面向原始数据域的生成式智能成像

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面向原始数据域的生成式智能成像

1. Background: From CS to AI

2. Part1: Diffusion Model (DM)

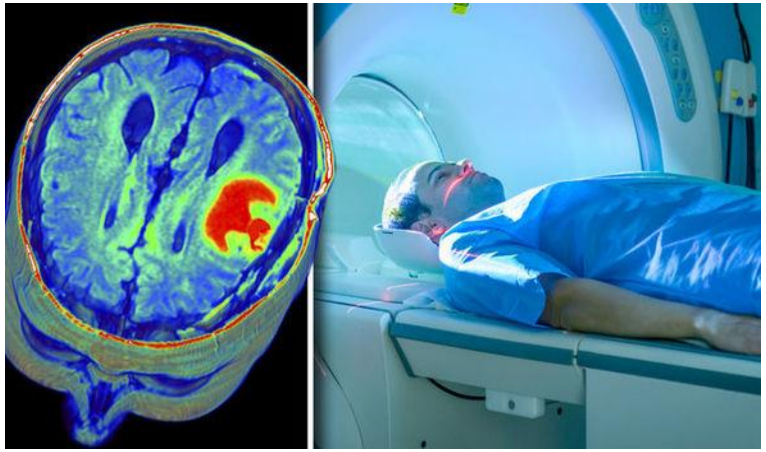
DM Learning from Image to Projection Domain

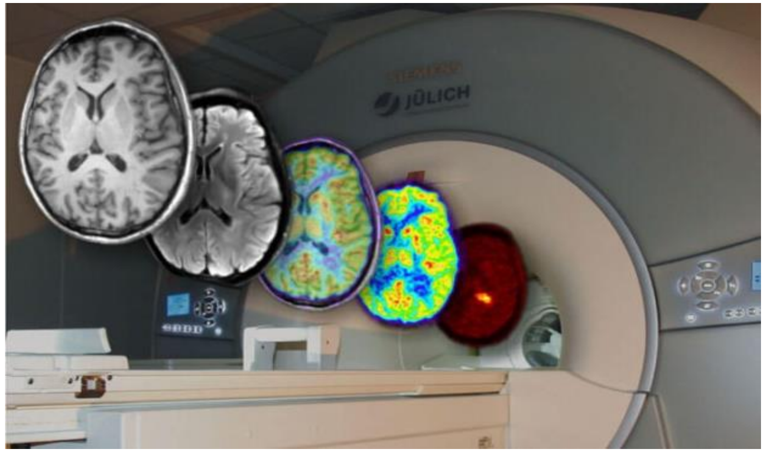
3. Part2: DM Learning from Large to Small Dataset

DM Learning from Single to Multiple Models

DM Learning from Regular to Irregular Samples

From CS to AI





Fast MRI Techniques:

- ✓ **MR physics (1970's)**

  Pulse sequence design

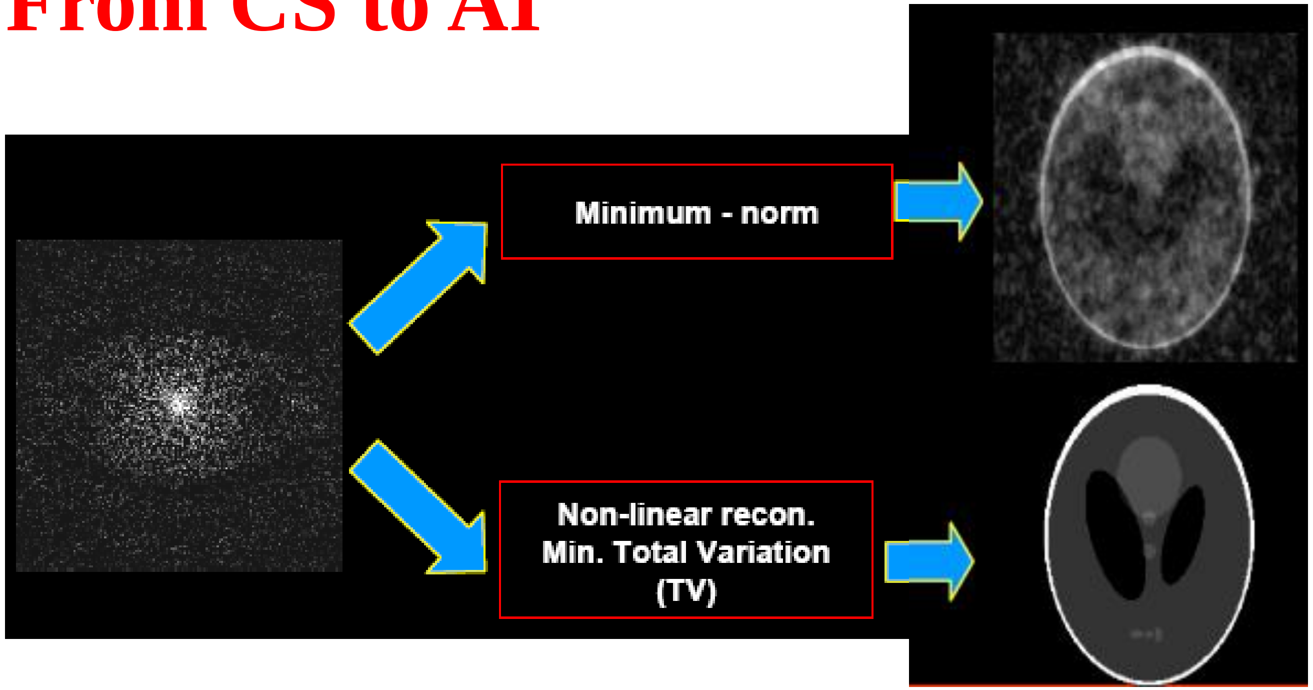
- ✓ **Hardware (2000's)**

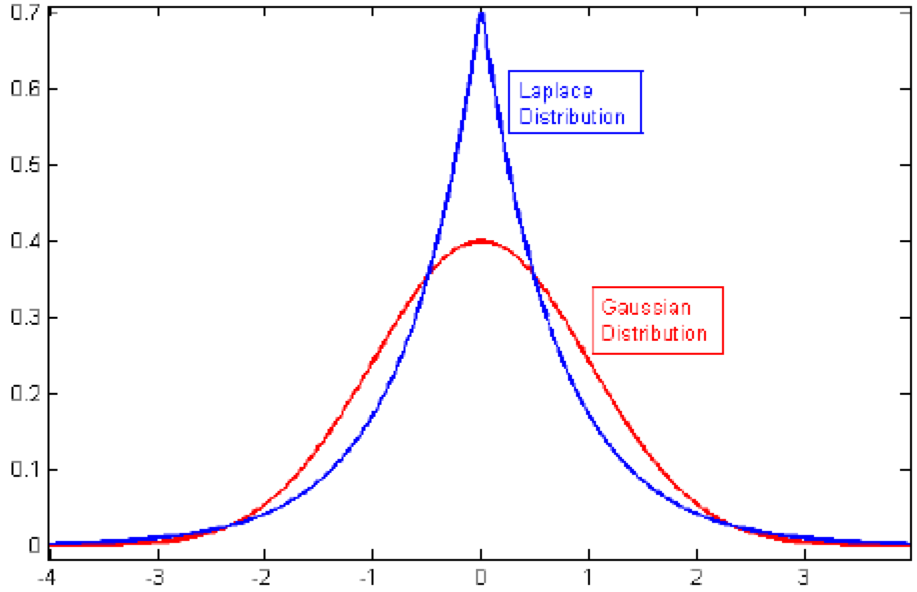
  Parallel imaging with phased array coils

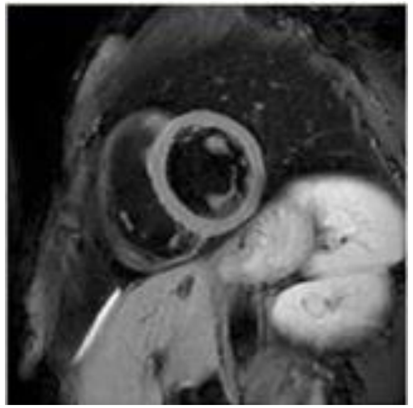
- ✓ **Partial K-space reconstruction** (past two decades)

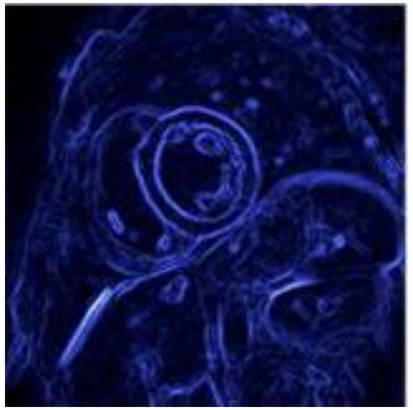
  Modeling using priori knowledge, etc.

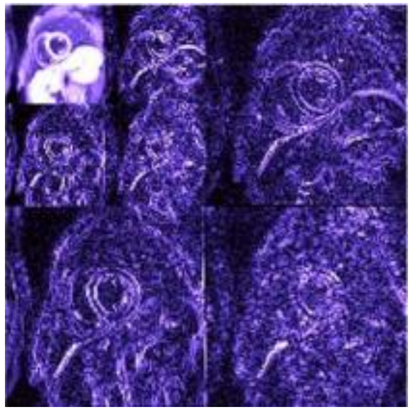
From CS to AI





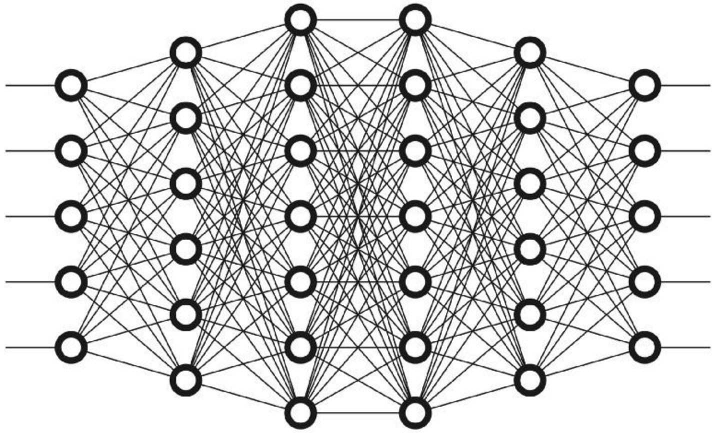






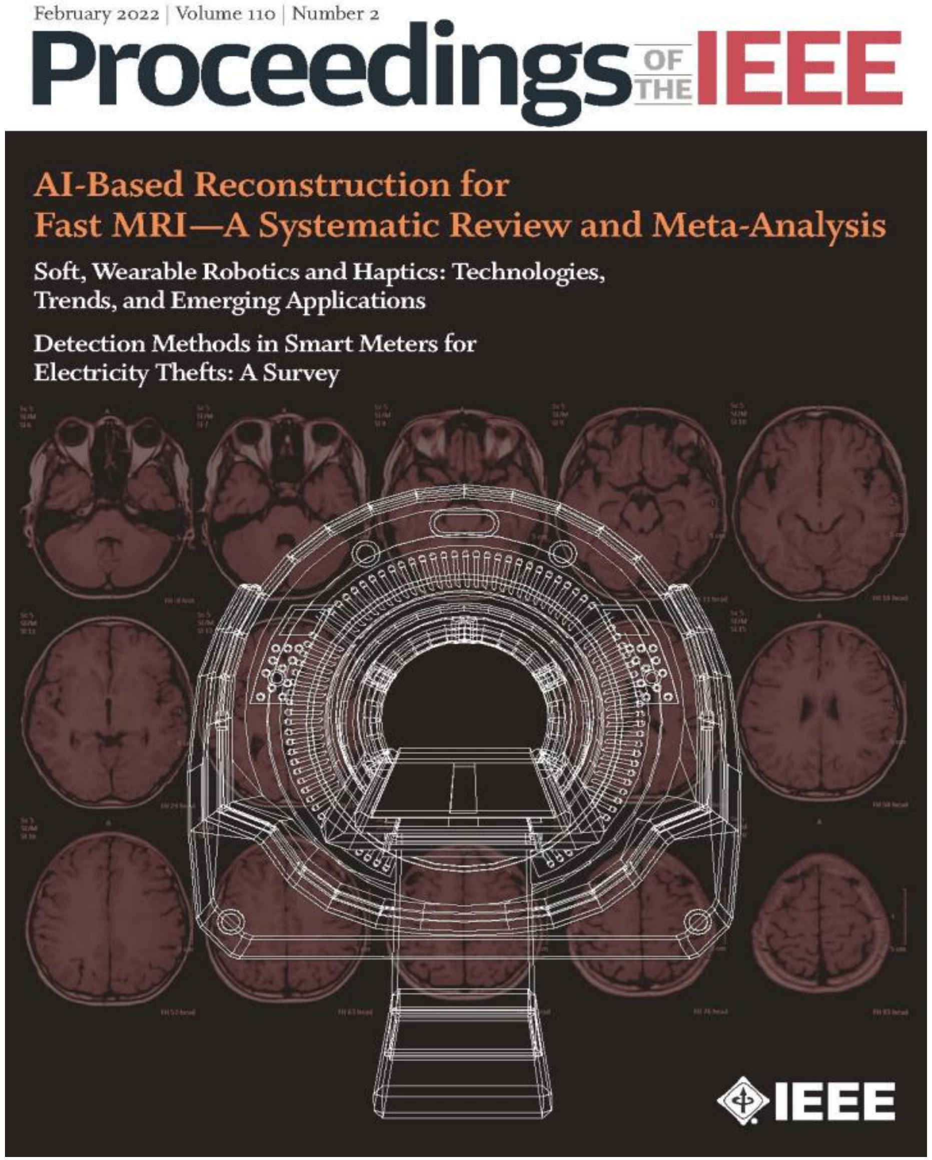
Sparse in Gradient

Sparse in Wavelet

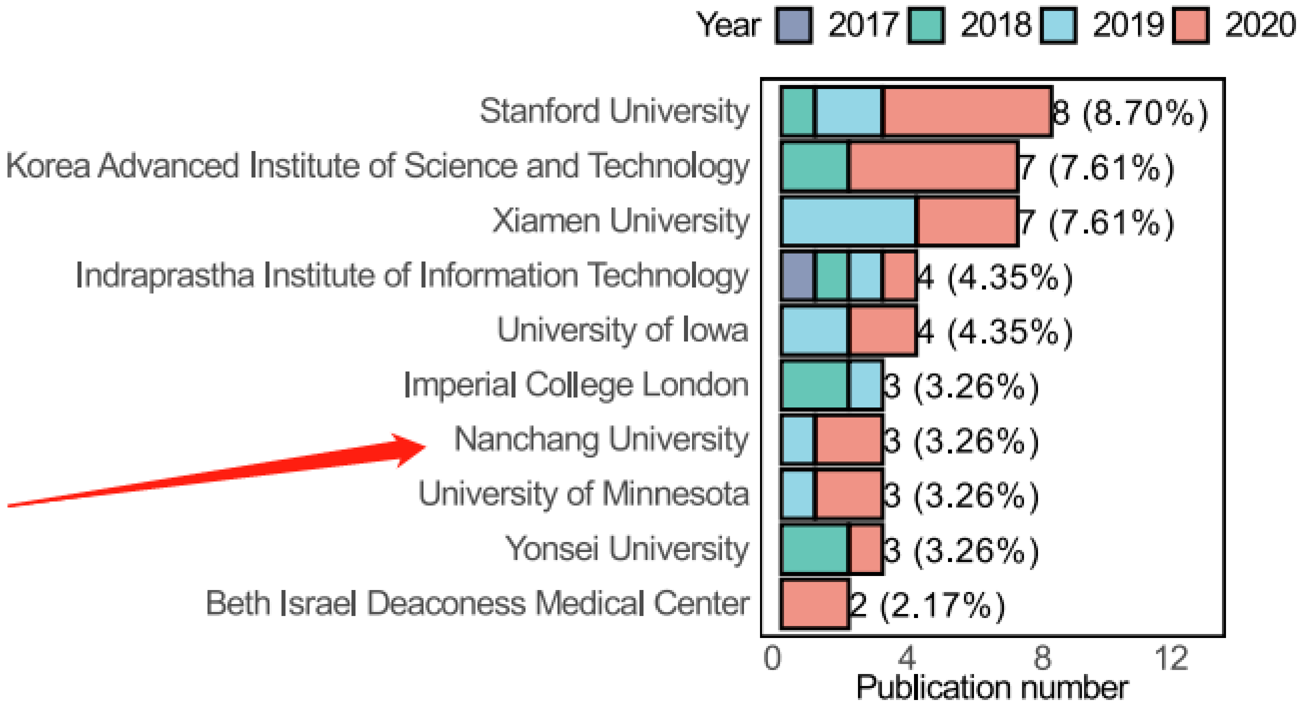


From compressed sensing (CS) to Artificial intelligence (AI)

