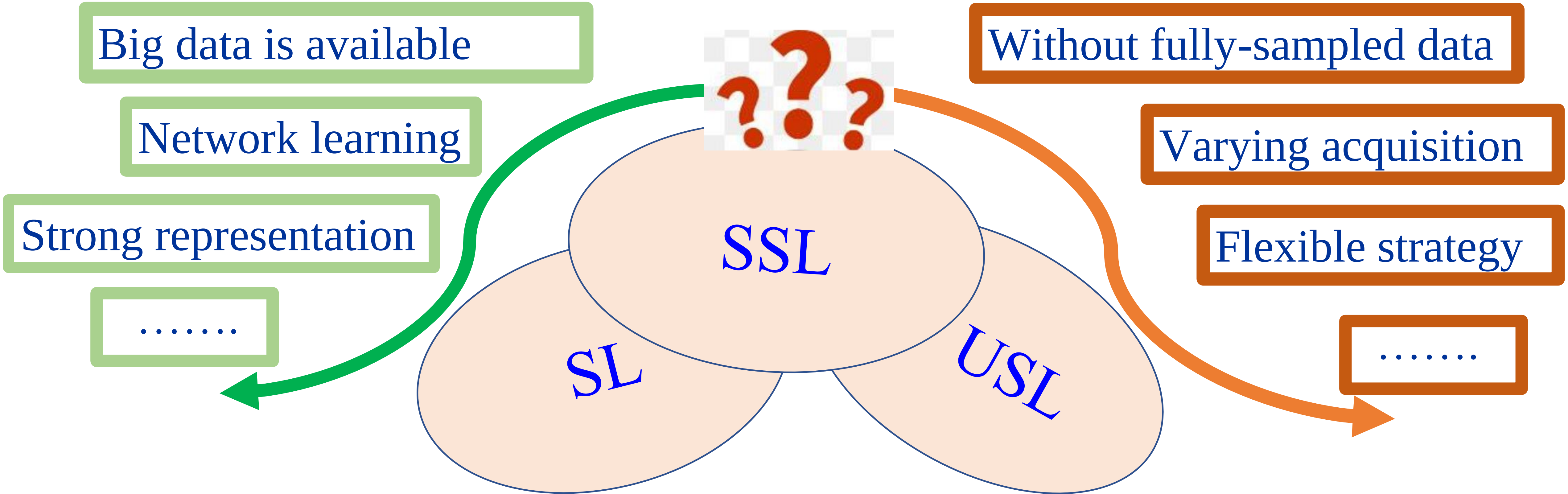


SL for MRI Rec

S. Wang, D. Liang, et al., “Accelerating magnetic resonance imaging via deep learning,” *ISBI*, 2016.
J. Sun, Z. Xu, et al., “Deep ADMM-net for compressive sensing MRI,” *NIPS*, 2016.
K Kwon, et al., “Learning-based reconstruction using artificial neural network for higher acceleration,” *ISMRM*, 2016.

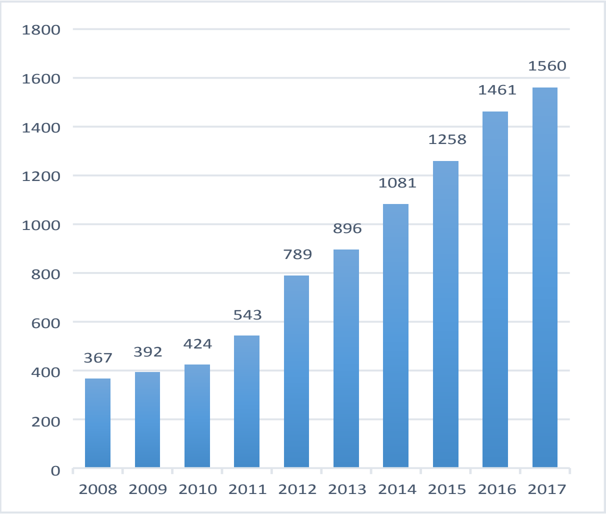
D. Lee, et al., “Compressed sensing and parallel MRI using deep residual learning,” *ISMRM*, 2017.
K. Kwon, et al., “A parallel MR imaging method using multilayer perceptron,” *MP*, 2017.

J. Schlemper, et al., “A deep cascade of convolutional neural networks for dynamic MR image reconstruction,” *IEEE TMI*, 2018.
D. Lee, J. Ye, et al., “Deep residual learning for accelerated MRI using magnitude and phase networks,” *IEEE TBME*, 2018.
Y. Han, et al., “Deep learning with domain adaptation for accelerated projection-reconstruction MR,” *MRM*, 2018.
T. Eo, et al., “KIKI-net: Cross-domain convolutional neural networks for reconstructing undersampled magnetic resonance images,” *MRM*, 2018.
C. Qin, et al., “Convolutional recurrent neural networks for dynamic MR image reconstruction,” *IEEE TMI*, 2018.
G. Yang, et al., “Dagan: Deep de-aliasing generative adversarial networks for fast compressed sensing MRI reconstruction,” *IEEE TMI*, 2018.
M. Akçakaya , et al., “Subject-specific convolutional neural networks for accelerated magnetic resonance imaging,” *IJCNN*, 2018.
B. Zhu, et al., “Image reconstruction by domain-transform manifold learning,” *Nature*, 2018.

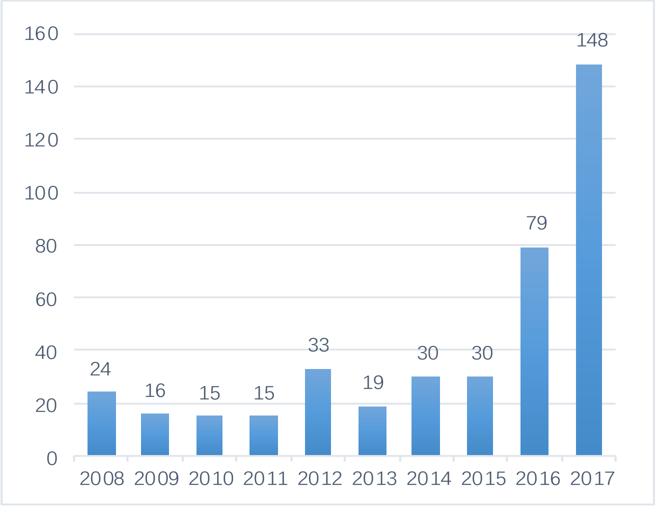
W. Zeng, et al., “A comparative study of CNN-based super-resolution methods in MRI reconstruction and its beyond,” *Signal Processing: Image Communication*, 2020.

“Web of Science”