From CS to AI

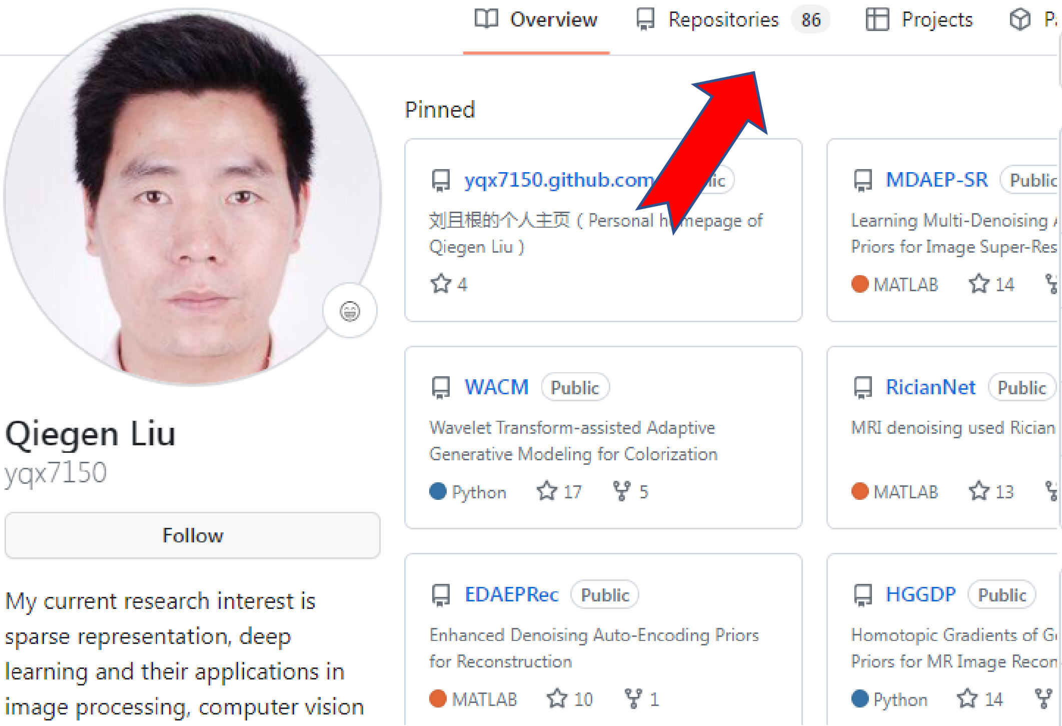


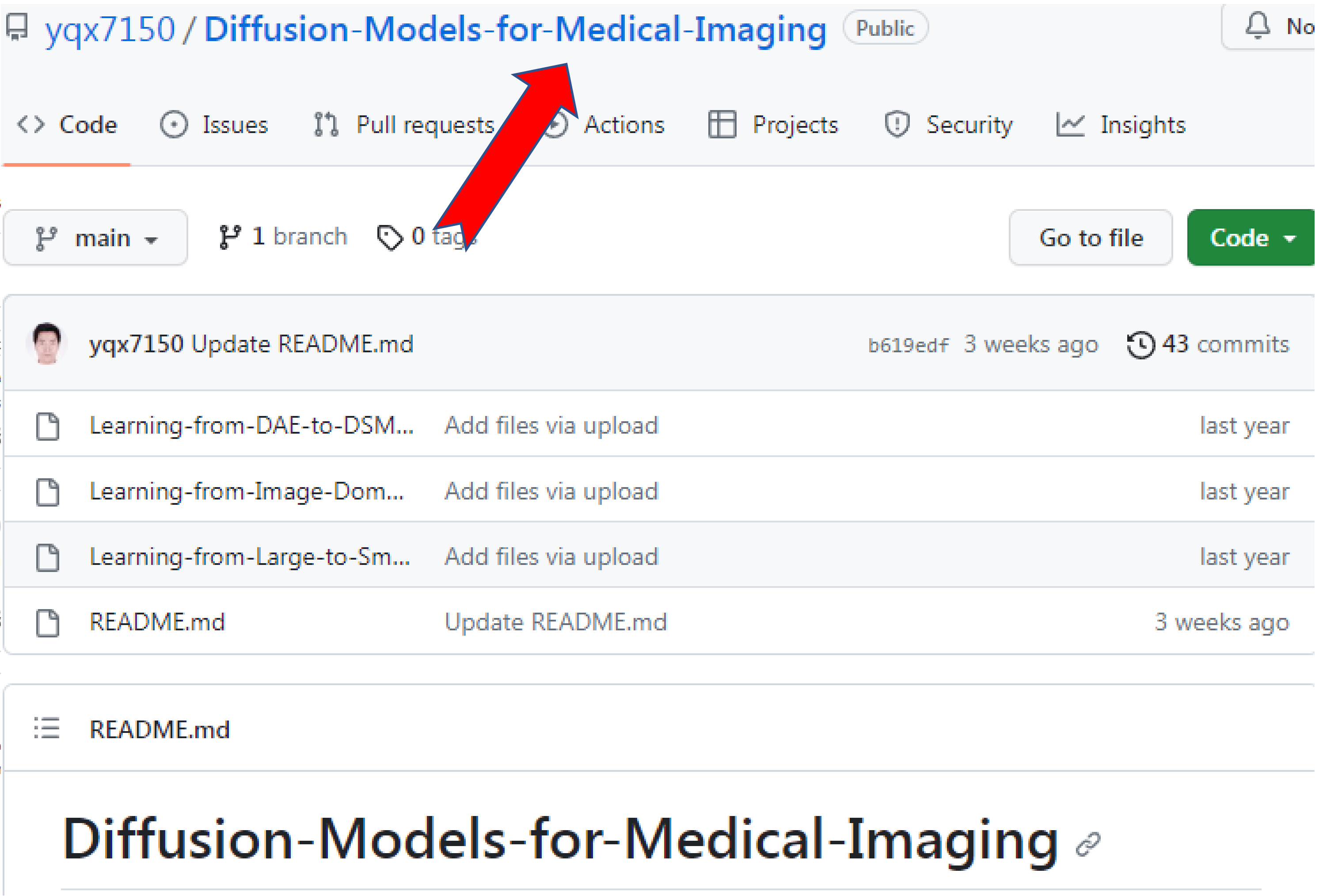
AI-Based Reconstruction for Fast MRI—A Systematic Review and Meta-Analysis



From CS to AI

https://github.com/yqx7150

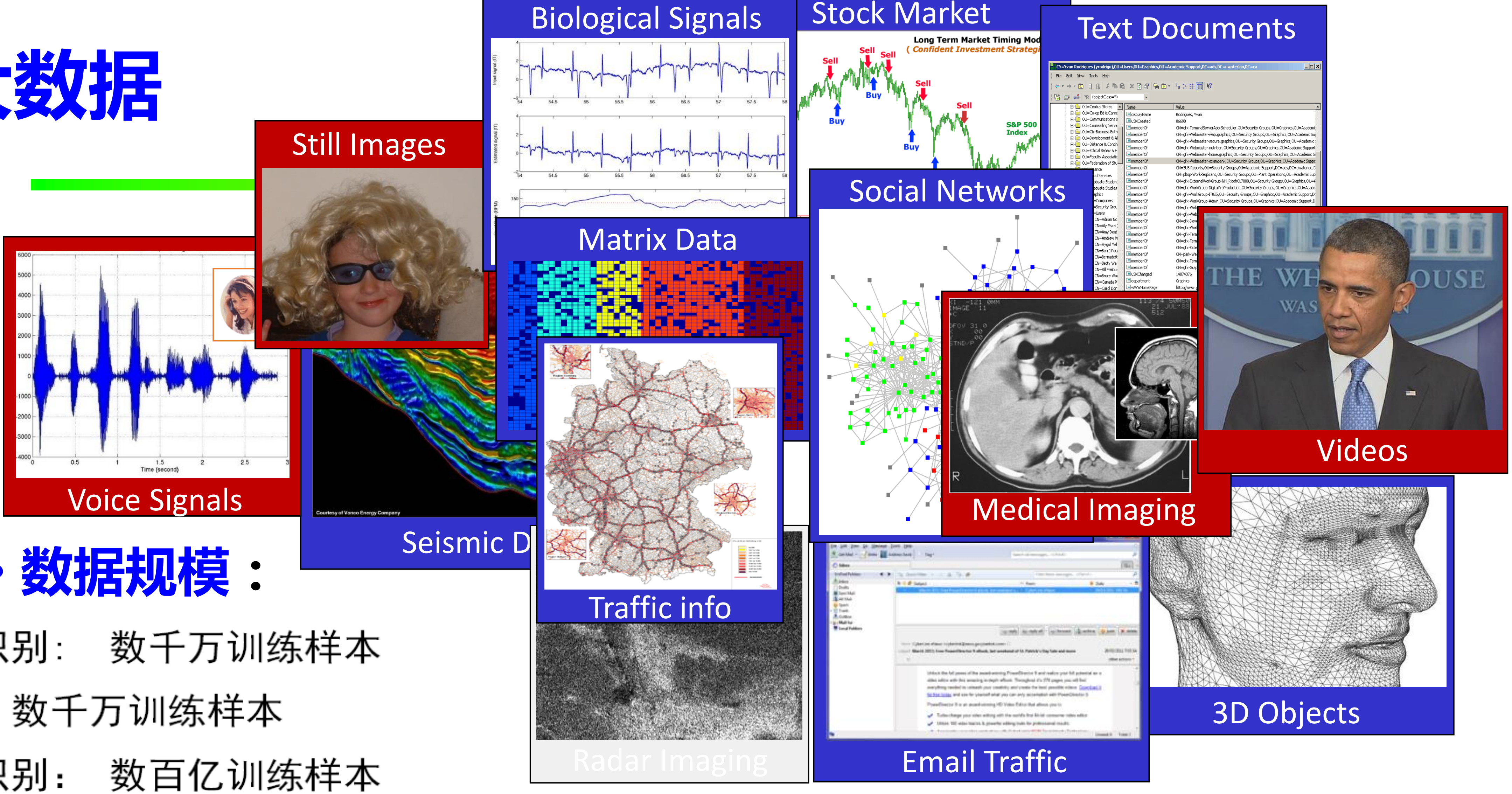




S. Wang, R. Wu, S. Jia, A. Diakite, C. Li, Q. Liu, H. Zheng, L. Ying, Knowledge-driven deep learning for fast MR imaging: Undersampled MR image reconstruction from supervised to un-supervised learning. Magn Reson Med, 92(2):496-518, 2024.

S. Wang, T. Xiao, Q. Liu, H. Zheng, Deep learning for fast MR imaging: a review for learning reconstruction from incomplete k-space data, Biomedical Signal Processing and Control, 68, 102579, 2021.

各种大数据



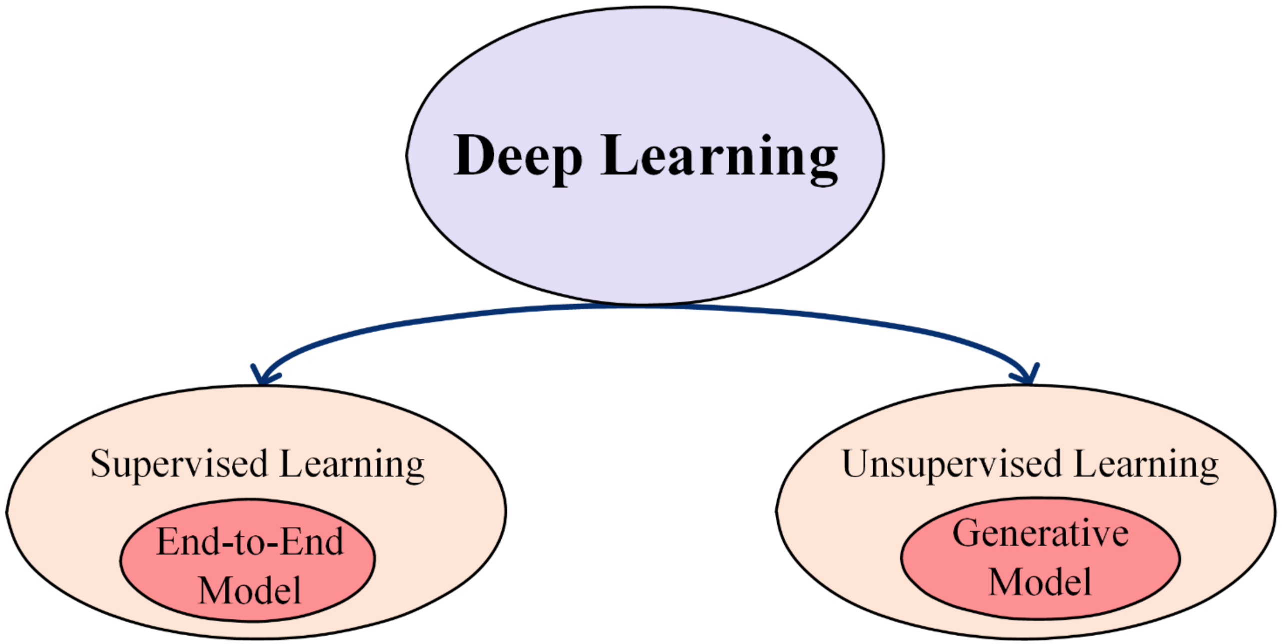
- **数据规模：**

- 图像识别：　数千万训练样本
- OCR：　数千万训练样本
- 语音识别：　数百亿训练样本
- 广告：千亿训练样本
- …

训练数据每年成倍增长 …

我们怎么表示？

大数据中的深度生成表示



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.

大数据中的深度生成表示

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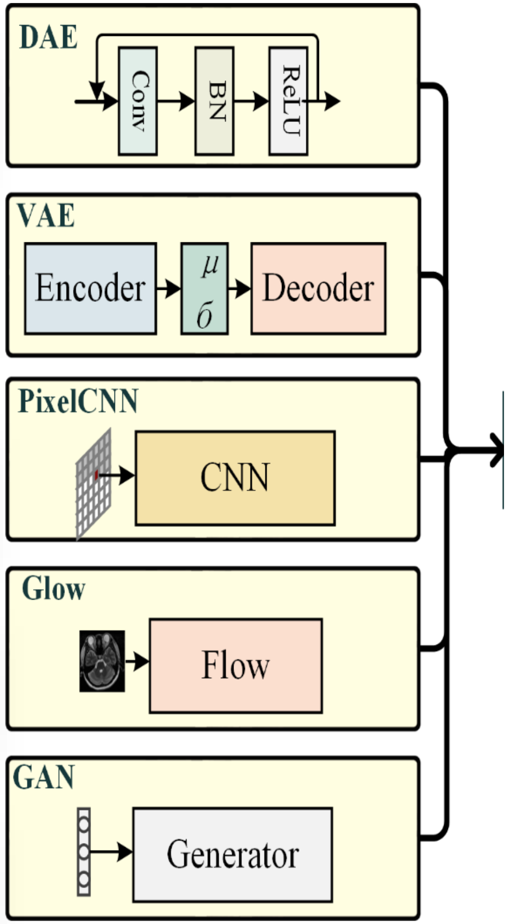
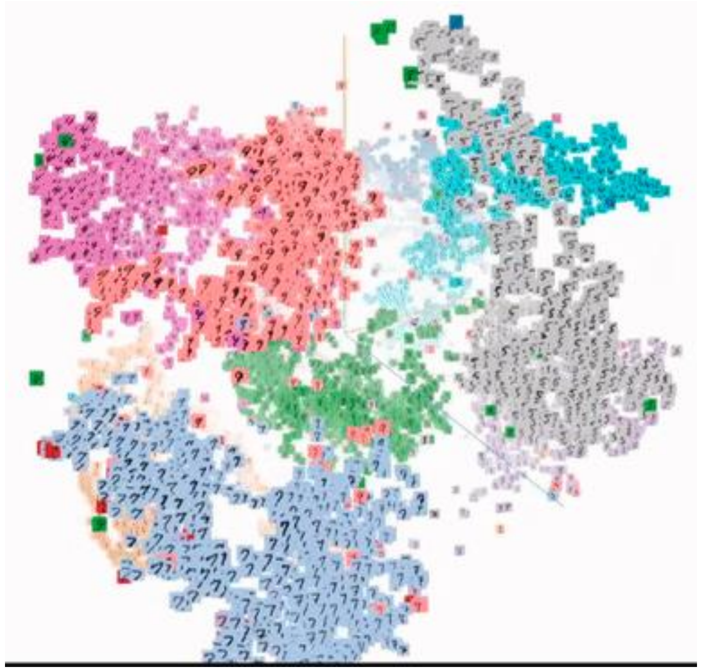


Data distribution $\log p(x)$



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

图像生成王者不是GAN？扩散模型最近有点火，效果直达SOTA

原创 2021-12-29 14:08 · 量子位

博雯 发自 凹非寺
量子位 报道 | 公众号 QbitAI

OpenAI刚刚推出的年末新作GLIDE，又让**扩散模型**小火了一把。

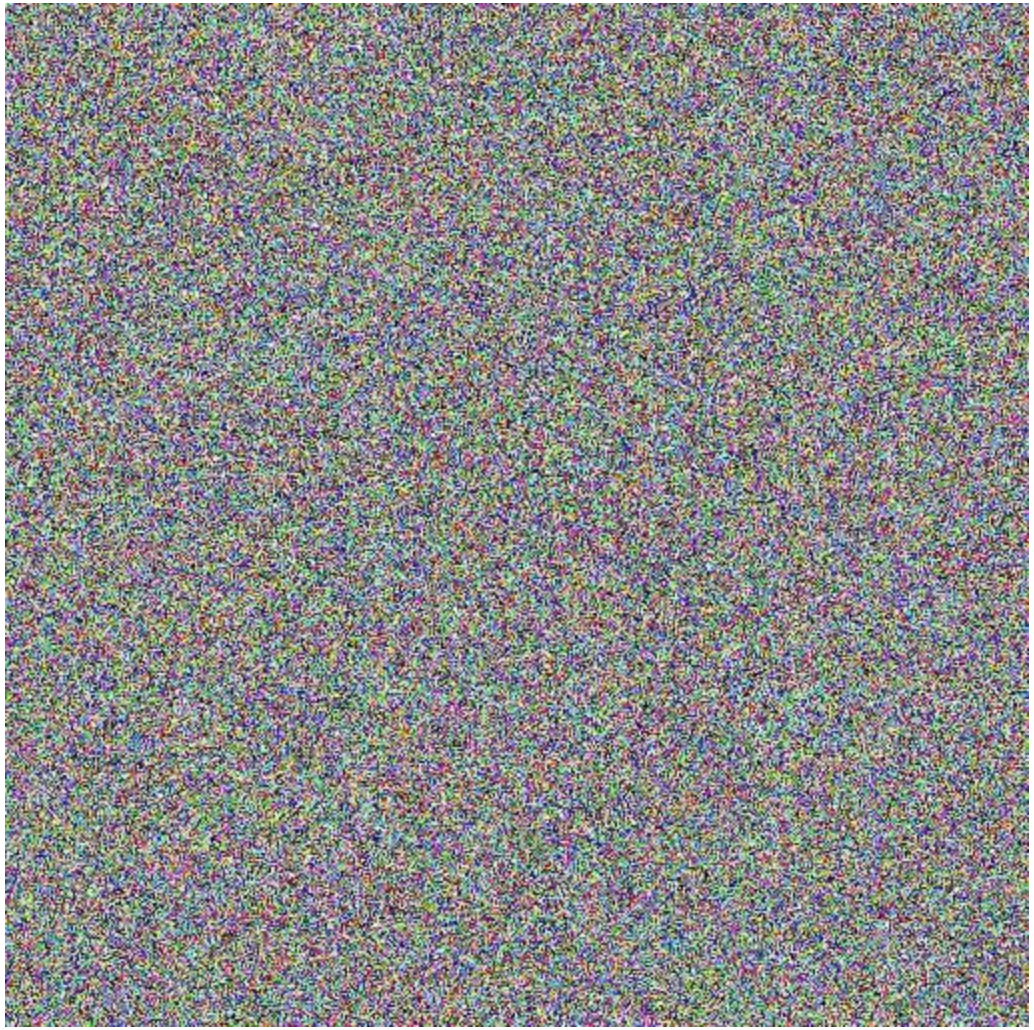
这个基于扩散模型的文本图像生成大模型参数规模更小，但生成的图像质量却更高。

于是，依旧是OpenAI出品，论文标题就直接号称“在图像生成上打败GAN”的**ADM-G模型**也重新进入了大众眼中：

Diffusion Models Beat GANs on Image Synthesis

Prafulla Dhariwal*
OpenAI
prafulla@openai.com

Alex Nichol*
OpenAI
alex@openai.com



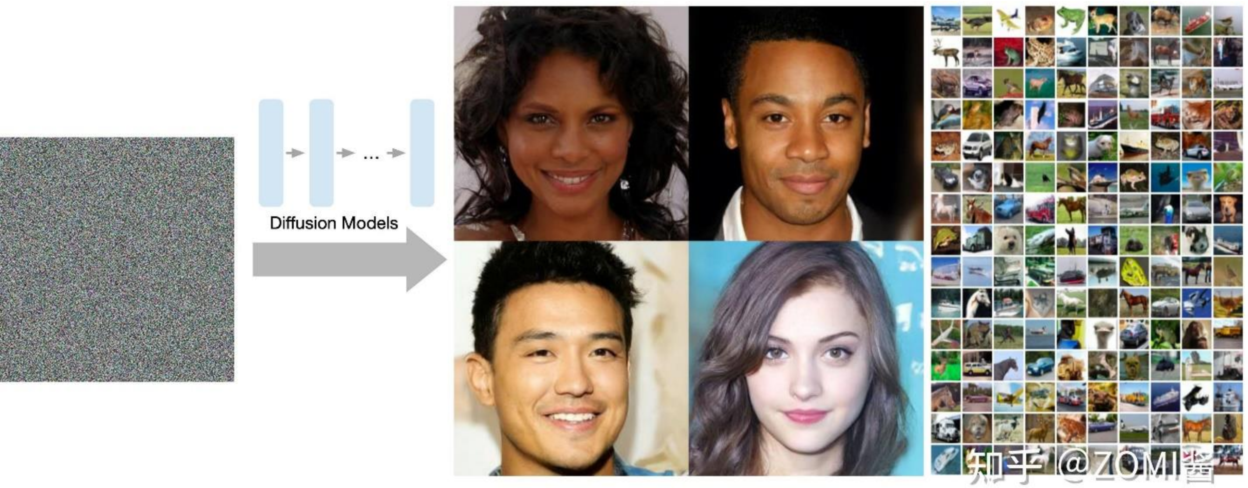
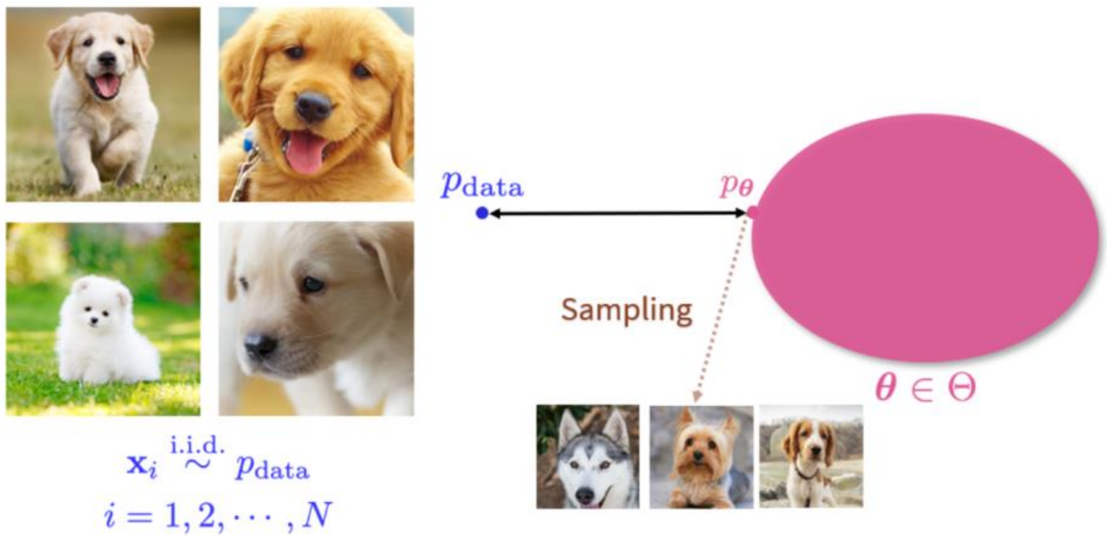


Figure 1: Generated samples on CelebA-HQ 256 × 256 (left) and unconditional CIFAR10 (right)



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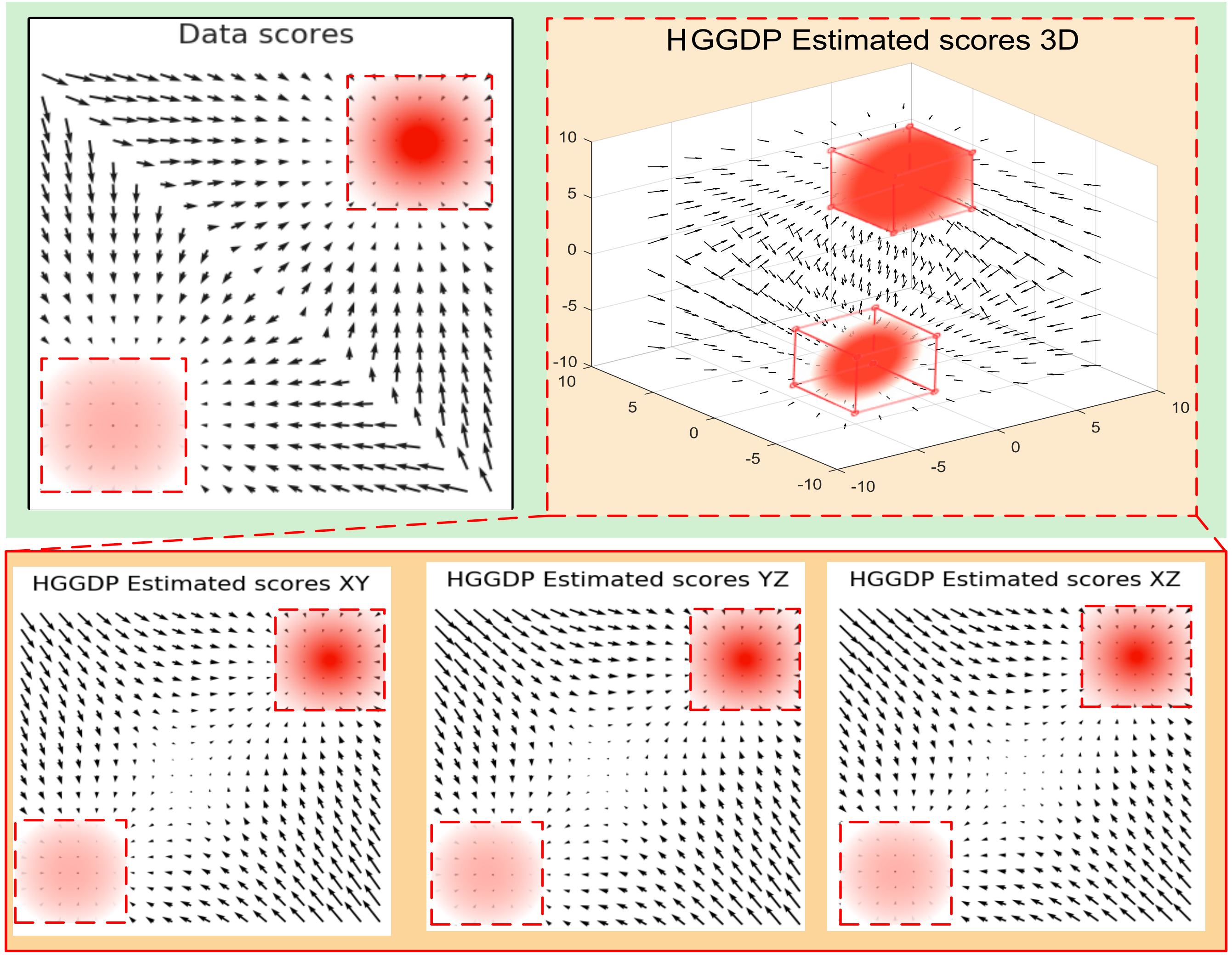
Underlying ideas for improvements

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 priors for MR image reconstruction, *IEEE Trans. Med. Imag.*, 2021.

Underlying ideas for improvements

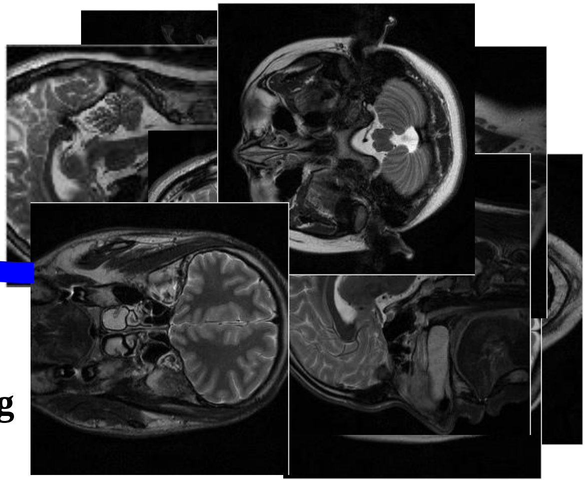
Learning prior density in different modality

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.

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

DAE Prior (DAEP)

DAE is trained by minimizing the following objective function:

$$L_{DAE}(A) = E_{x,\,\mu}[\|A_\sigma(x+\mu) - x\|^2]$$

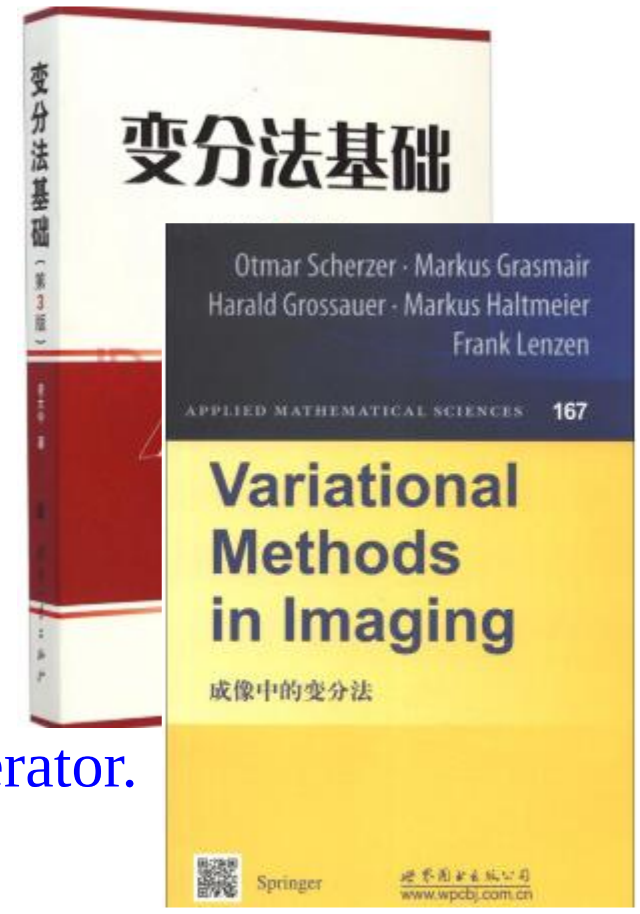
The autoencoder error is proportional to the gradient of the log -likelihood of the smoothed density

$$A_\sigma(x) = x + \sigma^2 \nabla \log[g_\sigma * p](x)$$

where *p*(x) denotes the data density. * represents the convolutional operator.

$$R(x) = \|A_\sigma(x) - x\|^2 = \|\sigma^2 \nabla \log[g_\sigma * p](x)\|^2$$

Regularization term



G. Alain, Y. Bengio, What regularized auto-encoders learn from the data-generating distribution. Journal of machine learning research. 15, 3743-3773, 2014.

EDAEPRec

Algorithm overview

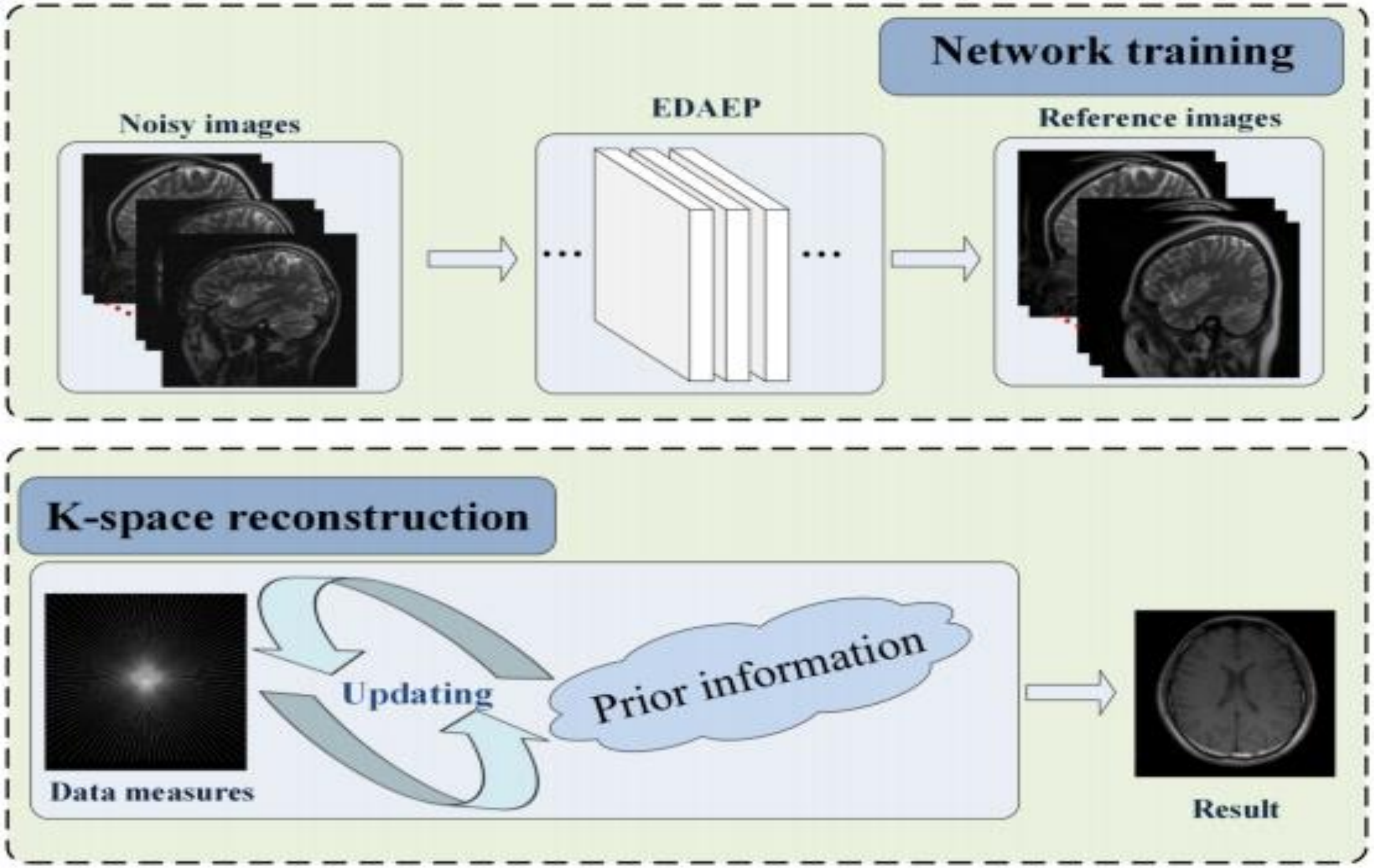
Multi-channel learning scheme (self-copy)

Training stage:

$$\{X = [x, x, x]\}$$

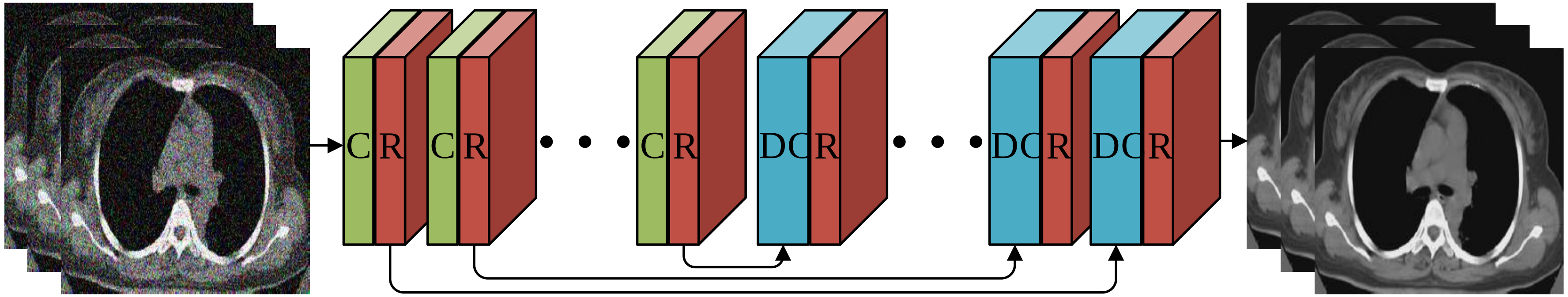
Testing stage:

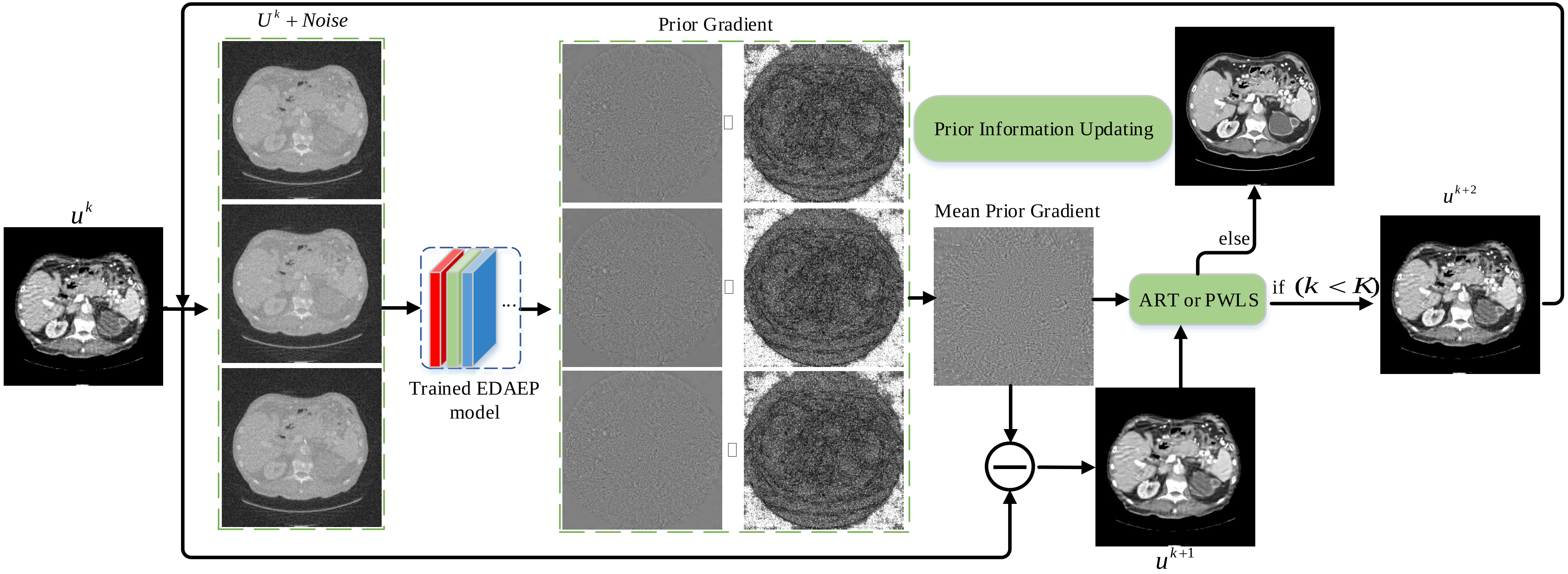
$$X^k = [x^k, x^k, x^k]$$



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.

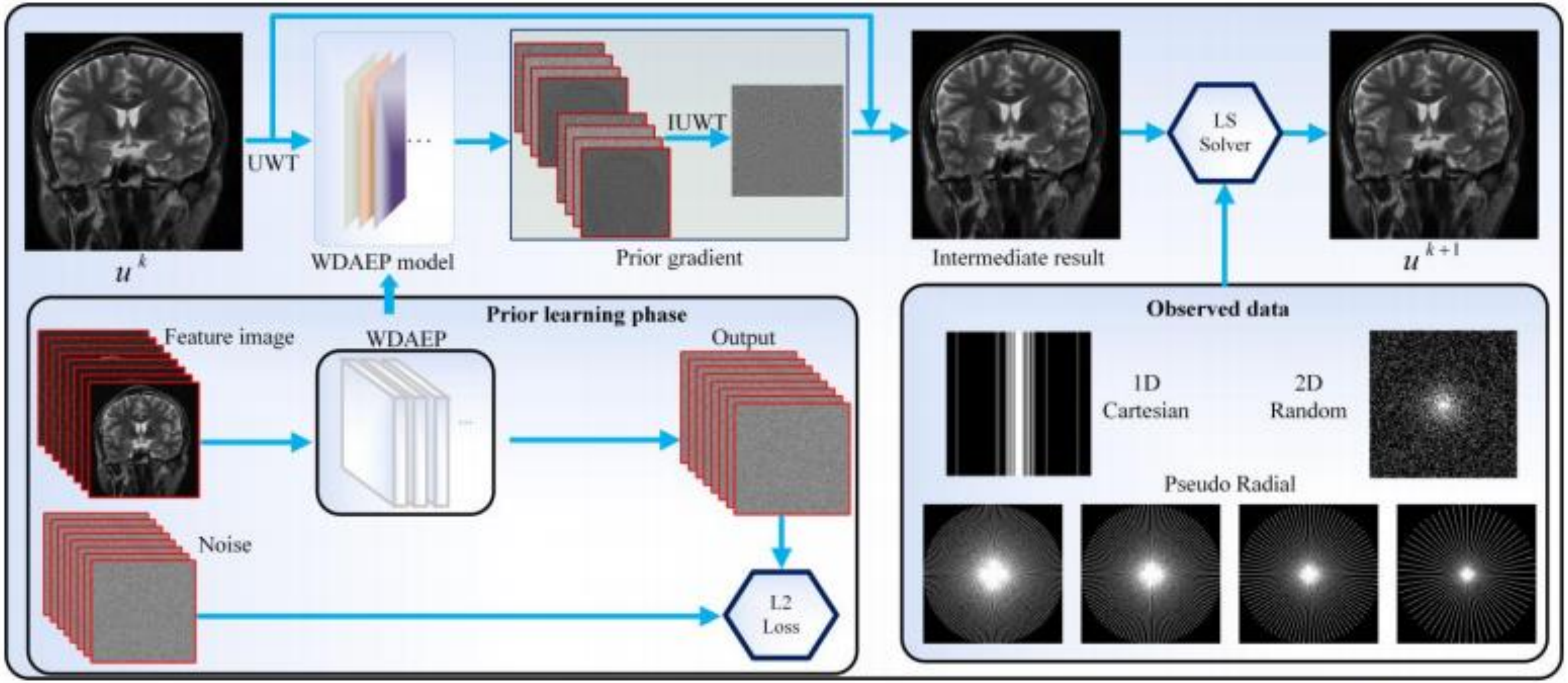
对多线圈MRI或彩色自然图像进行训练也有效果!





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.*, vol. 5, no. 1, pp. 108-119, 2020.

WDAEPRec



Schematic flowchart of the proposed WDAEPRec algorithm. At the training stage, we train the WDAEP model to get the prior. Then, the learned prior is used at the iterative reconstruction phase. Various sampling masks are used in our experiment. Top line: Cartesian sampling and variable density 2D Random sampling with the same acceleration factor R=6.7; Bottom line: Pseudo Radial sampling with the different acceleration factors R=4, 5, 6.7, 10.

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.

From DAEP to Score-based generative model

Deep mean-shift prior (DMSP):

$$\nabla prior(x) = \nabla \log \int g_\sigma(\eta) p(x+\eta) d\eta$$
$$= [(A_\sigma(x) - x)] / \sigma^2$$

Denoising score matching (DSM):

$$S(x) \to \nabla \log p_\sigma(x)$$

Theorem 1. The DAE loss $\quad L_{DAE}(A) = E_{x\sim p,\ \eta\sim g_\sigma}[\|A(x+\eta) - x\|^2]$

and the DSM loss $\quad L_{DSM}(S) = E_{p_\sigma}[\|S(x) - \nabla \log p_\sigma(x)\|^2]$

with $\quad S(x) = \dfrac{A(x) - x}{\sigma^2}$

are equivalent up to a term that does not depend on A or S.

Score-based generative model

Prior learning stage:

$$p_\sigma(\tilde{x} \mid x) = N(\tilde{x} \mid x, \sigma^2 \mathrm{I})$$

$$\nabla_{\tilde{x}} \log p_\sigma(\tilde{x} \mid x) = -(\tilde{x} - x)/\sigma^2$$

$$\begin{aligned}
\ell(\theta;\sigma) &\triangleq \frac{1}{2} E_{p_\sigma(x)}[\|S_\theta(x,\sigma) - \nabla_x \log p_\sigma(x)\|_2^2] \\
&= \frac{1}{2} E_{p_\sigma(\tilde{x},x)}[\|S_\theta(\tilde{x},\sigma) - \nabla_{\tilde{x}} \log p_\sigma(\tilde{x} \mid x)\|_2^2] + C \\
&= \frac{1}{2} E_{p_\sigma(\tilde{x},x)}[\|S_\theta(\tilde{x},\sigma) + (\tilde{x} - x)/\sigma^2\|_2^2] + C
\end{aligned}$$

$$L(\theta; \{\sigma_i\}_{i=1}^{I}) \overset{\Delta}{=} \frac{1}{I} \sum_{i=1}^{I} \lambda(\sigma_i) \ell(\theta; \sigma_i)$$

Training DSM network S_θ for all $\{\sigma_i\}_{i=1}^{I}$

Beside of the statistical derivation to Eq. (8) [33], [34], we provide a new intuitive derivation for it. In fact, as stated in **Theorem 1**, we get $S_\theta(x,\sigma) = [A(x+\eta) - (x+\eta)]/\sigma^2$. On the other hand, as described in Fig. 3, if we denote $D_\theta(x,\sigma) = (x+\eta) - A(x+\eta)$ and $A(x+\eta) \to x$, then we get $S_\theta(x,\sigma) = -D_\theta(x,\sigma)/\sigma^2 \to -\eta/\sigma^2 = -(\tilde{x} - x)/\sigma^2$.

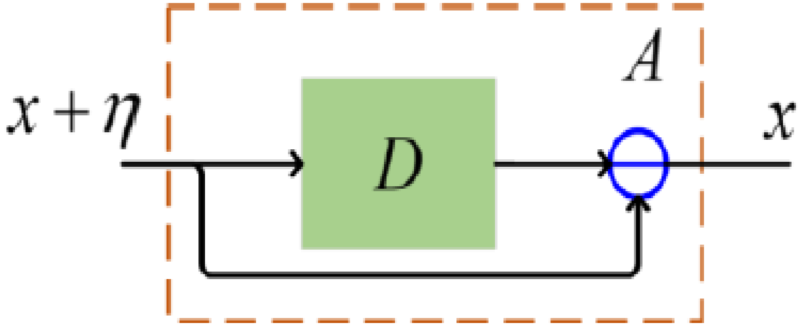


Fig. 3. Visual exhibition of the network A and D.

Score-based generative model

Iterative reconstruction stage： Annealed Langevin dynamics

Langevin dynamics

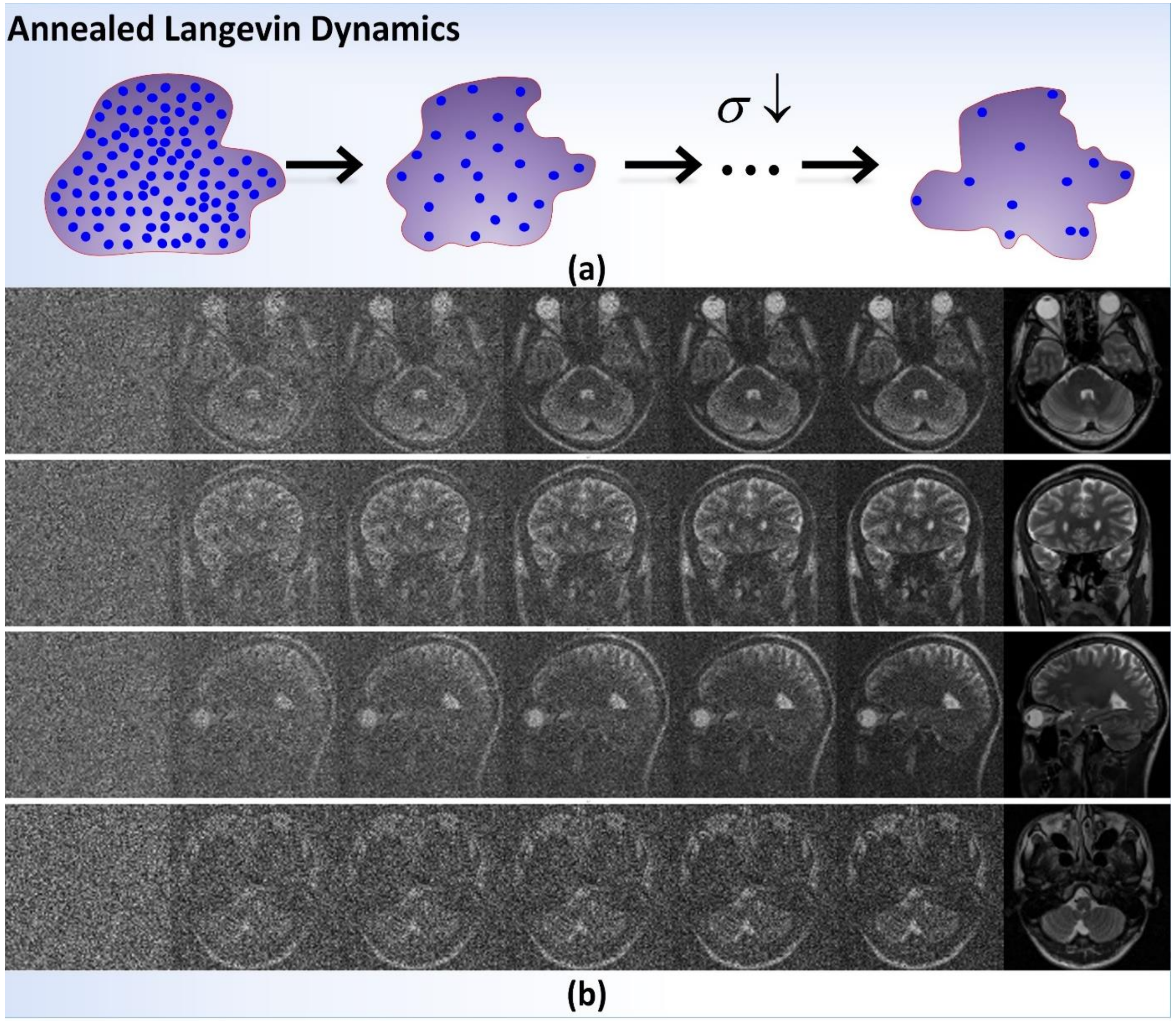
$$
\begin{aligned}
\tilde{x}_t &= \tilde{x}_{t-1} + \frac{\alpha_i}{2} \nabla_x \log p_{\sigma_i}(\tilde{x}_{t-1}) + \sqrt{\alpha_i}\, z_t \\
&= \tilde{x}_{t-1} + \frac{\alpha_i}{2} S_\theta(\tilde{x}_{t-1}, \sigma_i) + \sqrt{\alpha_i}\, z_t
\end{aligned}
$$

Algorithm 1 Annealed Langevin dynamics.

Require: $\{\sigma_i\}_{i=1}^L, \epsilon, T$.

```
Initialize x̃_0
for i ← 1 to L do
    α_i ← ε · σ_i^2 / σ_L^2        ▷ α_i is the step size.
    for t ← 1 to T do
        Draw z_t ~ N(0, I)
        x̃_t ← x̃_{t-1} + (α_i / 2) s_θ(x̃_{t-1}, σ_i) + √α_i z_t
    end for
    x̃_0 ← x̃_T
end for
return x̃_T
```

Iterative image generation



(a) Conceptual diagram of the sampling on high-dimensional noisy data distribution with multi-view noise.

(b) Intermediate samples of annealed Langevin dynamics.