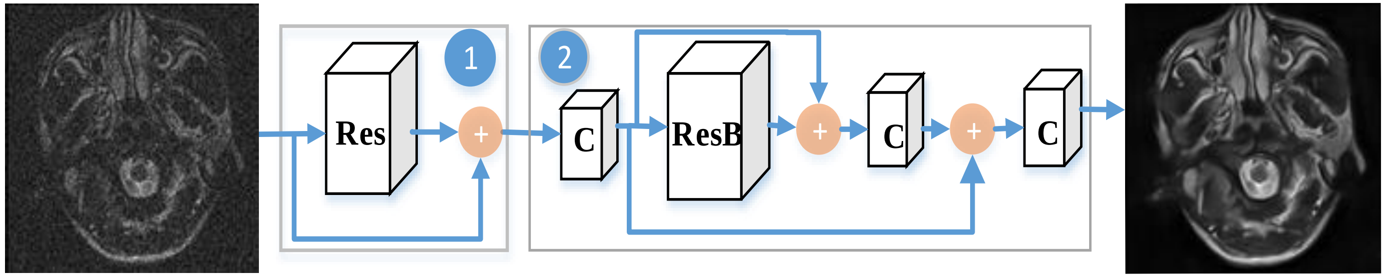
Image Reconstruction



CNN-based Reconstruction



SL for MRI Rec



有监督学习缺点：
-----当测试环境改变时，
训练环境也要改变

MRI 2020 论文

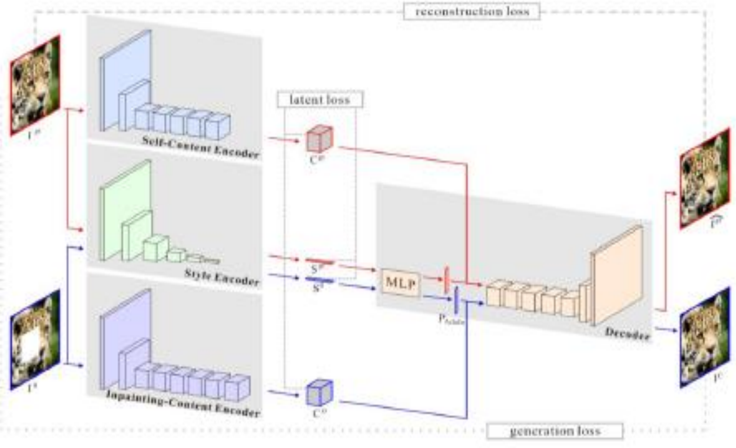
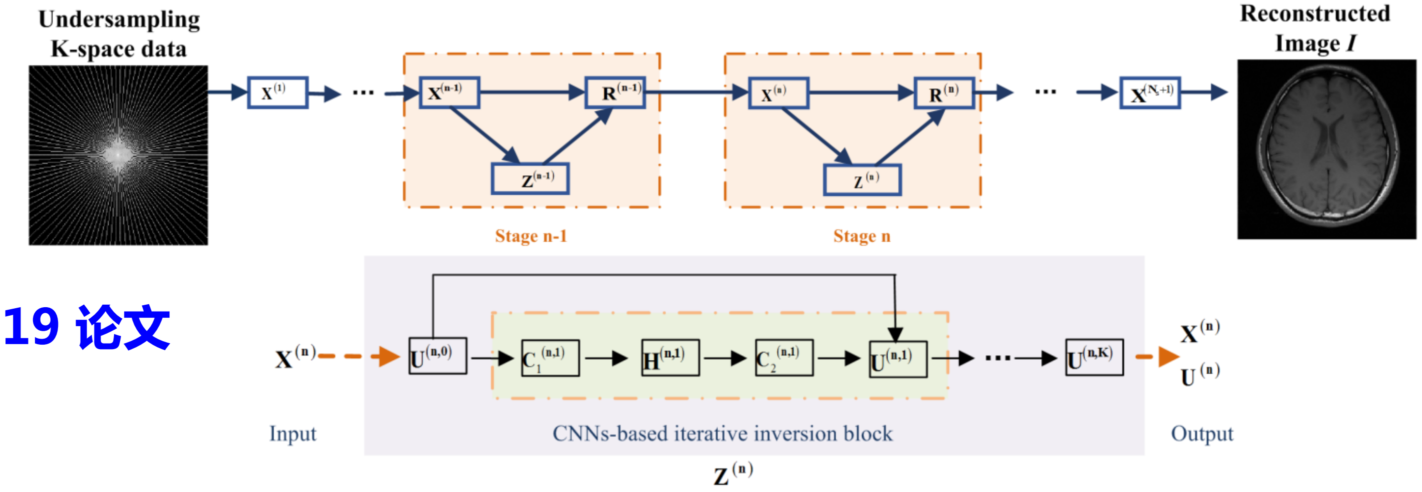


Figure 2. Architecture of inpainting network

AAAI 2019 论文



TCI 2020 论文

Y. Liu#, Q. Liu#, M. Zhang, Q. Yang, et al., "IFR-Net: Iterative feature refinement network for compressed sensing MRI", TCI, vol. 6, pp. 434-446, 2020.
S. Li, J. Zhou, D. Liang, Q. Liu, "MRI denoising using progressively distribution-based neural network", MRI, 2020. https://doi.org/10.1016/j.mri.2020.04.006.
J. Xiao, L. Liao, Q. Liu, R. Hu, "CISI-Net: Explicit latent content inference and imitated style rendering for image inpainting", AAAI, 354-362, 2019.

SL for MRI Rec

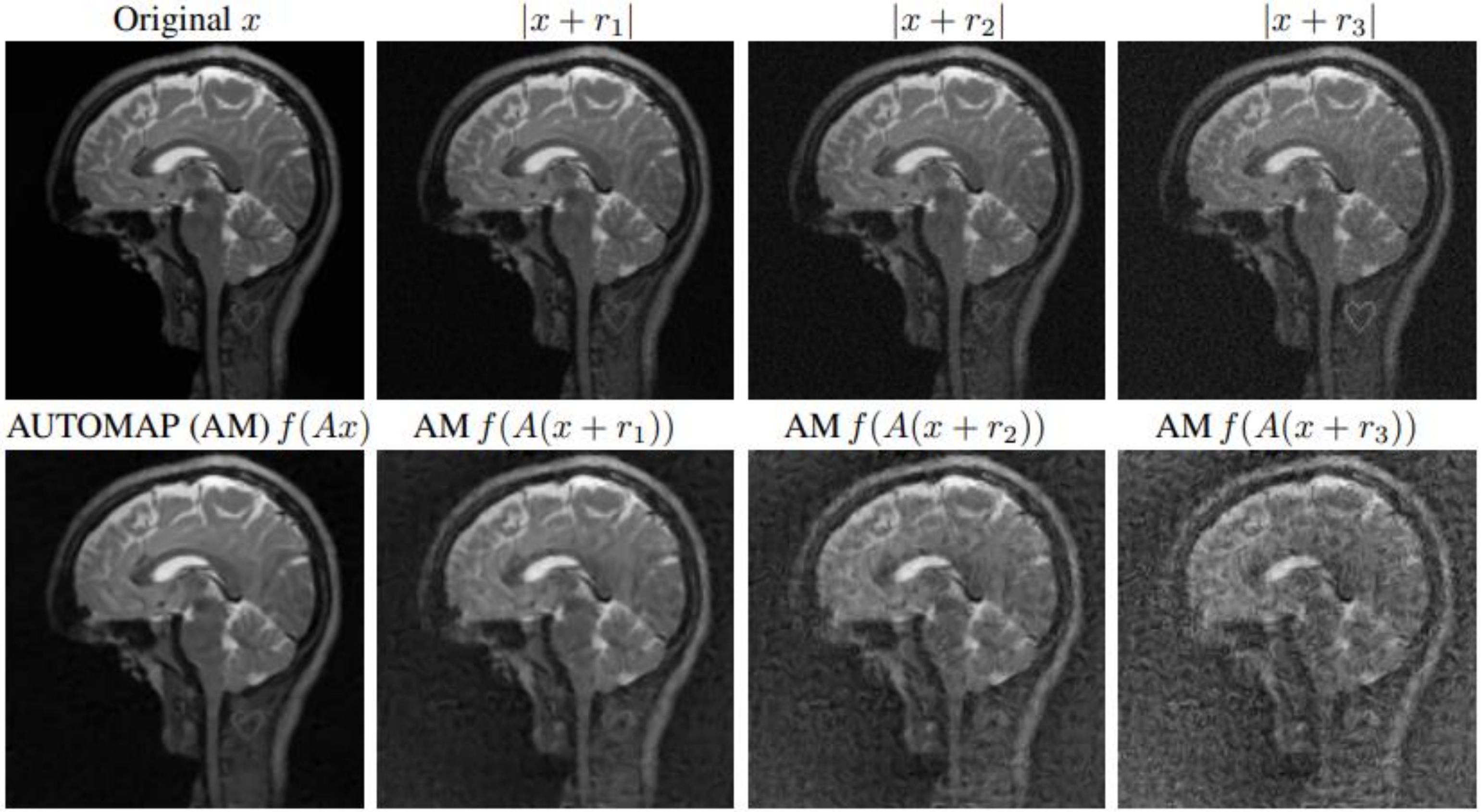
PNAS 2020

They also lack flexibility and stability when the environments of under-sampling schemes and acceleration factors has some perturbations

部分成像：$Ax = y, \quad A = F_p$

端对端学习重建：$\tilde{x} = f(y)$

存在扰动：$x \to x + r$



Antun V, Renna F, Poon C, et al., On instabilities of deep learning in image reconstruction and the potential costs of AI, PNAS, 2020.

SL for MRI Rec

PNAS 2020

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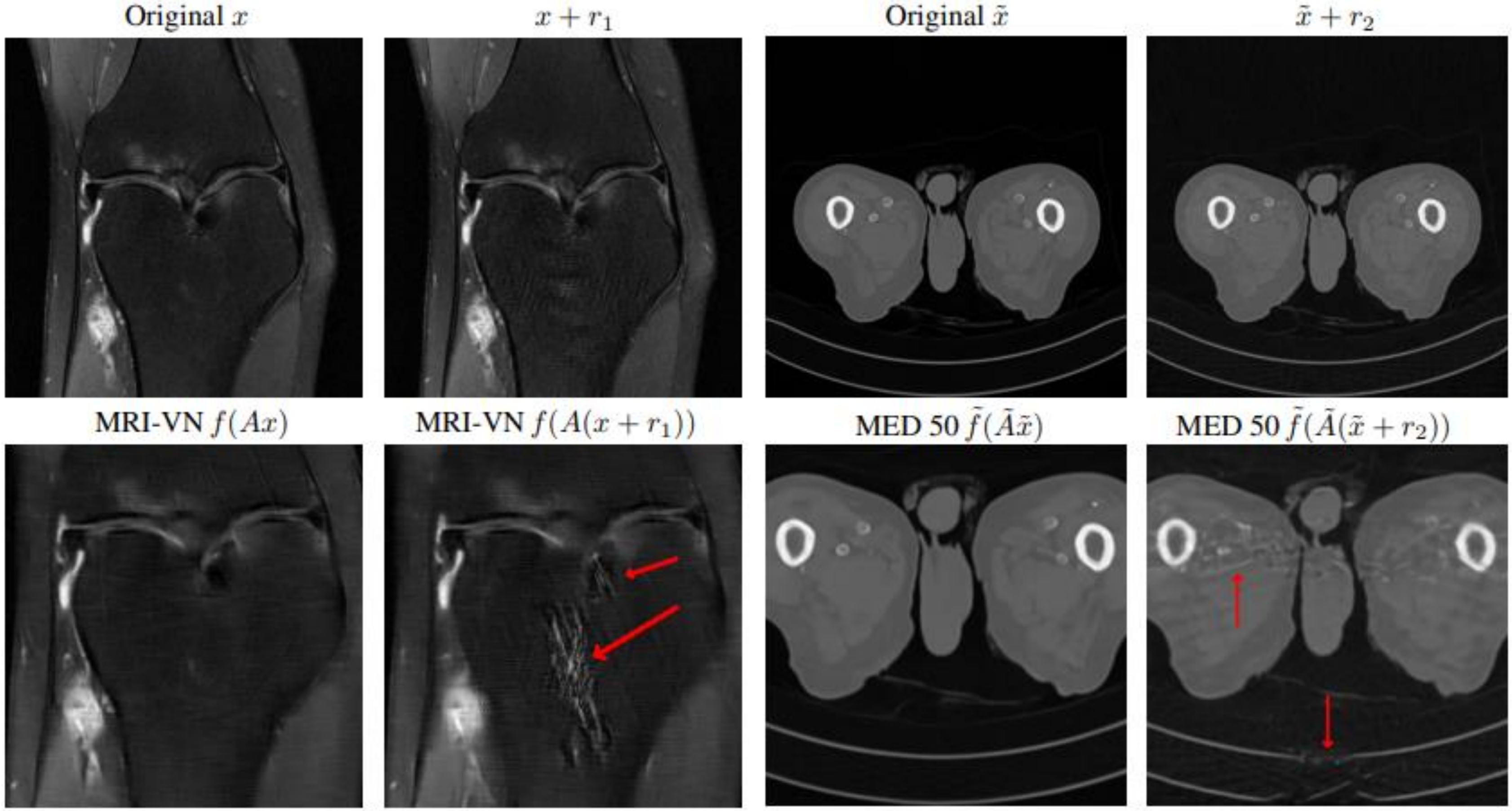

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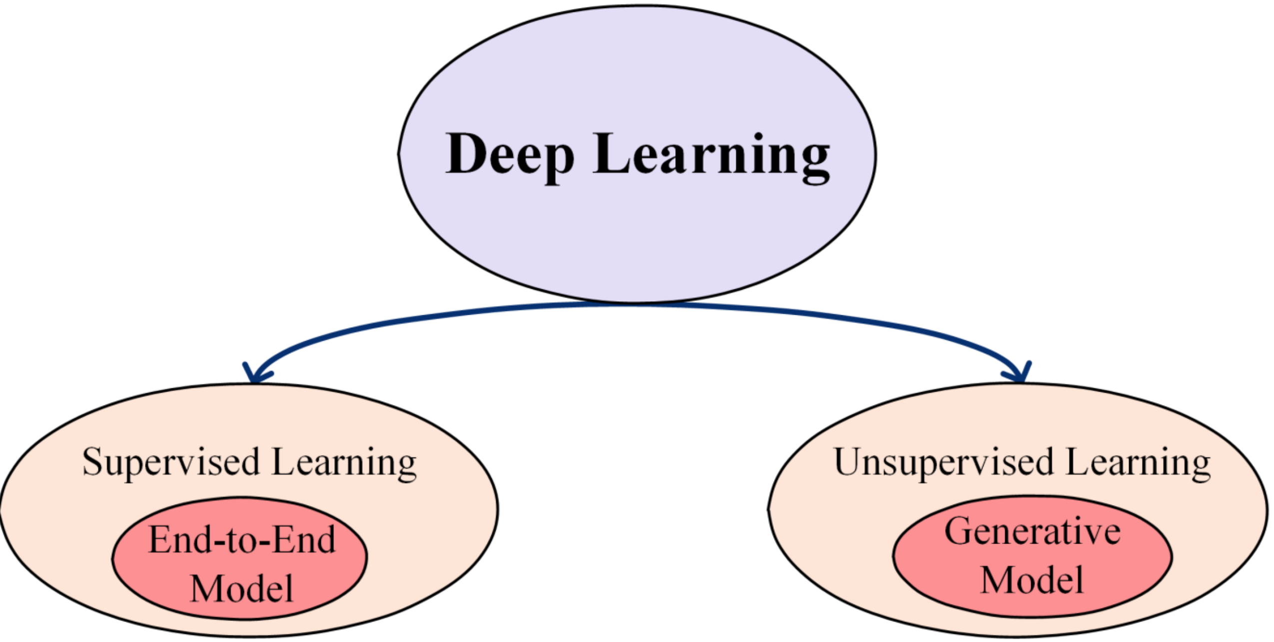
Five representatives of USL



Generative model

- 01 Denoising autoencoding(DAE)
- 02 Variational Autoencoders (VAE)
- 03 Generative Adversarial Network (GAN)
- 04 PixelCNN
- 05 Generative Flow (Glow)

Z. He, Q. Liu, et al., A comparative study of unsupervised deep learning methods in MRI reconstruction, *iMRI*, 2020.

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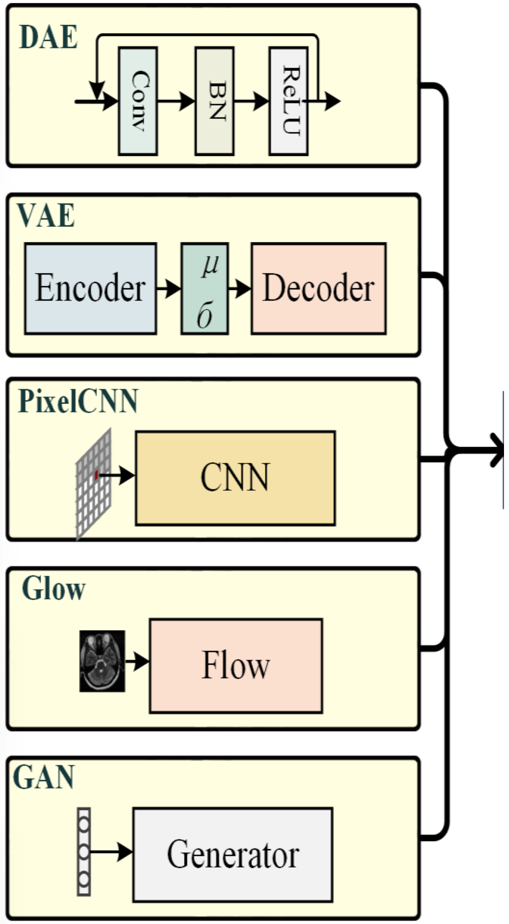
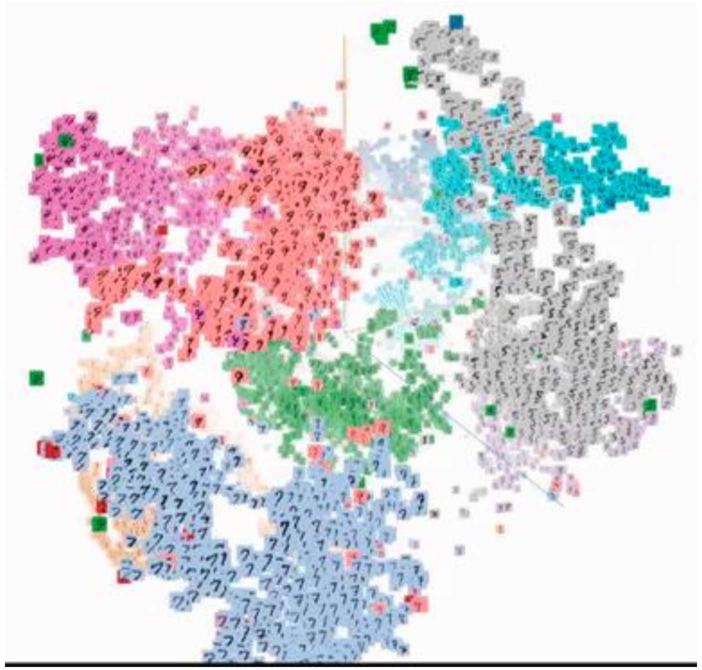