Iterative reconstruction stage

Algorithm 1 HGGDPRec

Training stage

Dataset: Multi- channel dataset: $X=\{X_1,X_2,X_3,\cdots X_N\}$

Outputs: Trained HGGDP $S_\theta(X,\sigma)$

Reconstruction stage

Setting: $\sigma\in\{\sigma_i\}_{i=1}^{I}, \in, T$, and x^0

for $i\leftarrow 1$ to I **do (Outer loop)**

  $\alpha_i = \in\cdot\ \sigma_i^2/\sigma_I^2$

  for $t\leftarrow 1$ to T **do (Inner loop)**

    Draw $z_t\sim N(0,1)$ and $X^{t-1}=\{x^{t-1},x^{t-1},\cdots,x^{t-1}\}$

    $$X^t = X^{t-1}+\frac{\alpha_i}{2}S_\theta(X_l^{t-1},\sigma_i)+\sqrt{\alpha_i}z_t$$

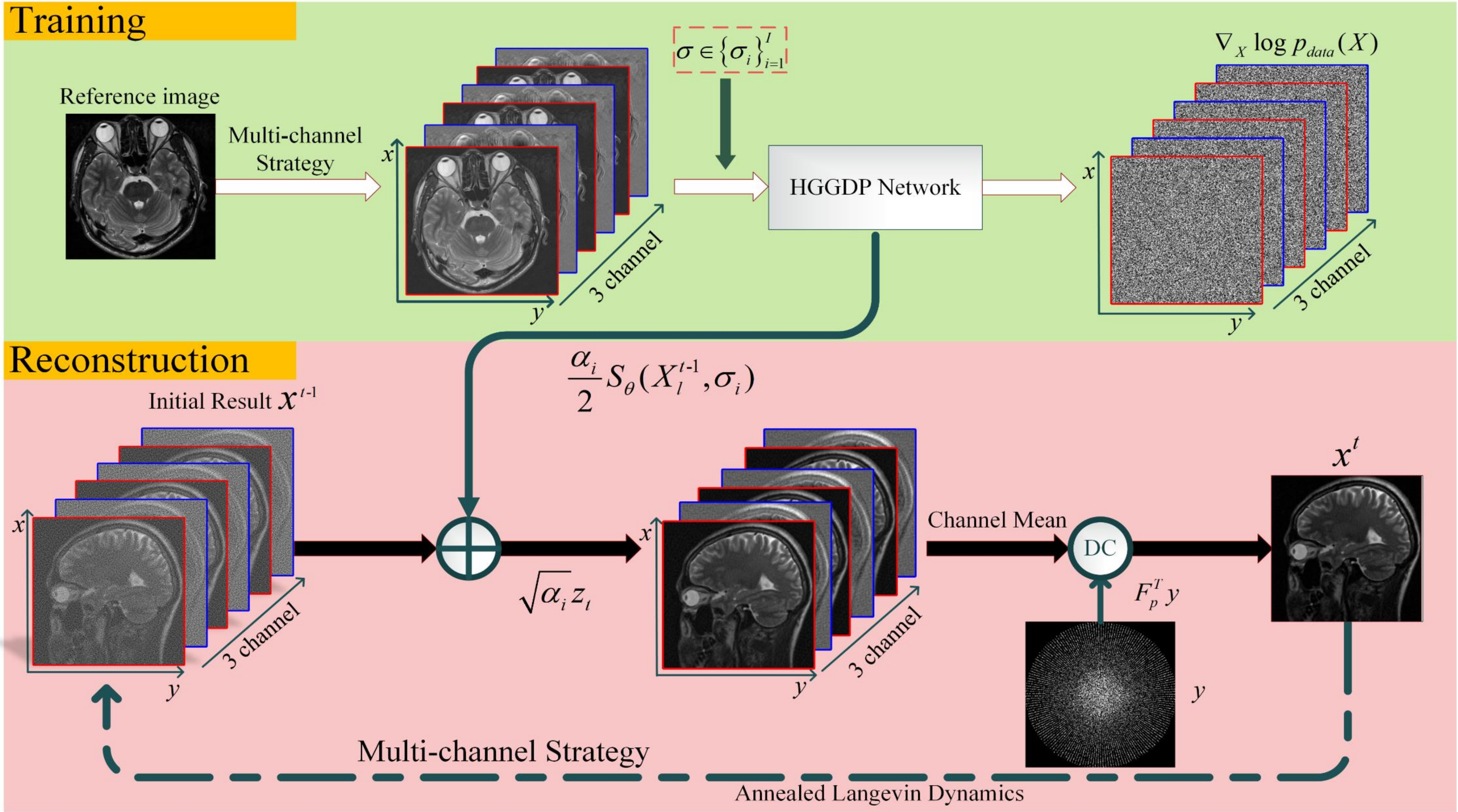
    Update $x^t = Mean(X^t)$ and Eq. (17)

  end for

  $x^0\leftarrow x^T$

end for

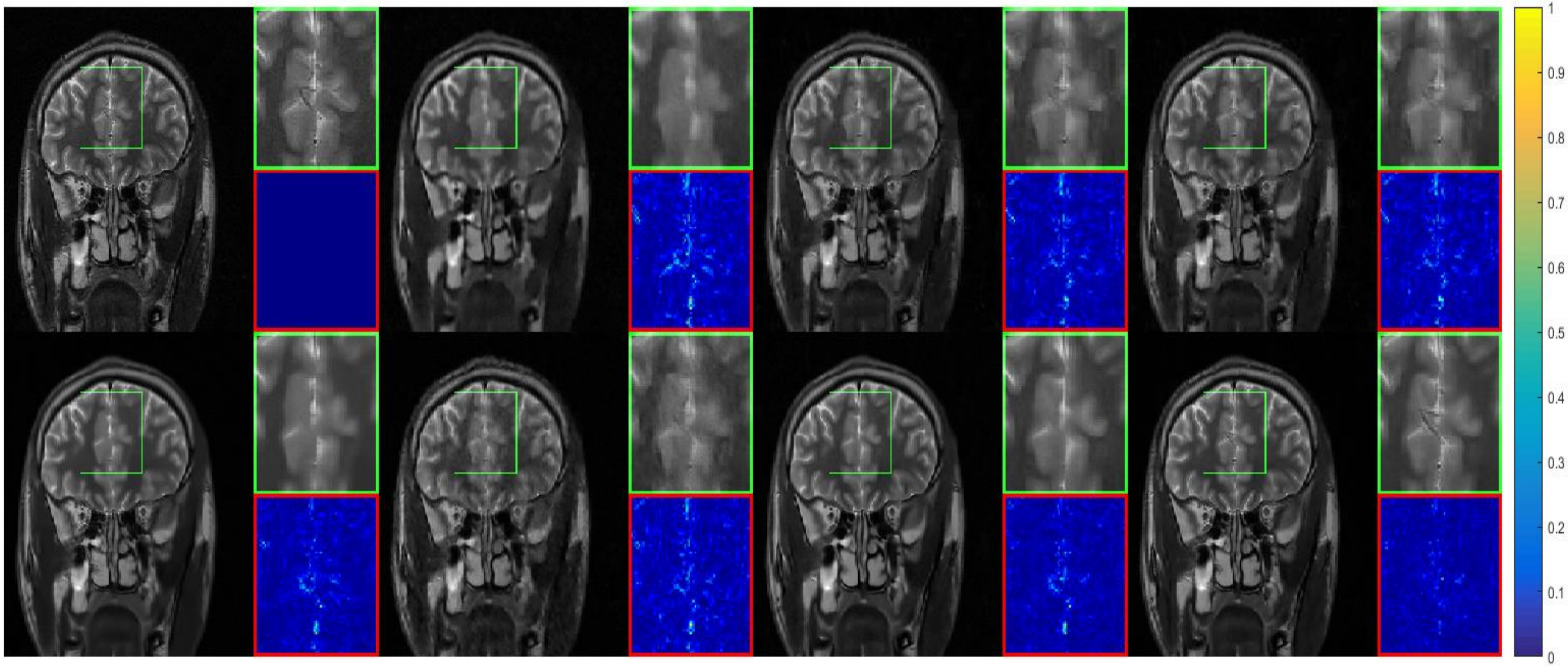
Return x^T



Pipeline of HGGDP training process for prior learning and HGGDPRec procedure for MRI reconstruction.

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.

Experimental results



Reconstruction comparison on 2D Random sampling at acceleration factor R=6.7. Top: Reference, reconstruction by DLMRI, PANO, FDLCP; Bottom: Reconstruction by NLR-CS, DC-CNN, EDAEPRec, HGGDPRec. Green and red boxes illustrate the zoom in results and error maps, respectively.

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.

EASEL for LDCT reconstruction

Algorithm 1 EASEL for Low Dose CT Imaging

Initialization: x^0 and w^0, $\sigma \in \{\sigma_l\}_{l=1}^{L}$, β, γ, τ

For $l = 1, 2, \cdots, L$

$\varepsilon_l = \tau \sigma_l^2 / \sigma_L^2$

For $t = 1, 2, \cdots, T$

Draw $z^{t-1} \sim N(0,1)$

$$u^t = x^{t-1} + \frac{\varepsilon_l}{2} s_\theta(x^{t-1}; \sigma_l) + \sqrt{\varepsilon_l} z^{t-1}$$

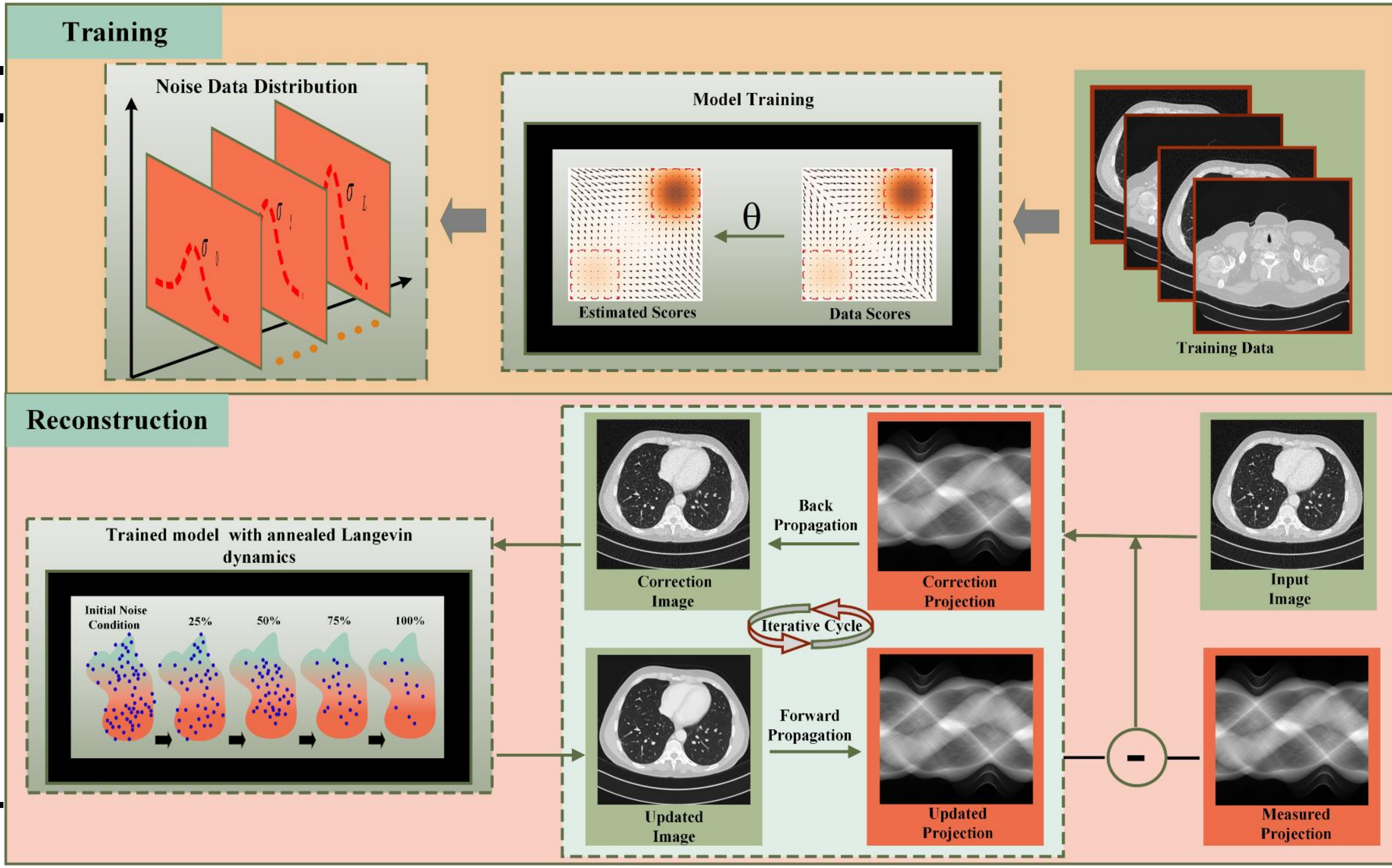
$$x^t = w^{t-1} - \frac{A^T(Ax^{t-1} - y) + \beta(x^{t-1} - u^t)}{A^T A \mathbf{1} + \beta \mathbf{1}}$$

$$w^t = x^t + \gamma(x^t - x^{t-1})$$

End for

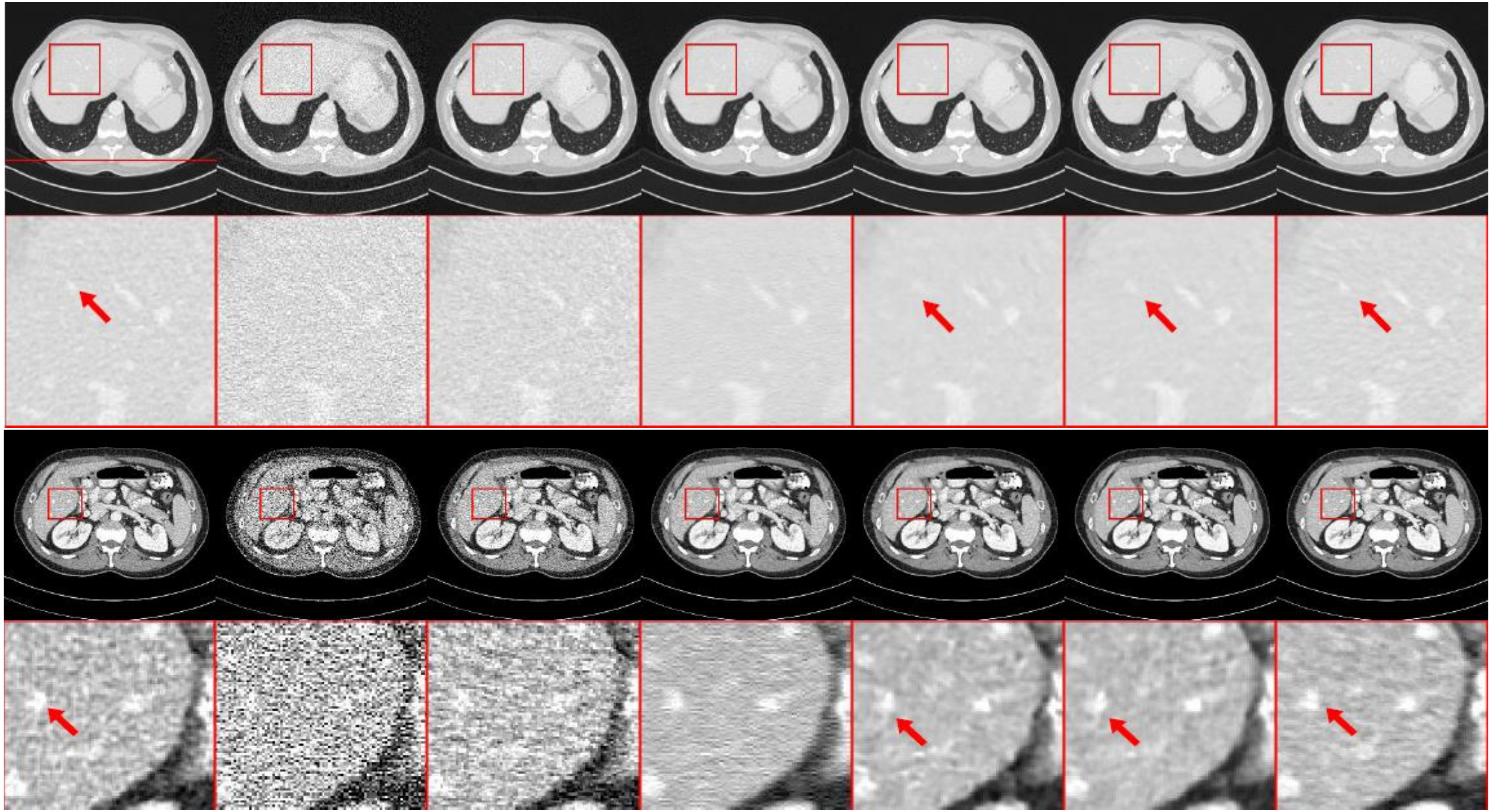
$x^0 \leftarrow w^T$

End for



Z. He, Y. Zhang, Y. Guan, S. Niu, Y. Zhang, Y. Chen, Q. Liu, Iterative reconstruction for low-dose CT using deep gradient priors of generative model, , *IEEE Trans. Radiat. Plasma Med. Sci.*, vol. 6, no. 7, pp. 741-754, 2022.