Data distribution $\log p(x)$



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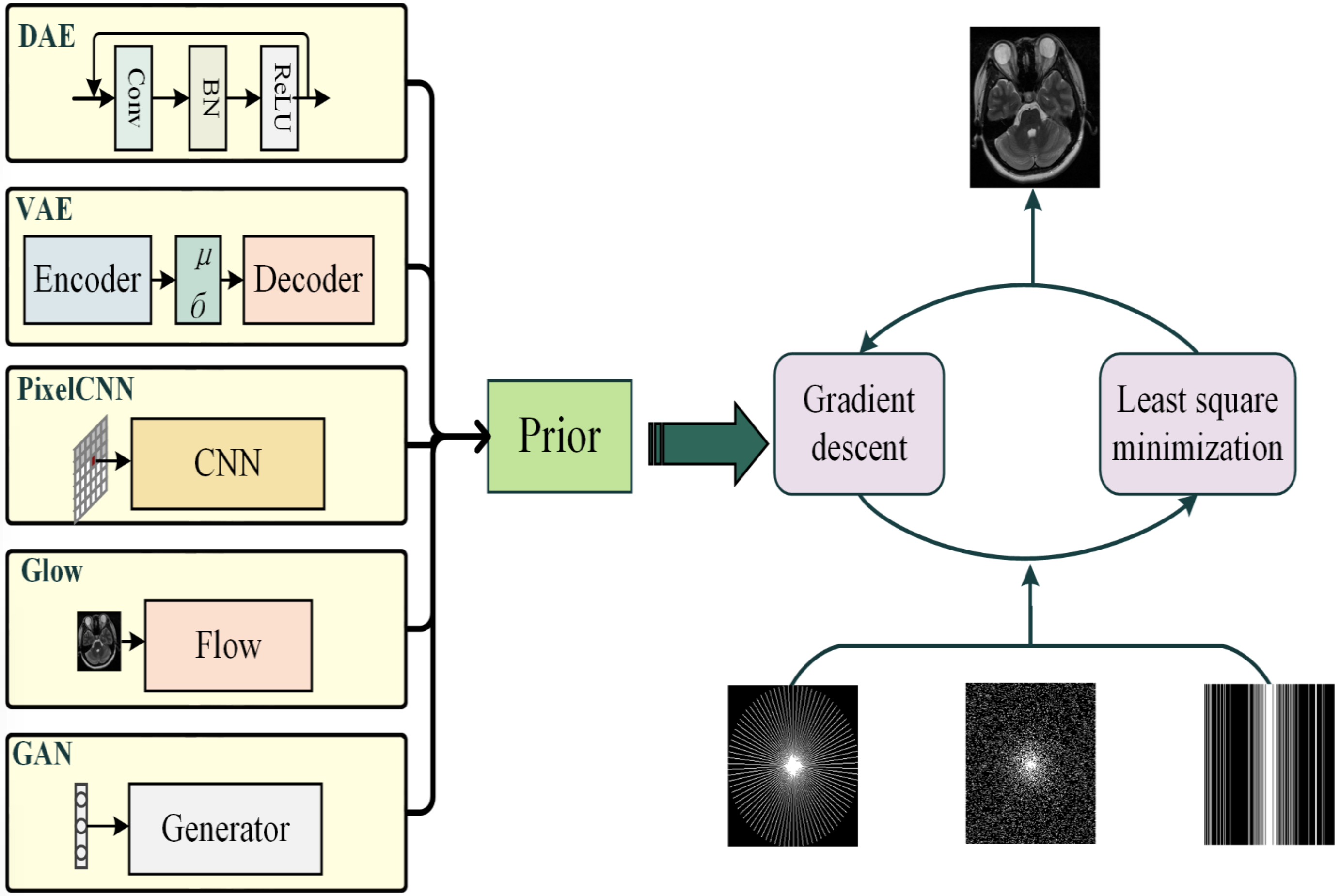
POCS-like scheme for MRI Rec



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POCS-like scheme for MRI Rec

$$\begin{cases} x^{k+1/2} = x^k - \alpha \nabla prior(x^k) & \text{Update on prior term} \\ x^{k+1} = \arg\min_x \|F_p x - y\|_2^2 + \lambda \|x - x^{k+1/2}\|_2^2 & \text{Update on data-consistency} \end{cases}$$

Algorithm 1: Unsupervised Learning for Reconstruction (USLearn)
Prior learning stage
Input: MR dataset: $x \in C^{n \times n}$
Output: Trained network model by learning $p(x)$
Iterative reconstruction stage
1: Initialization: $x^0 = F_p^H y$
2: For $k = 0, 1, 2, \cdots, K$ do
3: Pre-process to get the corresponding network input $m^k = pre(x^k)$
4: Get gradient $\nabla_m prior(m)$ at m^k
5: Update $m^{k+1} = m^k + \alpha \nabla_m prior(m^k)$
6: Post-process $x^{k+1} = post(m^{k+1})$ for projection
7: Projection x^{k+1} in Eq. (8)
8: Return x^K

Z. He, Q. Liu, et al., A comparative study of unsupervised deep learning methods in MRI reconstruction, *iMRI*, 2020.

Discussion of SL/USL/SSL

02 学习的有效性？
对特定场景分布的逼近

Strong representation

有监督学习在海量数据下怎样**增强**学习表示能力

自监督学习怎样**利用**特定成像场景构造数据标签

无监督学习怎样**吸收**更强先验信息

Flexible strategy

01 学习的灵活性？
各种成像场景的应用

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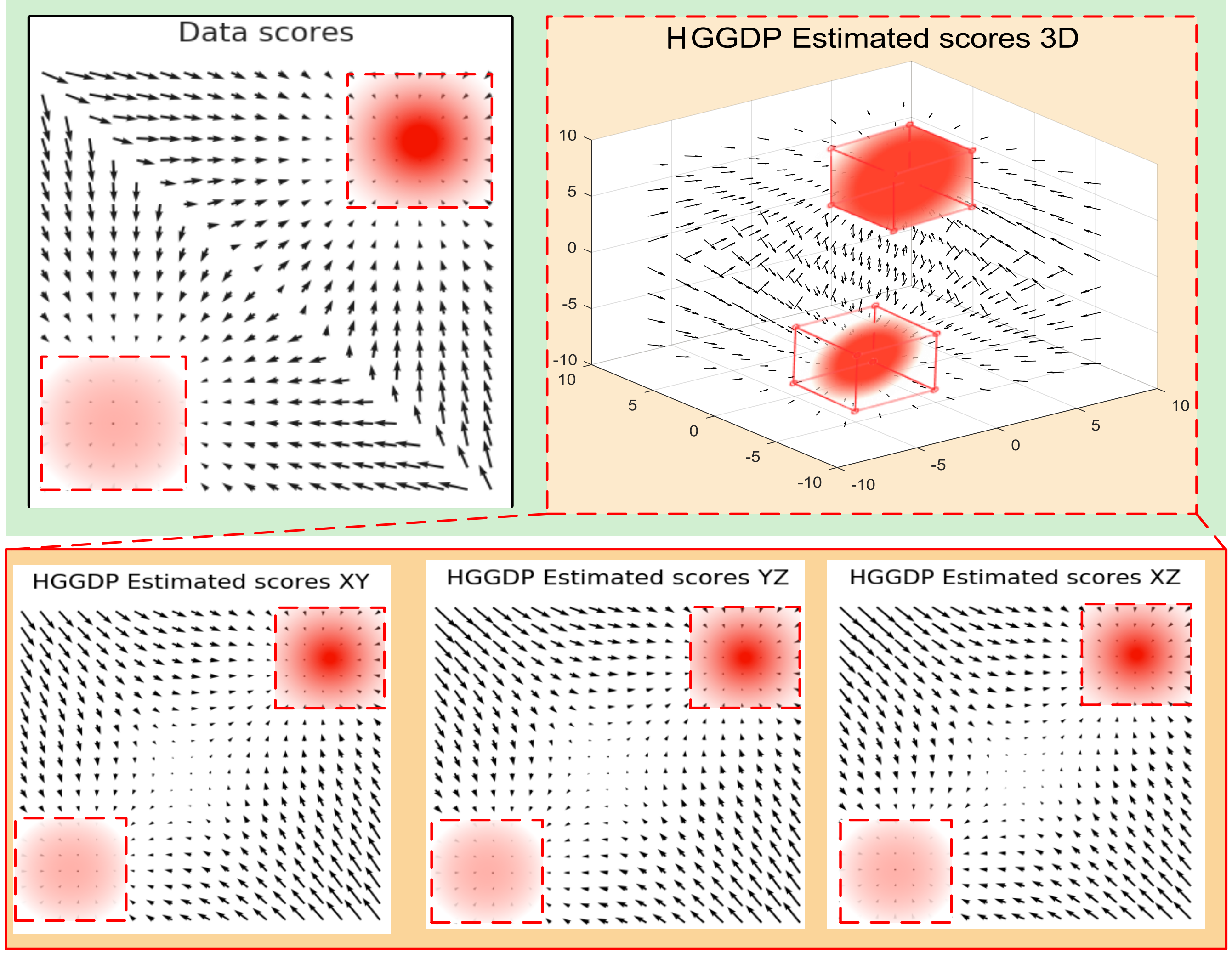
Underlying ideas for improvements

01

How to estimate $\nabla_x \log p_{data}(x)$?

Learning prior density in higher-dimensional space

With variable *X*, not with *x* itself



C. Quan, J. Zhou, Y. Zhu, Y. Chen, S. Wang, D. Liang, Q. Liu, Homotopic gradients of generative density prior s for MR image reconstruction, *IEEE Trans. Med. Imag.*, 2021.

Underlying ideas for improvements

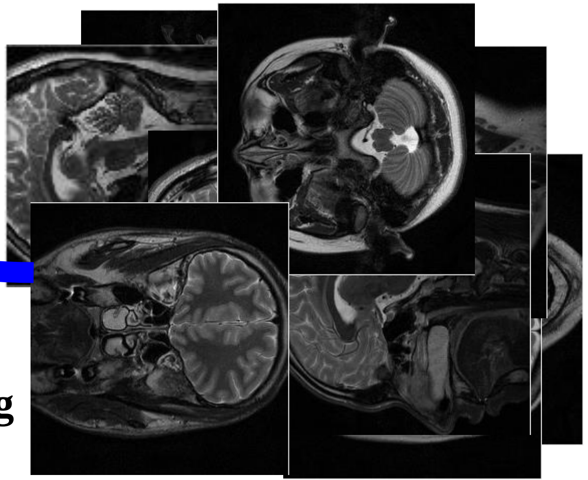
Learning prior density in different modality

02 Prior knowledge across modality?

With variable *z* , not with *x* itself

Prior learned from different modalities for CT recon

CT dataset	p = 0.8	47.47/0.9909
	p = 1	47.44/0.9908
	p = 1.5	47.18/0.9902
	p = 2	46.69/0.9888
DIV2K dataset	p = 0.8	47.54/0.9908
	p = 1	47.52/0.9907
	p = 1.5	47.24/0.9901
	p = 2	46.71/0.9887
MRI dataset	p = 0.8	46.69/0.9890
	p = 1	46.65/0.9889
	p = 1.5	46.41/0.9882
	p = 2	45.82/0.9863



F. Zhang, M. Zhang, B. Qin, Y. Zhang, Z. Xu, D. Liang, Q. Liu, REDAEP: Robust and enhanced denoising autoencoding prior for sparse-view CT reconstruction, *IEEE Trans. Radiat. Plasma Med. Sci.*, 2020.

USL from DAE to DSM

Q. Liu, Q. Yang, H. Cheng, S. Wang, M. Zhang, D. Liang, Highly undersampled magnetic resonance imaging reconstruction using autoencoding priors, ***Magn. Reson. Med.***, vol. 83, no. 1, pp. 322-336, 2020.

DAEP

DAE

S. Wang, J. Lv, Z. He, D. Liang, Y. Chen, M. Zhang, Q. Liu, Denoising auto-encoding priors in undecimated wavelet domain for MR image reconstruction, ***Neurocomputing***, vol.437, pp.325-338, 2021.

DMSP

DSM

Generative model

M. Zhang, M. Li, J. Zhou, Y, Zhu, S. Wang, D. Liang, Y. Chen, Q. Liu. High-dimensional embedding network derived prior for compressive sensing MRI reconstruction, ***Med. Image Anal.***, vol. 64, 101717, 2020.