EASEL for LDCT reconstruction

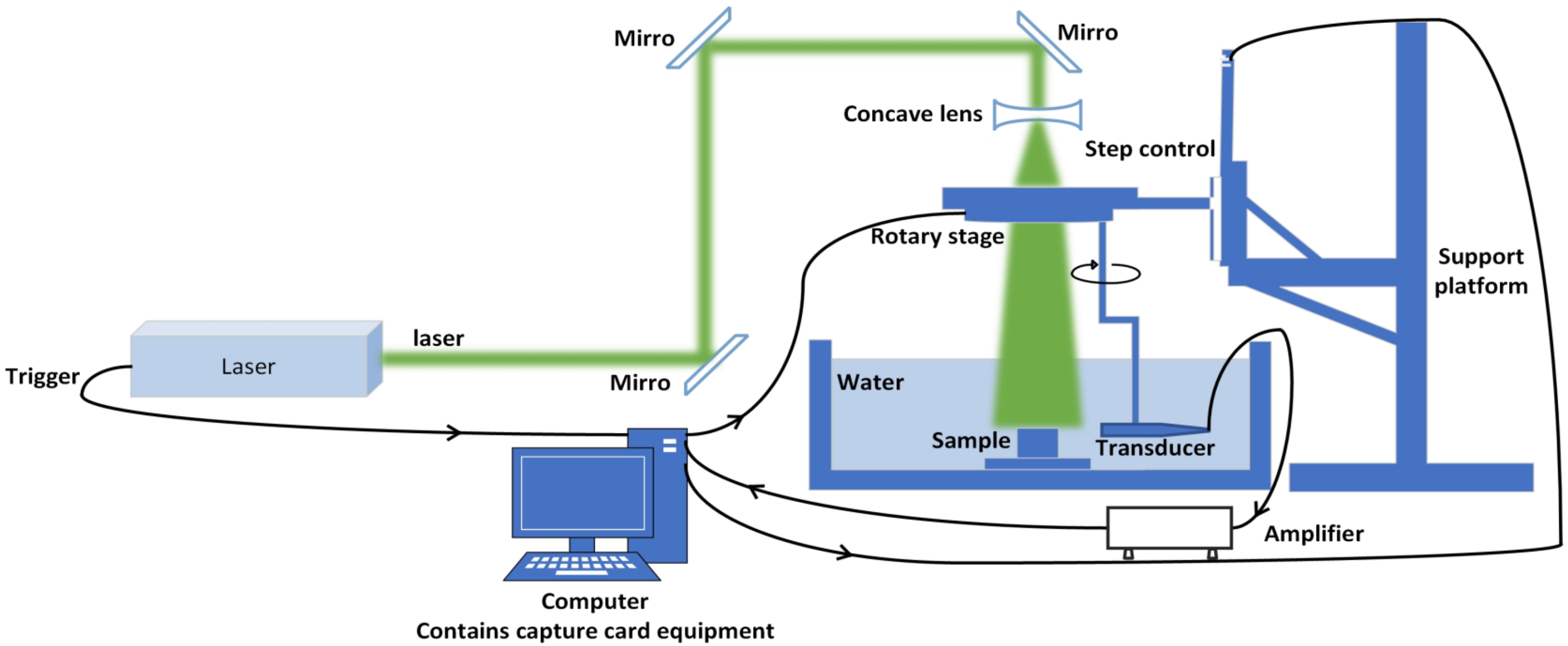


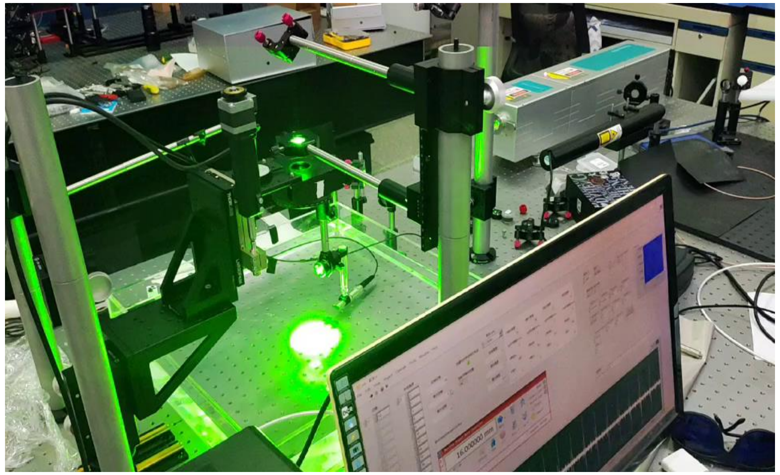
Reference FBP TV K-SVD RED-CNN DP-ResNet EASEL

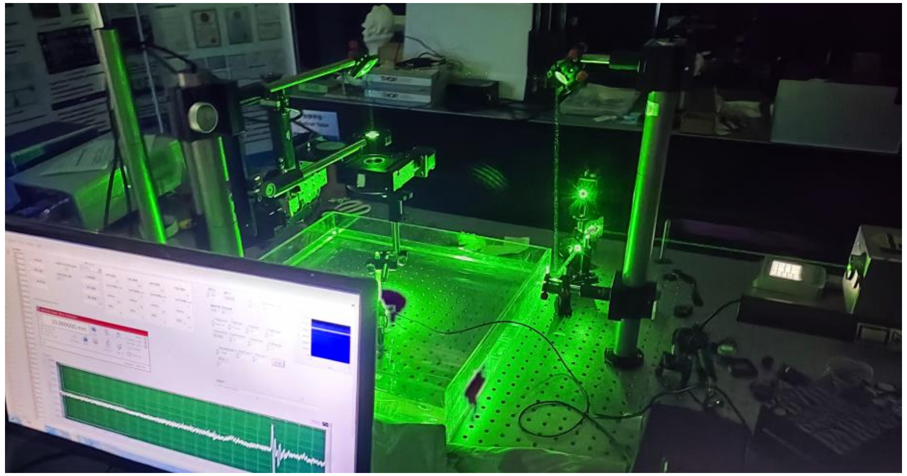
Z. He, Y. Zhang, Y. Guan, S. Niu, Y. Zhang, Y. Chen, Q. Liu, Iterative reconstruction for low-dose CT using deep gradient priors of generative model, *IEEE Trans. Radiat. Plasma Med. Sci.*, vol. 6, no. 7, pp. 741-754, 2022.

PAT-DM for sparse-view reconstruction

PAT system





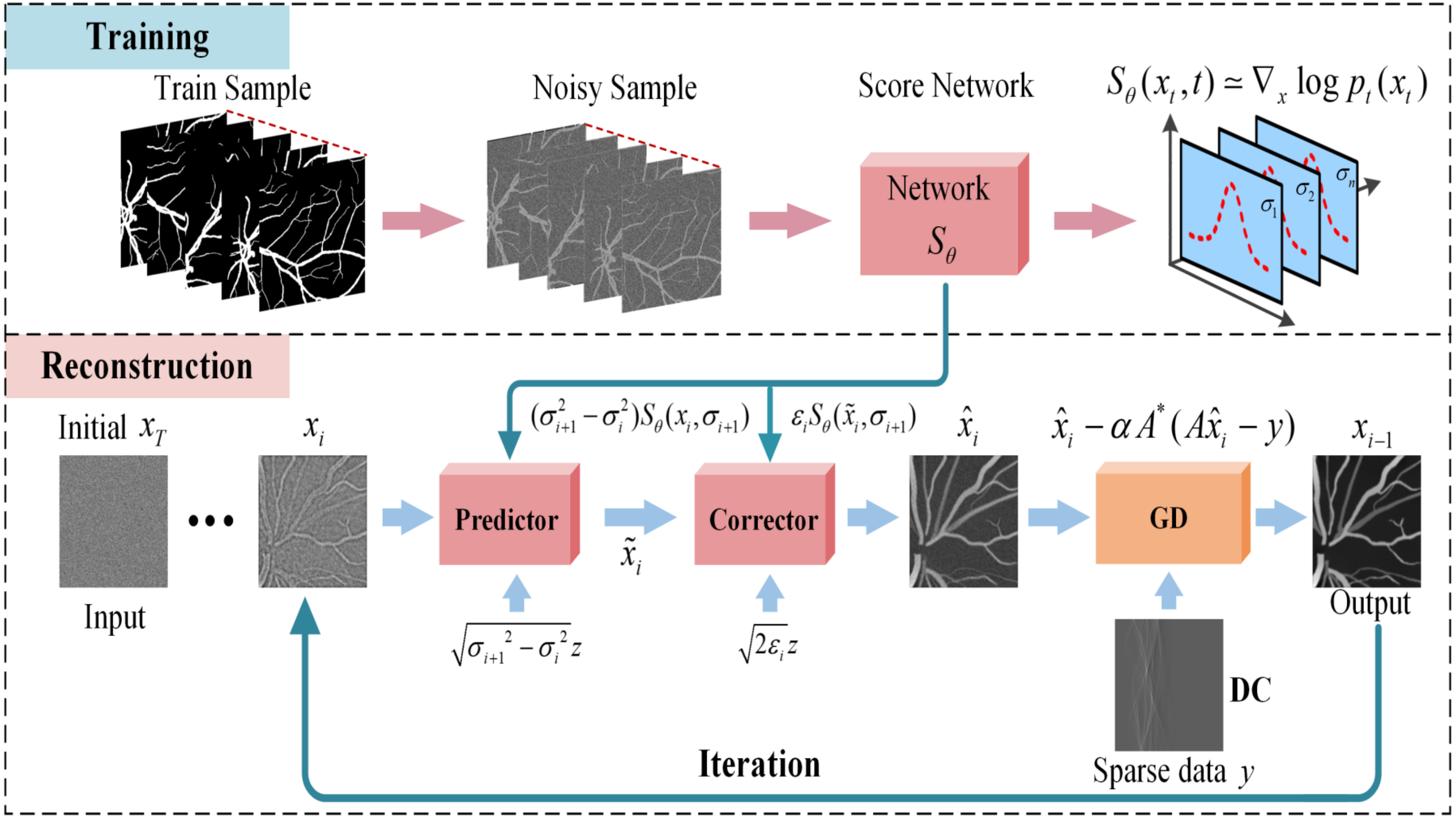


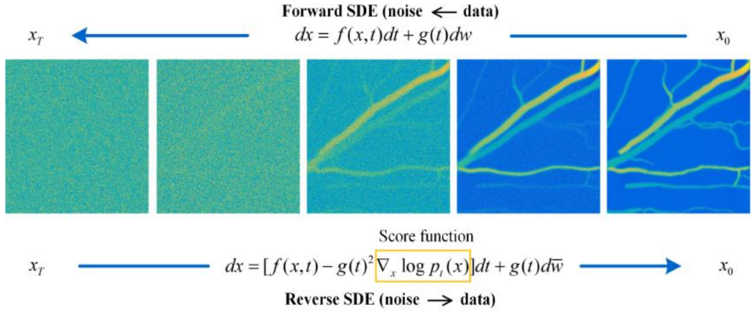
×**稀疏测量**导致重建质量下降

X.Song , G.Wang , W.Zhong, K.Guo, Z.Li, X.Liu, J.Dong, Q.Liu. Sparse-view reconstruction for photoacoustic tomography combining diffusion model with model-based iteration[J]. Photoacoustics, 2023, 33: 100558.

PAT-DM for sparse-view reconstruction

Diffusion model + model-based iteration





Algorithm 1

Training for prior learning

Dataset: Photoacoustic dataset: x

1: Training $S_\theta(x_t,t) \simeq \nabla_x \log p_t(x_t)$

2: Output: Trained $S_\theta(x_t,t)$

Iterative reconstruction

Setting: Score network S_θ, Noise iteration step ε_i, Noise scale σ_i, Number of discretization steps for the reverse SDE N, Number of corrector steps M

1: $x_N \sim \mathcal{N}(0,\sigma_{\max}^2 I)$

2: $z \sim \mathcal{N}(0,1)$

3: For $i = N$-1 to 0 **do (Outer loop)**

4: Update $\tilde{x}_i = x_i + (\sigma_{i+1}^2-\sigma_i^2)S_\theta(x_i,\sigma_{i+1}) + \sqrt{\sigma_{i+1}^2-\sigma_i^2}\,z$ **(Prediction)**

5: For $j = 1$ to M **do (Inner loop)**

6: Update $\hat{x}_i \leftarrow \tilde{x}_{i,j} + \varepsilon_i S_\theta(\tilde{x}_{i,j},\sigma_{i+1}) + \sqrt{2\varepsilon_i}\,z$ **(Correction)**

7: End for

8: Update $x_{i-1} = \hat{x}_i - \alpha A^*(A\hat{x}_i - y)$ **(Gradient descent)**

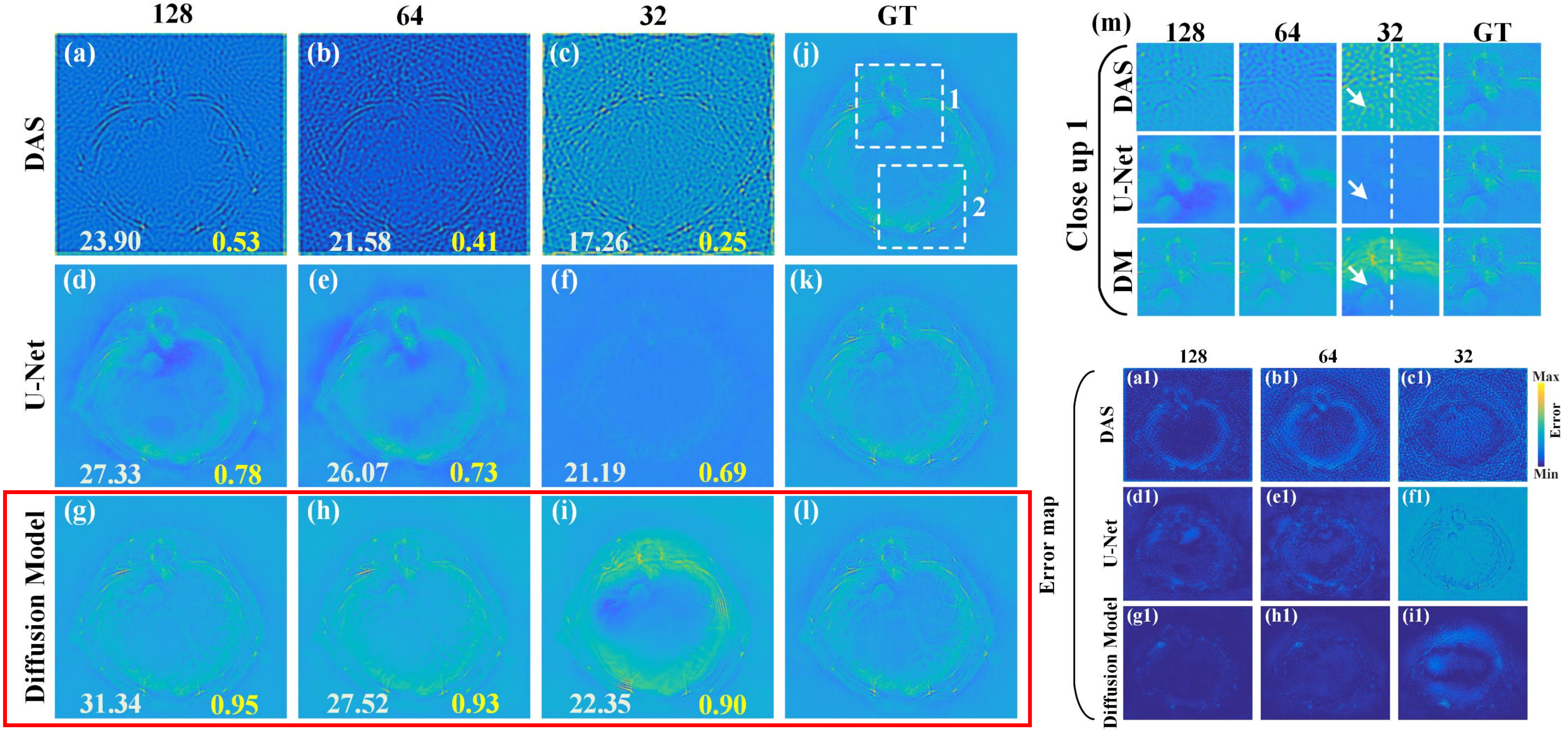
9: End for

Return x_0

X.Song , G.Wang , W.Zhong, K.Guo, Z.Li, X.Liu, J.Dong, Q.Liu. Sparse-view reconstruction for photoacoustic tomography combining diffusion model with model-based iteration[J]. Photoacoustics, 2023, 33: 100558.