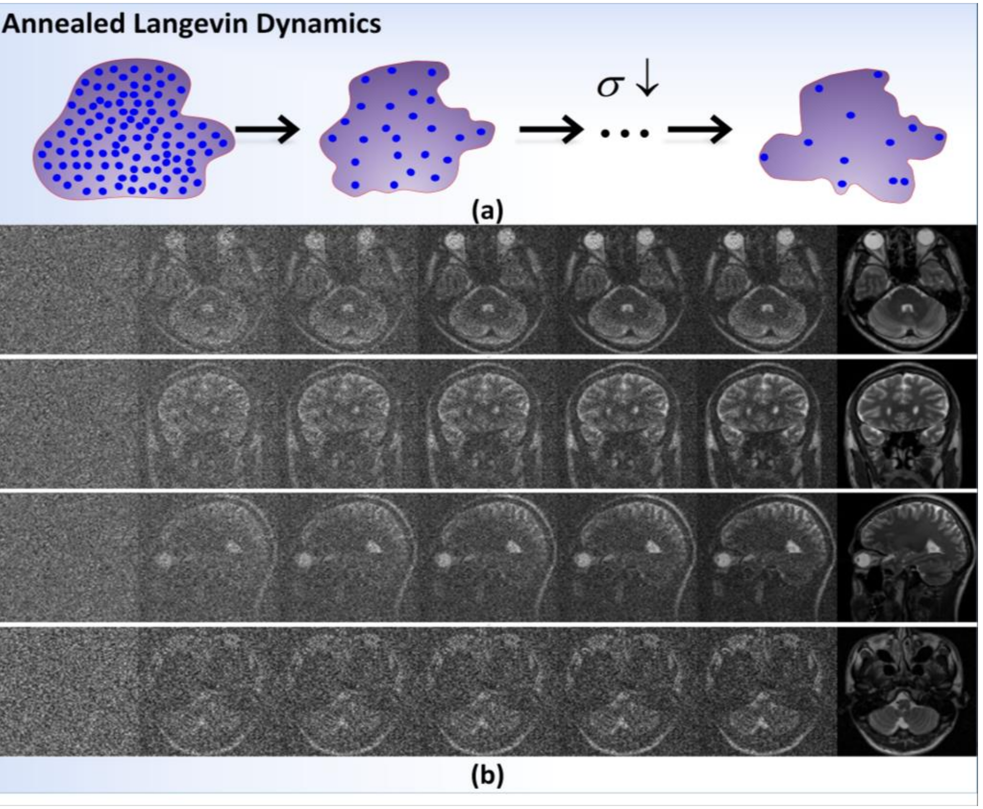
DMSP

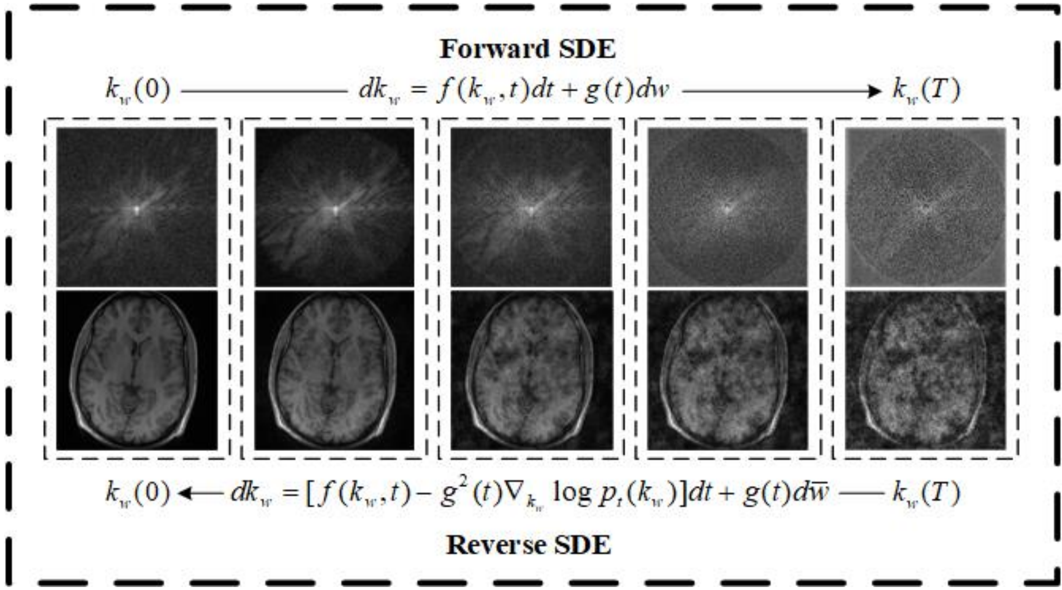
C. Quan, J. Zhou, Y. Zhu, Y. Chen, S. Wang, D. Liang, Q. Liu, Homotopic gradients of generative density priors for MR image reconstruction, ***IEEE Trans. Med. Imag.***, 2021.

DSM

DSM from image domain to k-space domain

Generative model in image domain





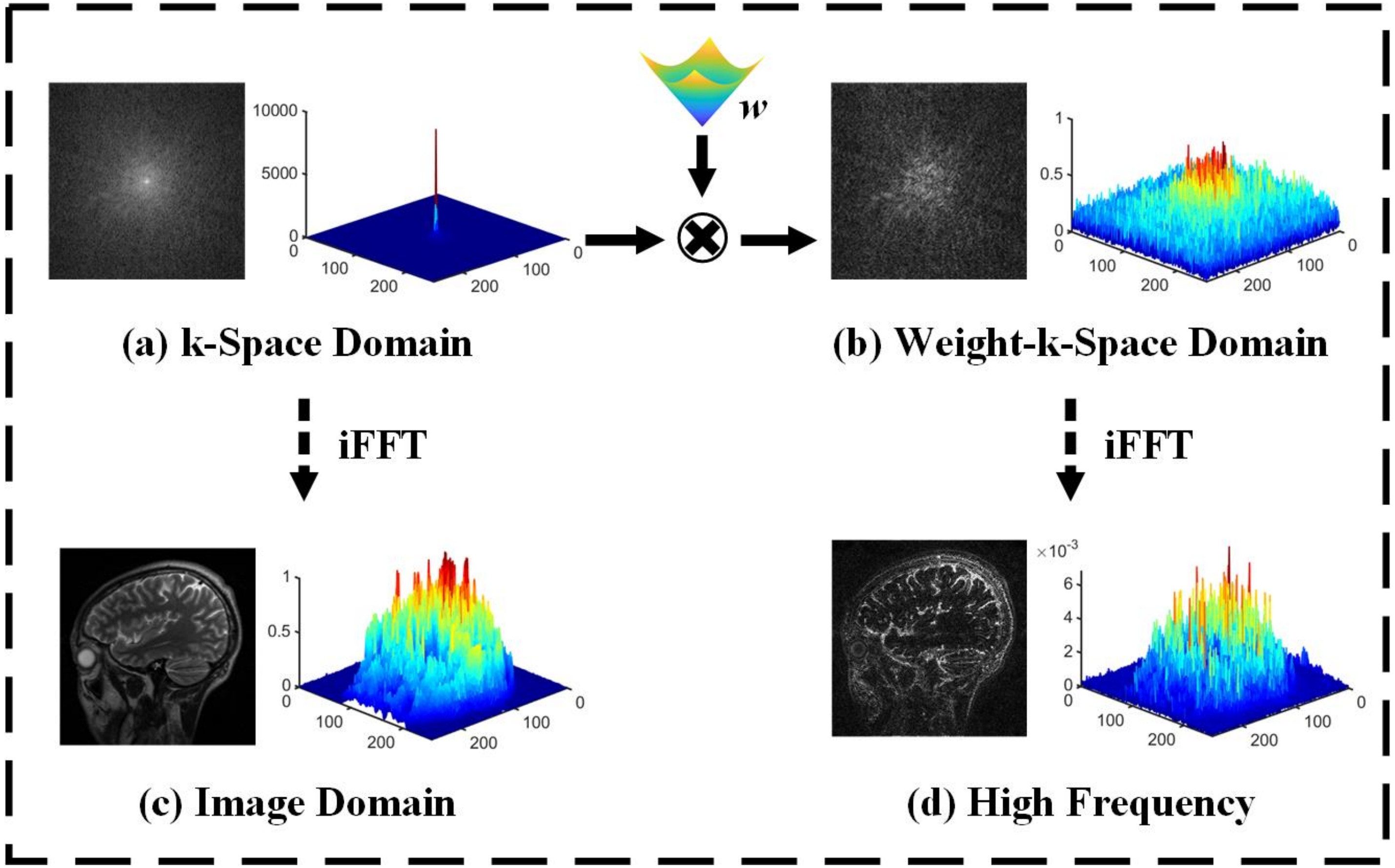
Generative model in k-space domain

Z. Tu, D. Liu, X. Wang, C. Jiang, M. Zhang, Q. Liu, D. Liang, WKGM: Weight-K-space generative model for parallel imaging reconstruction, xxx, 2022.

WKGM

https://github.com/yqx7150/WKGM

Algorithm overview



Visual comparison of the amplitude values in k-space domain and weight-k-space domain.

Prior learning in weighted k-space domain is more efficient !

Z. Tu, D. Liu, X. Wang, C. Jiang, M. Zhang, Q. Liu, D. Liang, WKGM: Weight-K-space generative model for parallel imaging reconstruction, https://arxiv.org/abs/2205.03883, 2022.