Experimental results

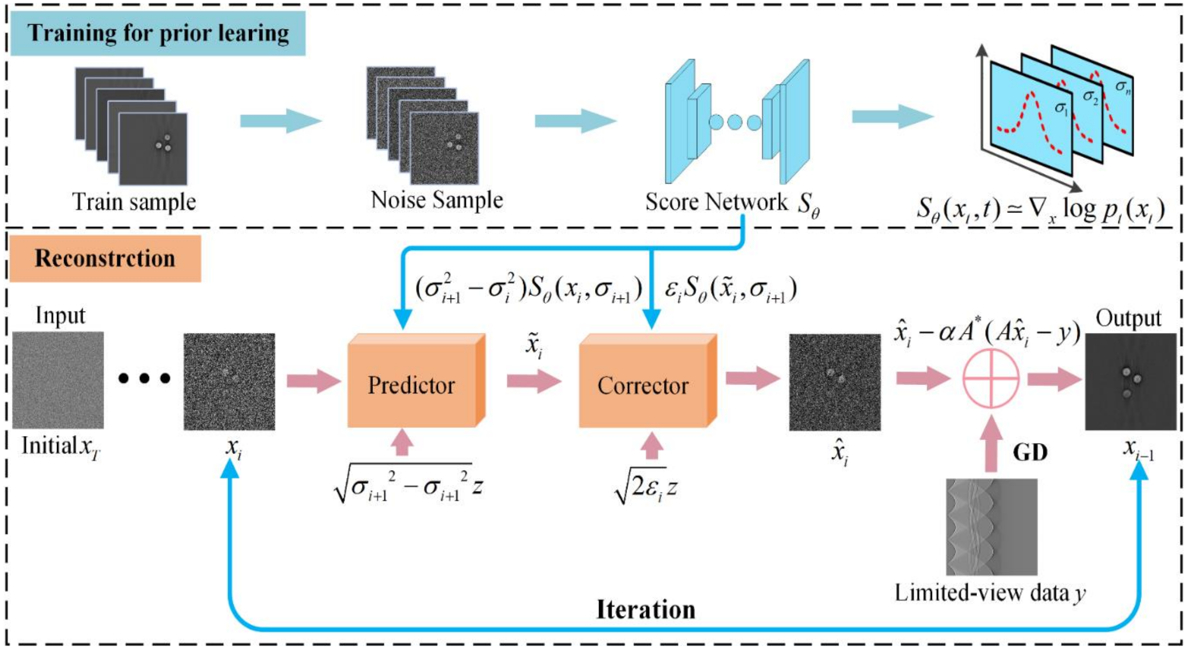
The result of *in vivio* mouse abdomen

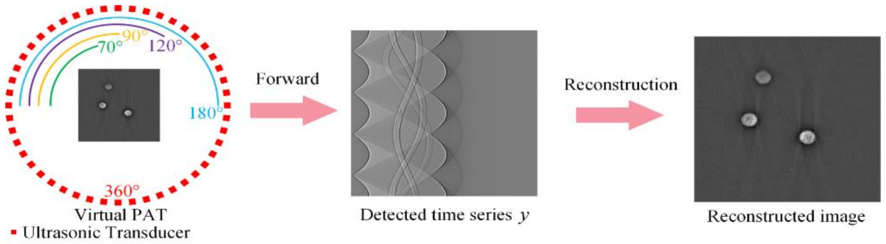


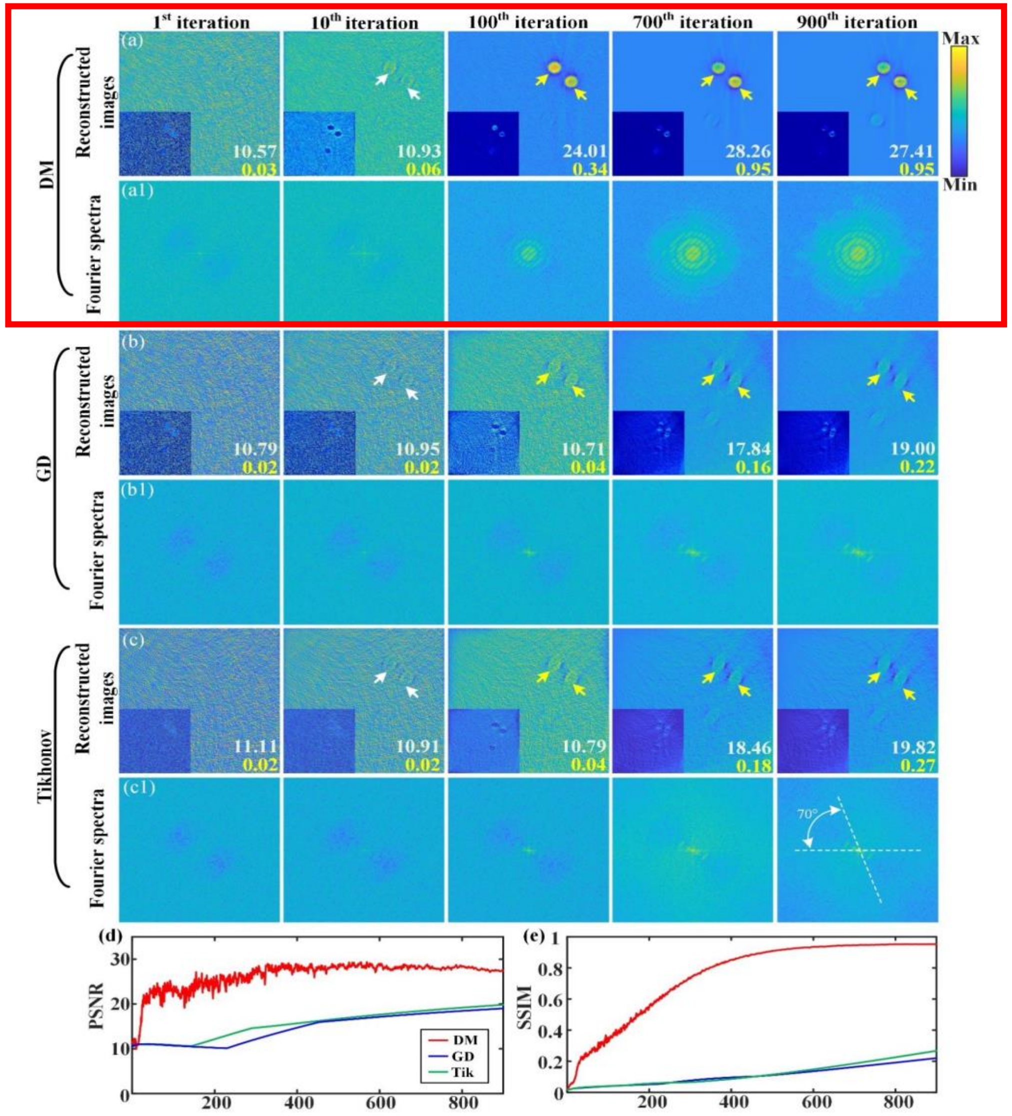
X.Song , G.Wang , W.Zhong, K.Guo, Z.Li, X.Liu, J.Dong, Q.Liu. Sparse-view reconstruction for photoacoustic tomography combining diffusion model with model-based iteration. Photoacoustics, 2023, 33: 100558.

PAT-DM for limited-view reconstruction

- **Diffusion model + model-based iteration**
- ✓ **70度有限视角高质量重建**



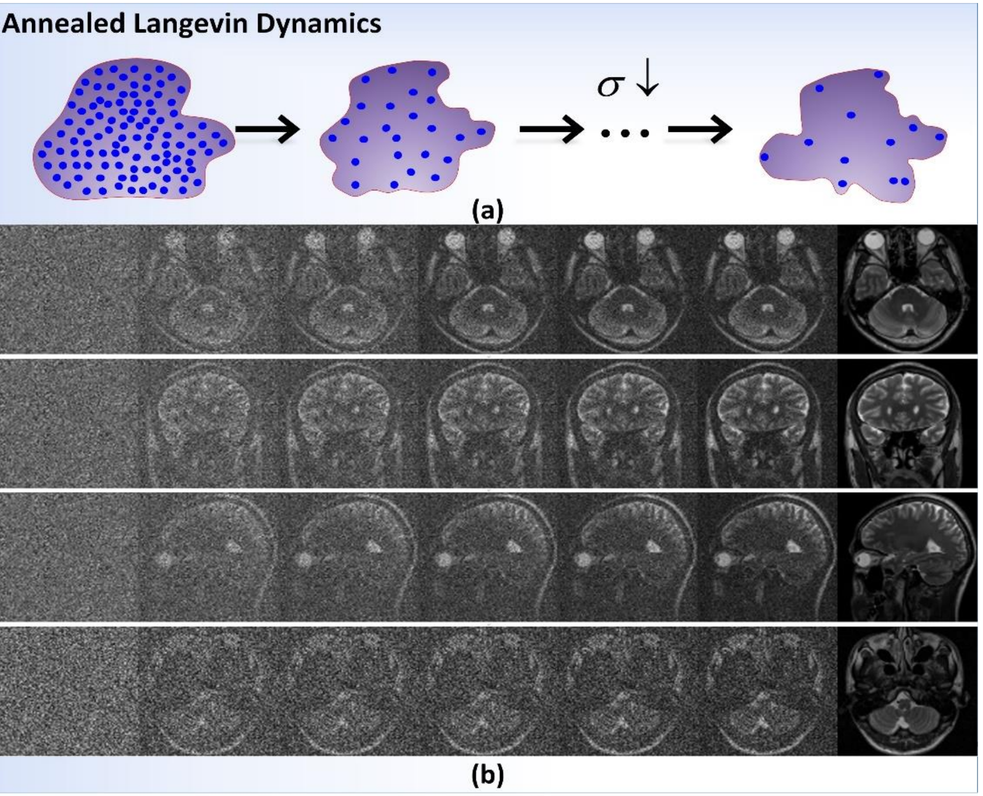


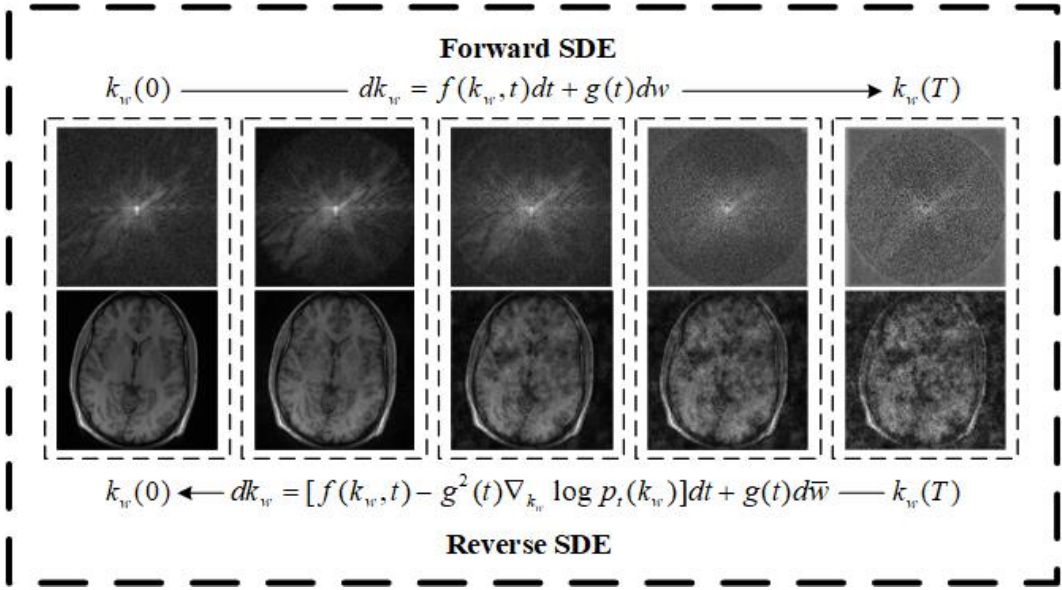


K. Guo, Z. Zheng, W. Zhong, Z. Li, G. Wang, J. Li, Y. Cao, Y. Wang, J. Lin, Q. Liu, X. Song. Score-based generative model-assisted information compensation for high-quality limited-view reconstruction in photoacoustic tomography. Photoacoustics, 2024, 38: 100623.

DSM from image domain to k-space domain

Generative model in image domain



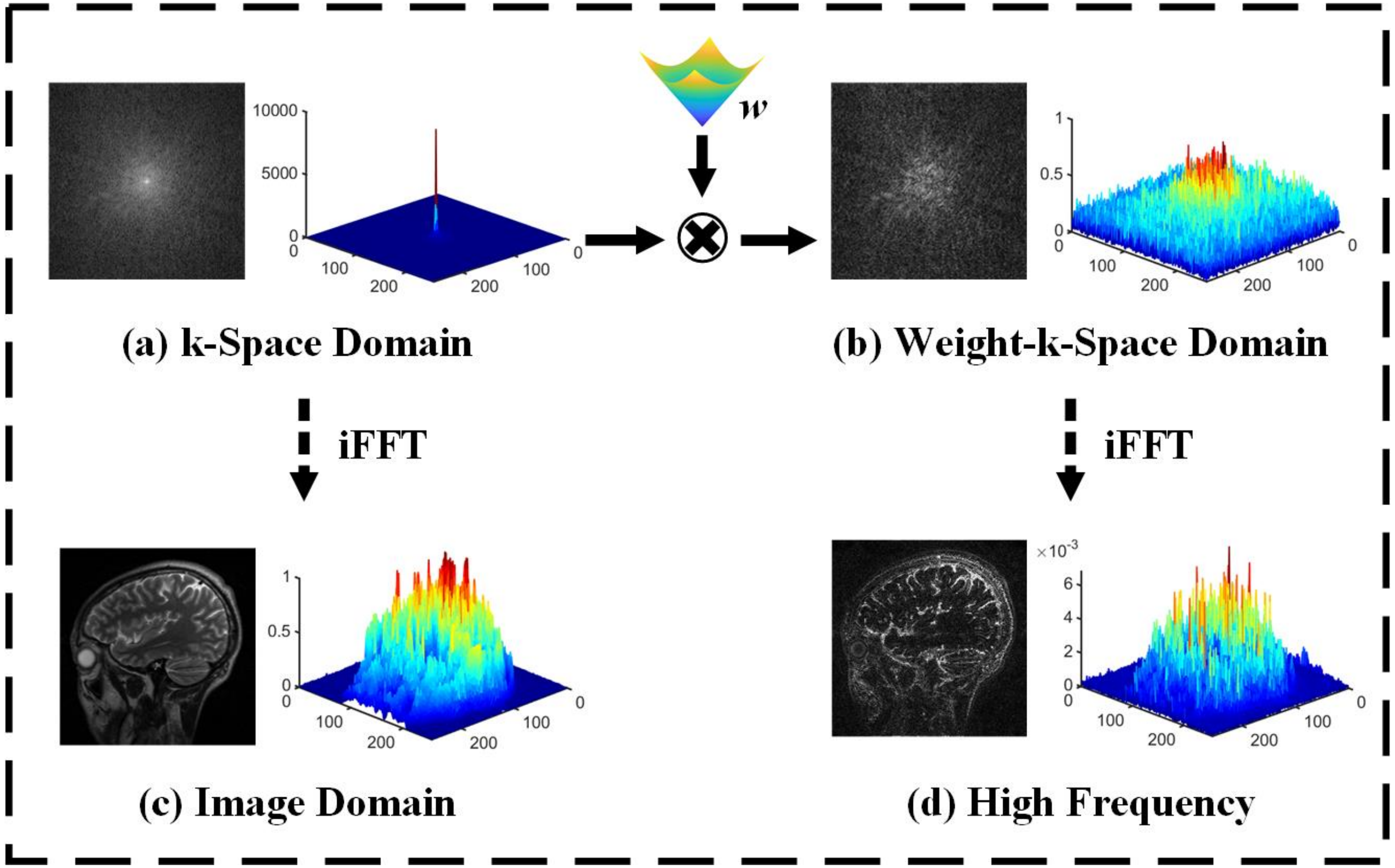


Generative model in k-space domain

Z. Tu, D. Liu, X. Wang, C. Jiang, M. Zhang, Q. Liu, D. Liang, WKGM: Weight-K-space generative model for parallel imaging reconstruction, *NMR in Biomedicine*, e5005, 2023.

WKGM

Algorithm overview



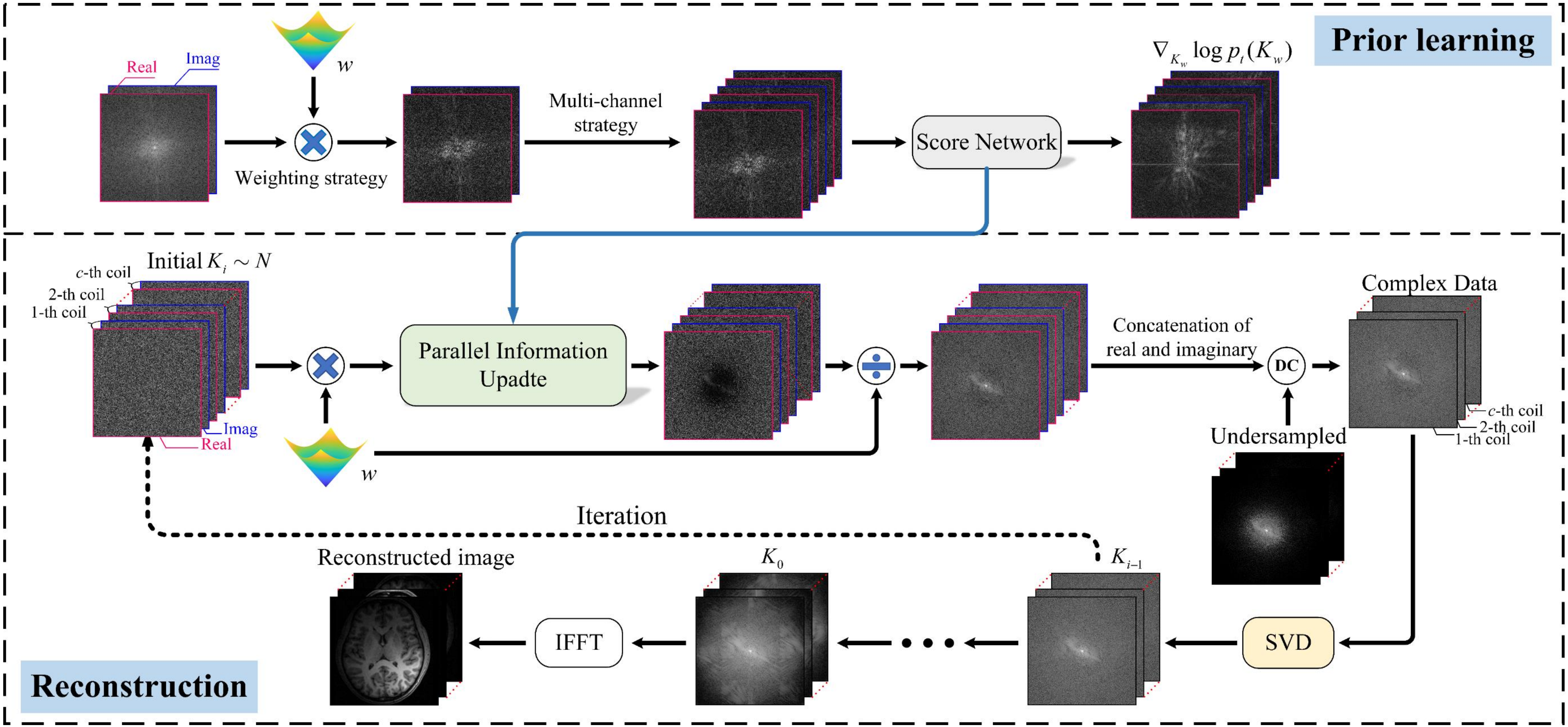
Visual comparison of the amplitude values in k-space domain and weight-k-space domain.

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, *NMR in Biomedicine*, e5005, 2023.

WKGM

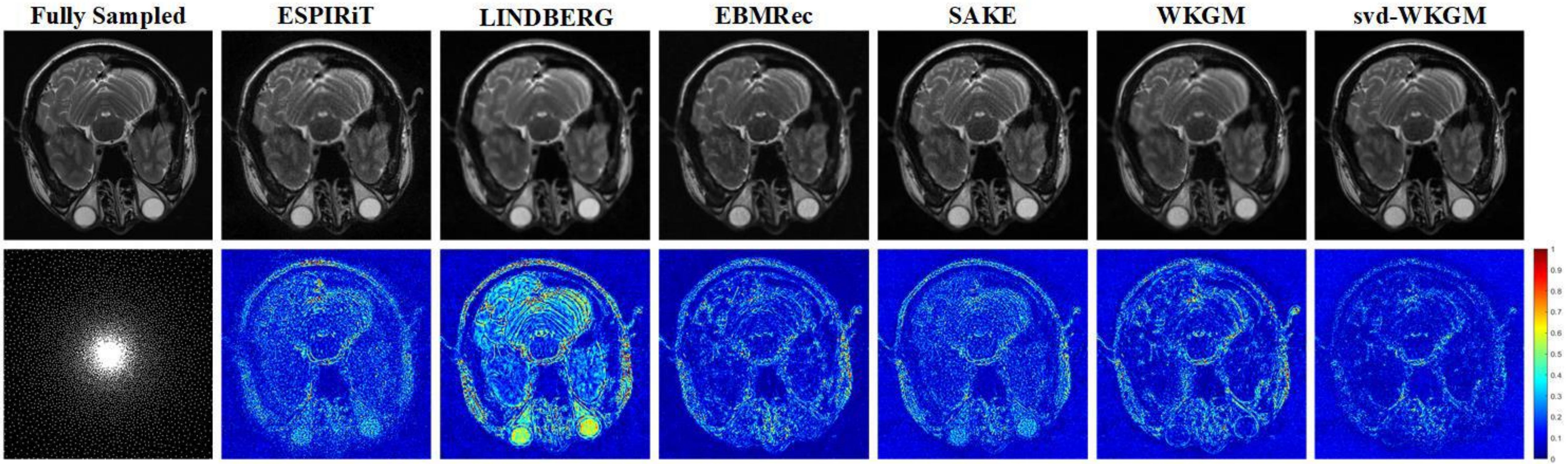
Algorithm overview



Z. Tu, D. Liu, X. Wang, C. Jiang, M. Zhang, Q. Liu, D. Liang, WKGM: Weight-K-space generative model for parallel imaging reconstruction, *NMR in Biomed icine*, e5005, 2023.