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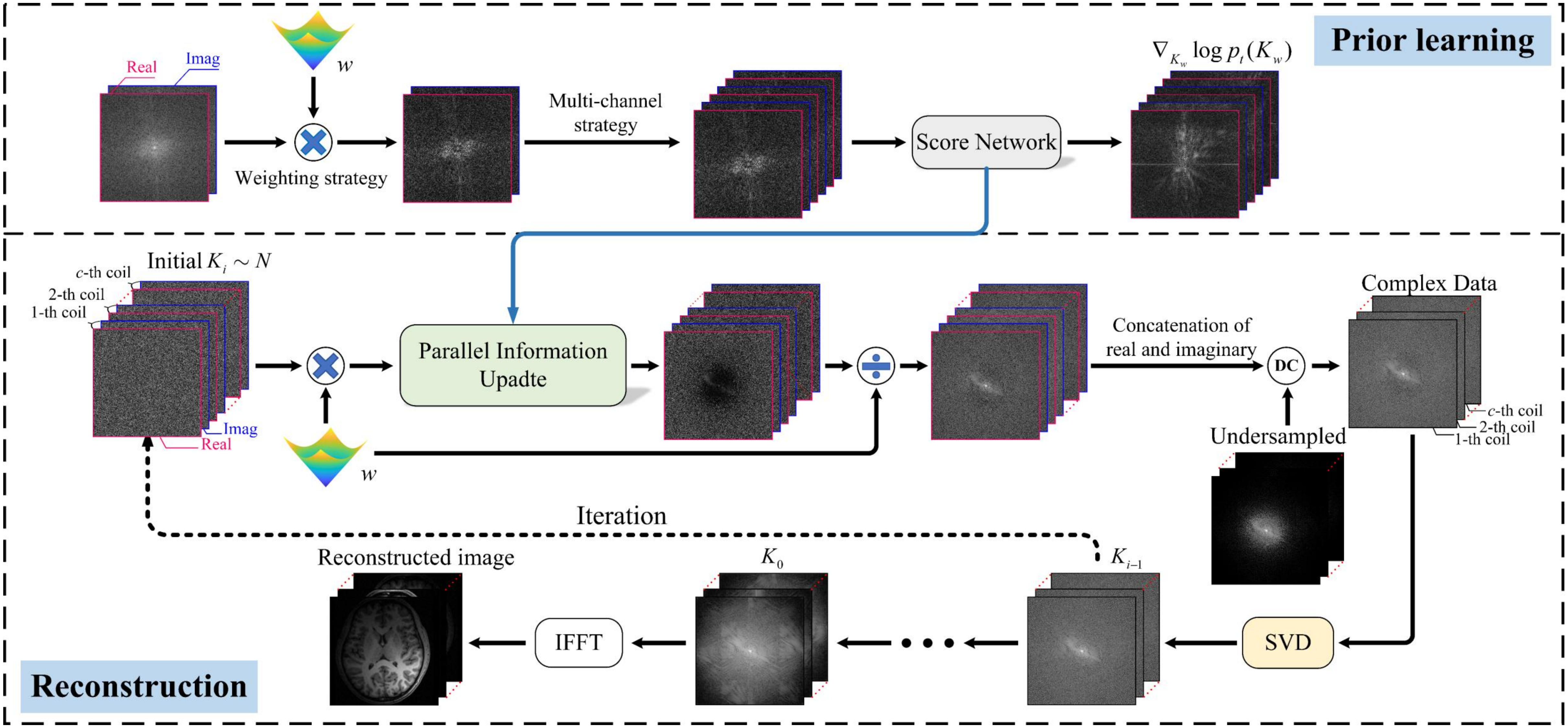

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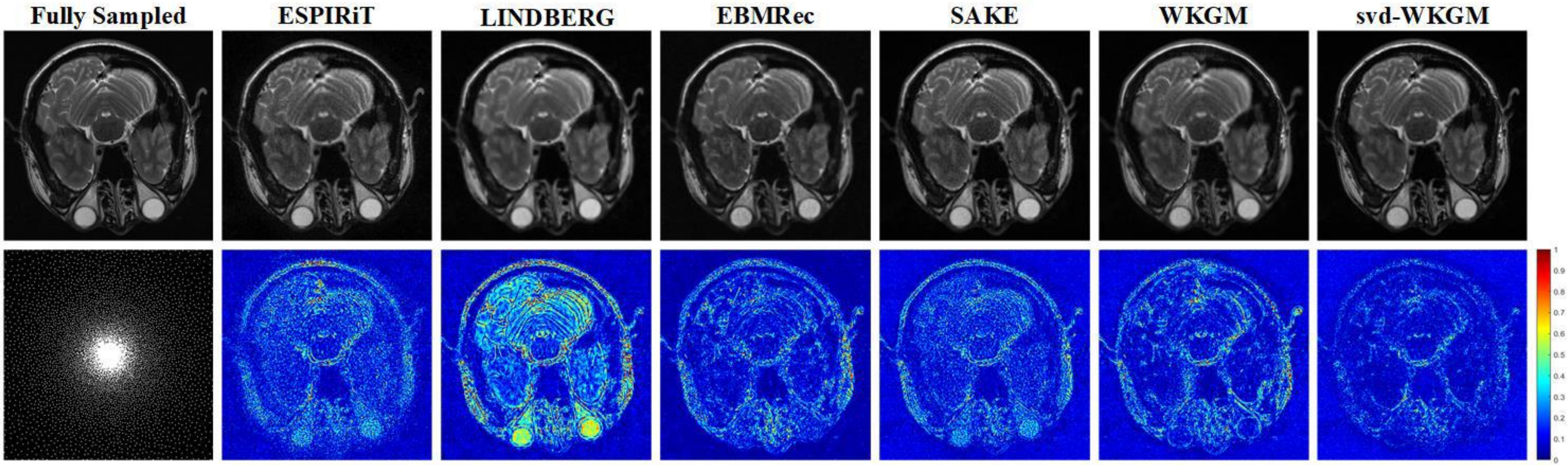
WKGM

Experimental results

https://github.com/yqx7150/WKGM



Parallel imaging reconstruction results by ESPIRiT, LINDBERG, EBMRec, SAKE, WKGM and svd-WKGM in *T 2 Transversal Brain* at *R*=10 2D Poisson disk under-sampling mask. The intensity of residual maps is five times magnify.

Z. Tu, D. Liu, X. Wang, C. Jiang, M. Zhang, Q. Liu, D. Liang, WKGM: Weight-K-space generative model for parallel imaging reconstruction, https://arxiv.org/abs/2205.03883, 2022.

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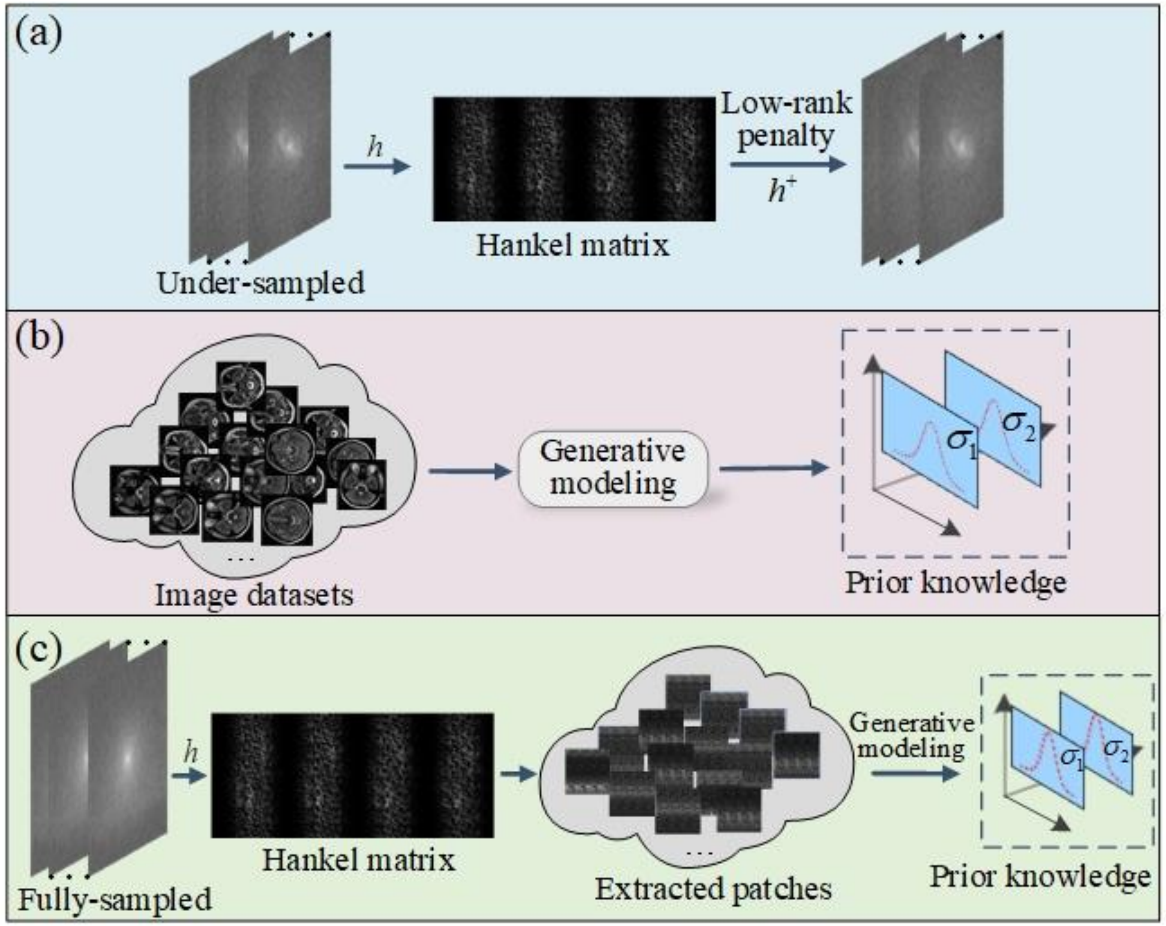

Conventional k-space iterative methods (e.g., SAKE) adopt low-rank penalty on Hankel matrix.

Existing generative modeling (e.g., HGGDP) on full y-sampled data.

HKGM on a single k-space measurement that condu cted on dataset of low-rank patches.

Prior learning in a single k-space measurement !

H. Peng, C. Jiang, X. Guan, C. Jiang, M. Zhang, D. Liang, Q. Liu. One-shot Generative Prior in Hankel-k-space for Parallel Imaging Reco nstruction, https://arxiv.org/abs/2208.07181, 2022.

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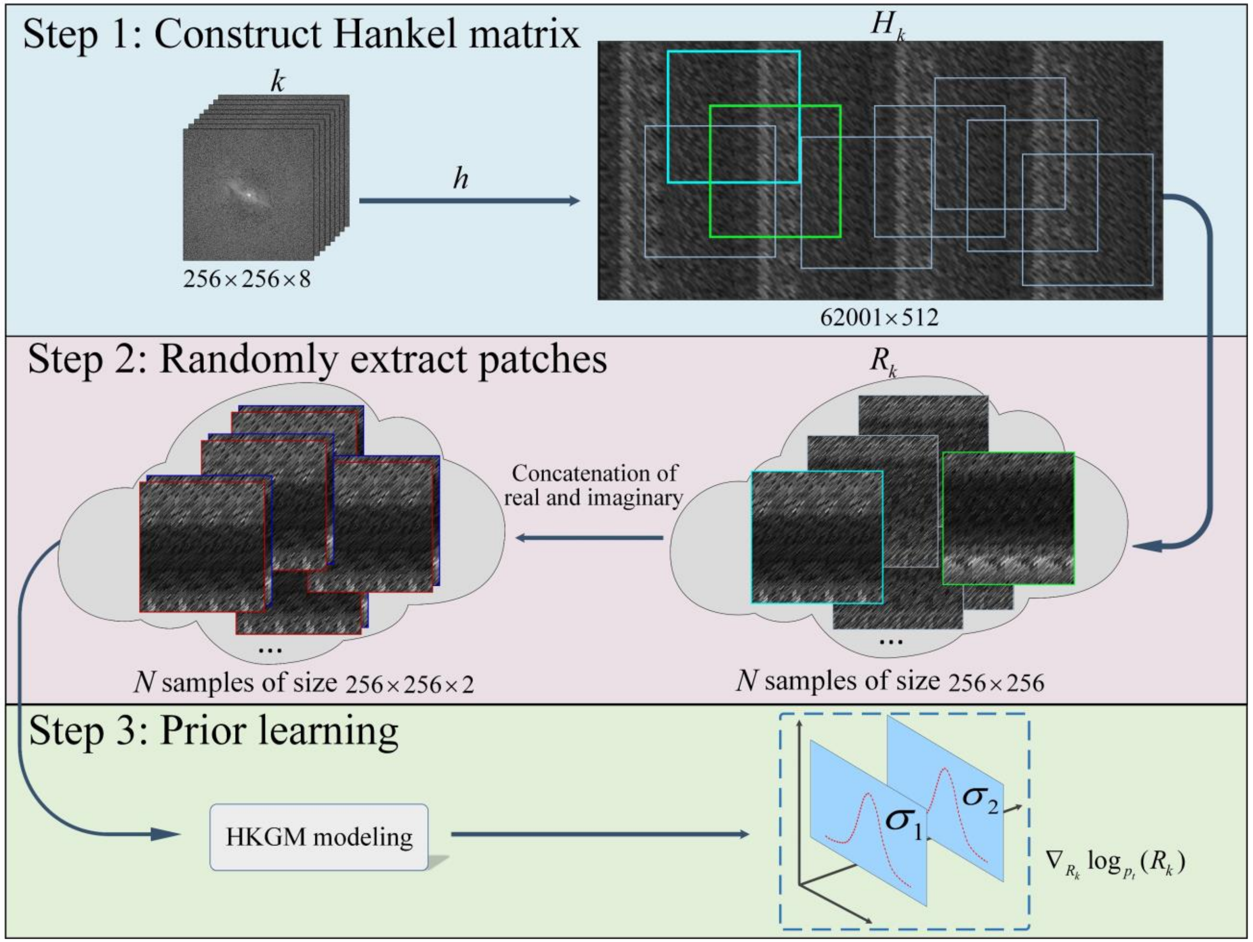
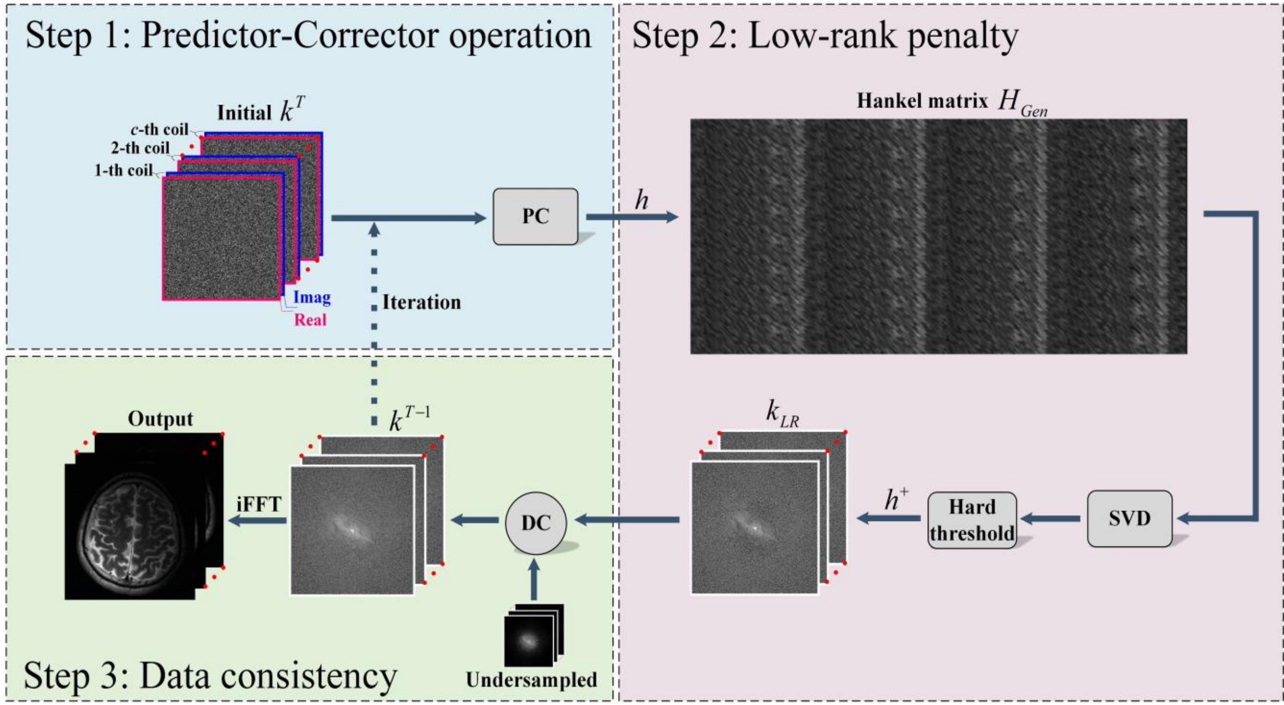


Prior learning



MRI reconstruction

H. Peng, C. Jiang, X. Guan, C. Jiang, M. Zhang, D. Liang, Q. Liu. One-shot Generative Prior in Hankel-k-space for Parallel Imaging Reconstruction, https://arxiv.org/abs/2208.07181, 2022.

Thanks all！

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