WKGM

Experimental results

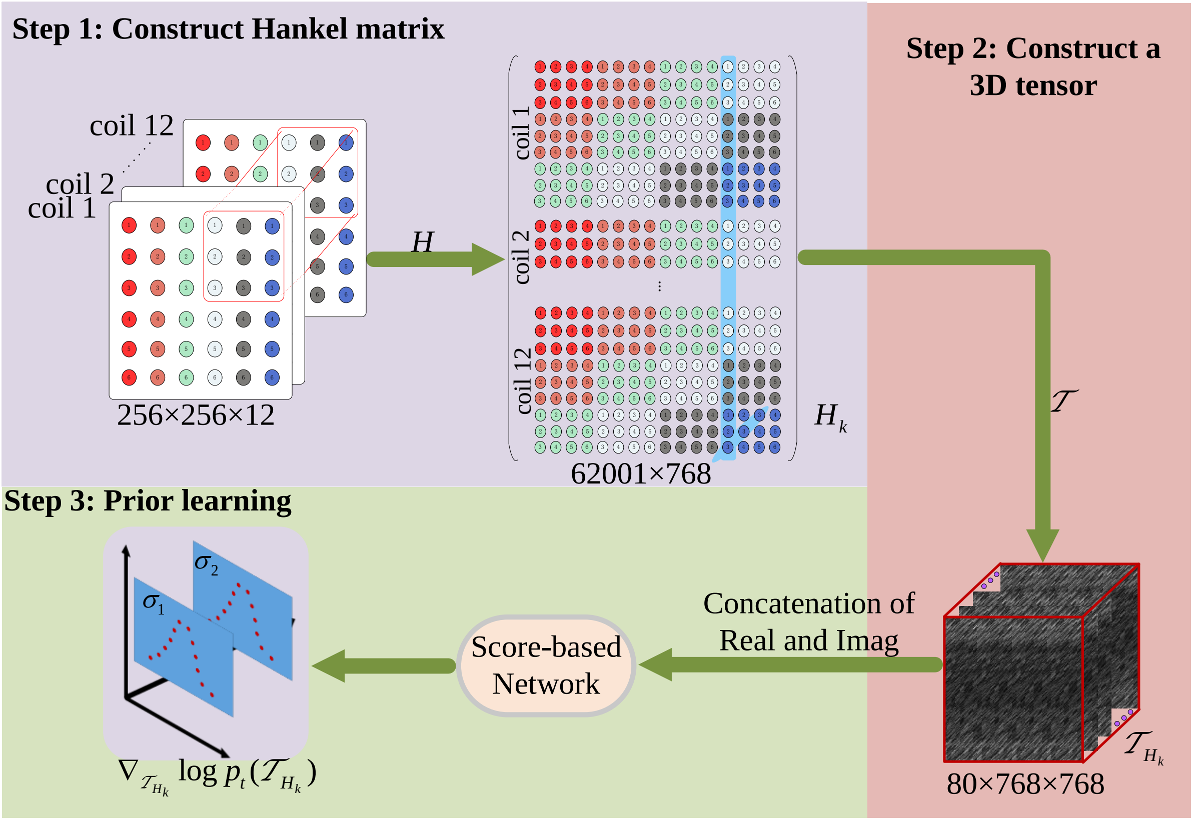


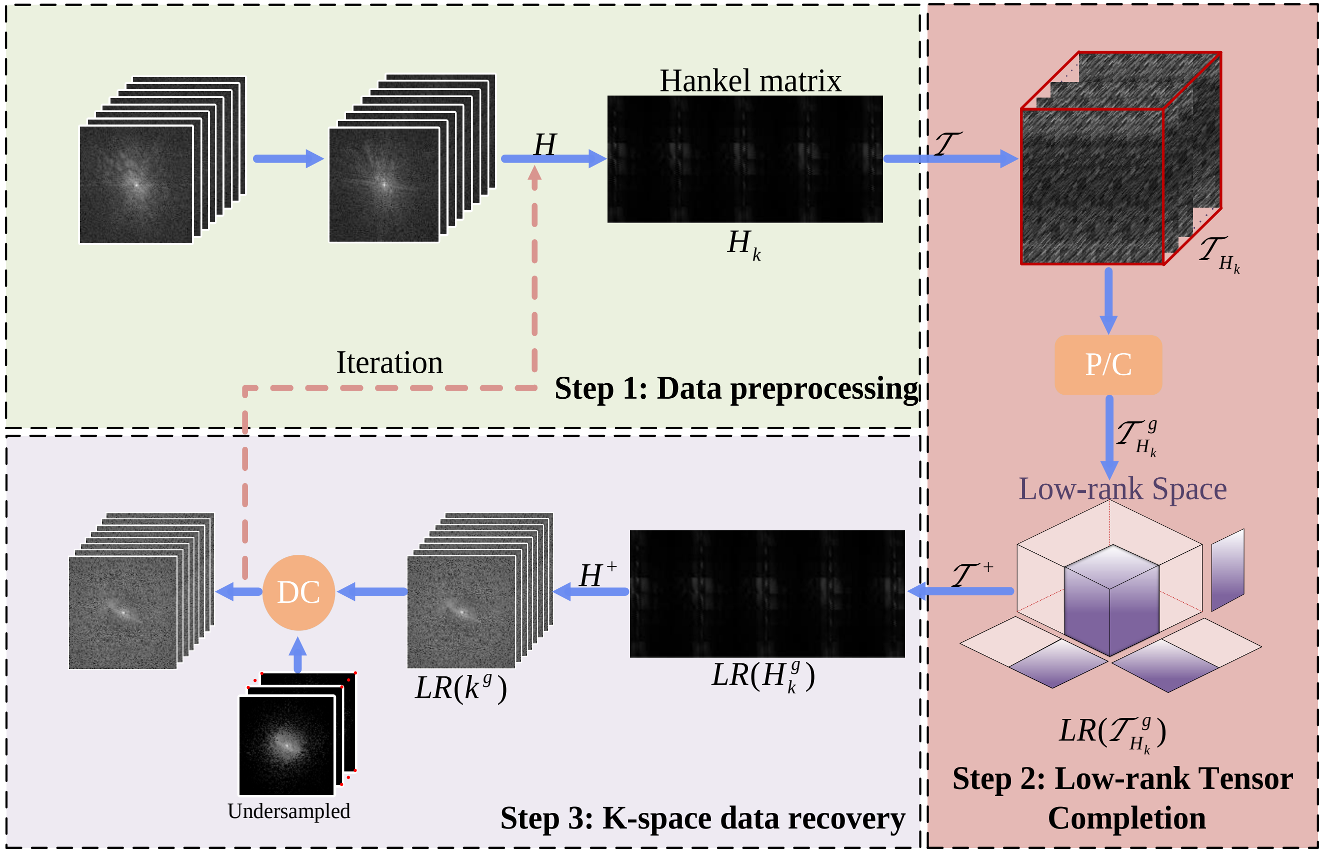
Parallel imaging reconstruction results by ESPIRiT, LINDBERG, EBMRec, SAKE, WKGM and svd-WKGM in *T2 Transversal Brain* at *R*=10 2D Poisson disk under-sampling mask. The intensity of residual maps is five times magnify.

Z. Tu, D. Liu, X. Wang, C. Jiang, M. Zhang, Q. Liu, D. Liang, WKGM: Weight-K-space generative model for parallel imaging reconstruction, NMR in Biomedicine, e5005, 2023.

LR-KGM

Algorithm overview





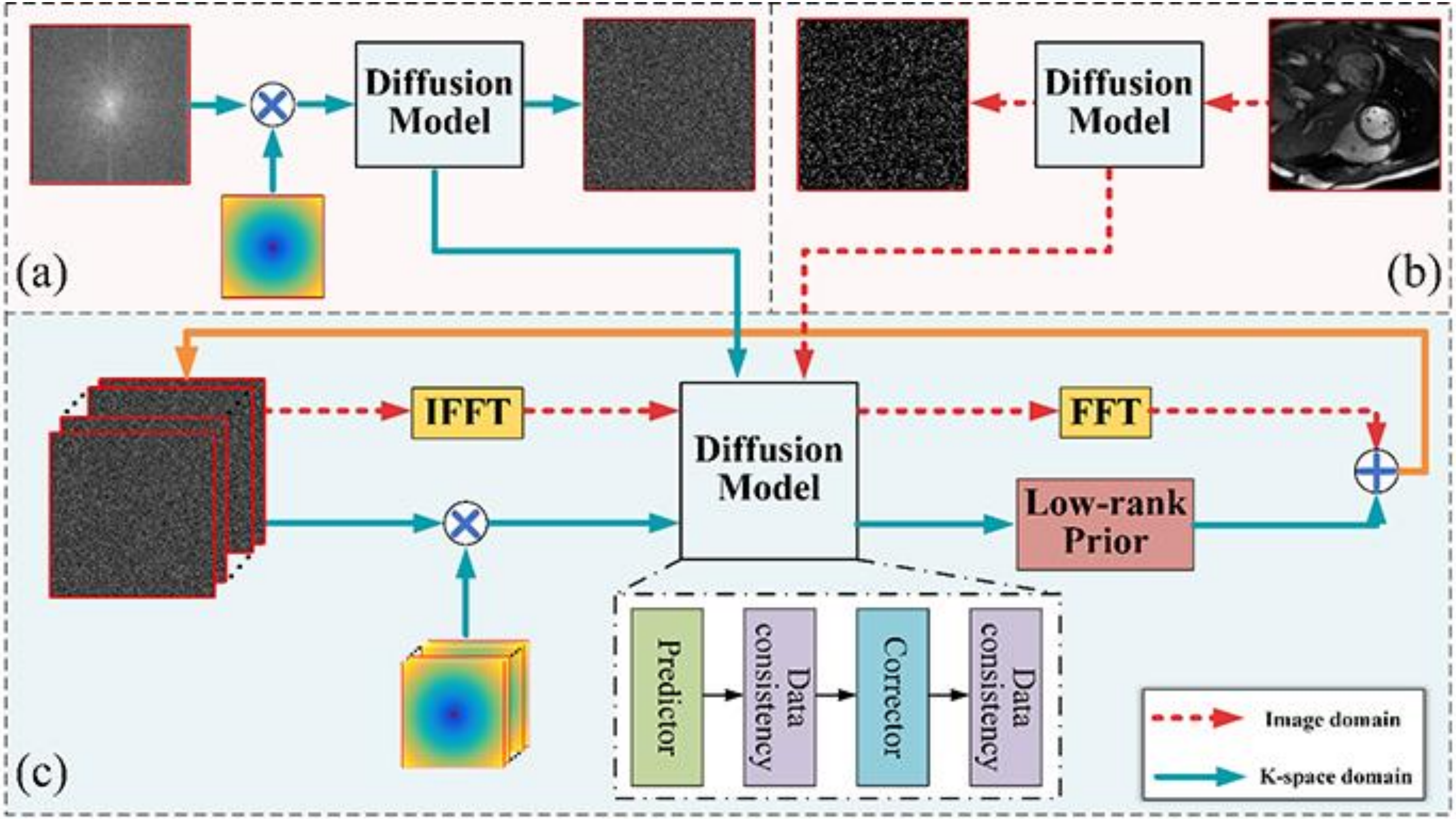
Prior learning

Iterative reconstruction

W. Zhang, Z. Xiao, H. Tao, M. Zhang, X. Xu, Q. Liu. Low-rank assisted k-space generative model for parallel imaging reconstruction, *Magnetic Resonance Imaging* 103, 198-207, 2022.

DD-UGM

Algorithm overview

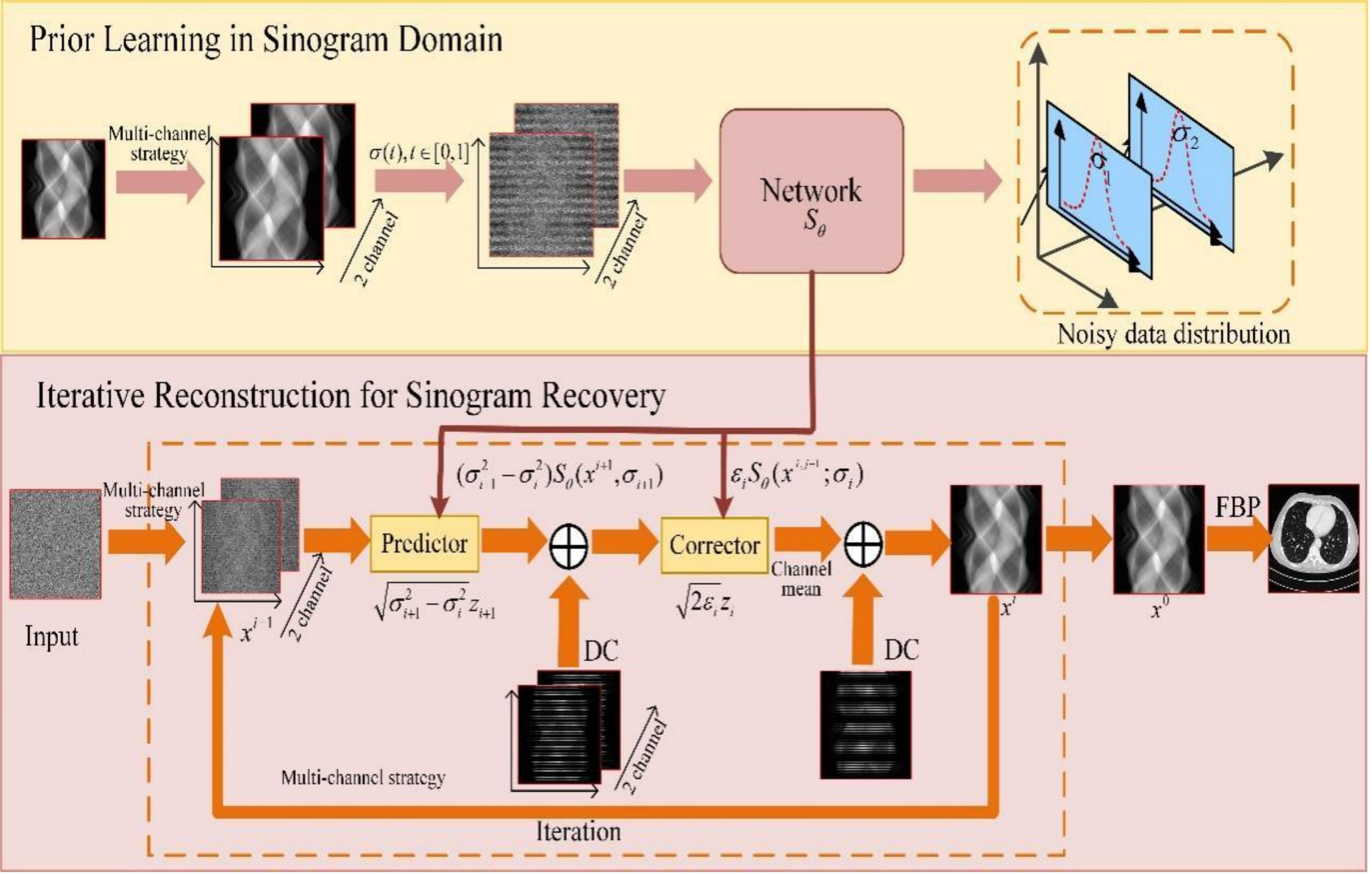


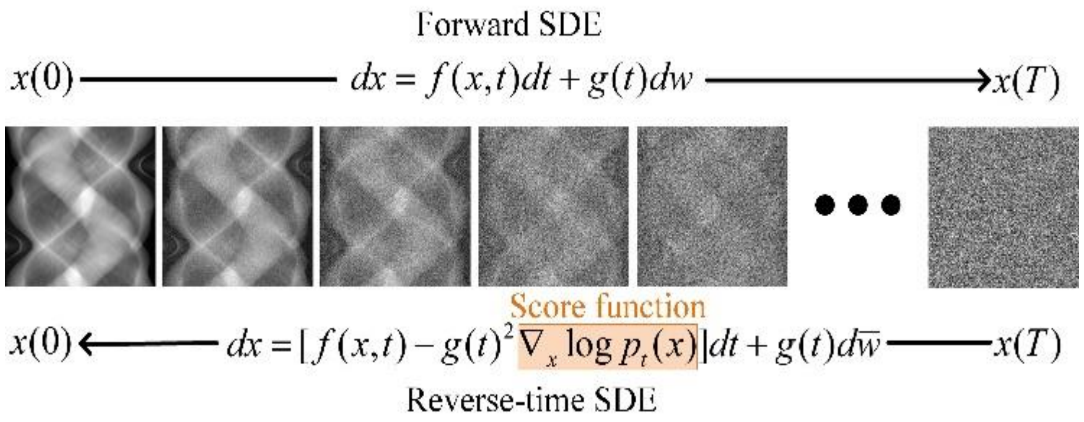
Prior learning in dual-domain for dMRI reconstruction

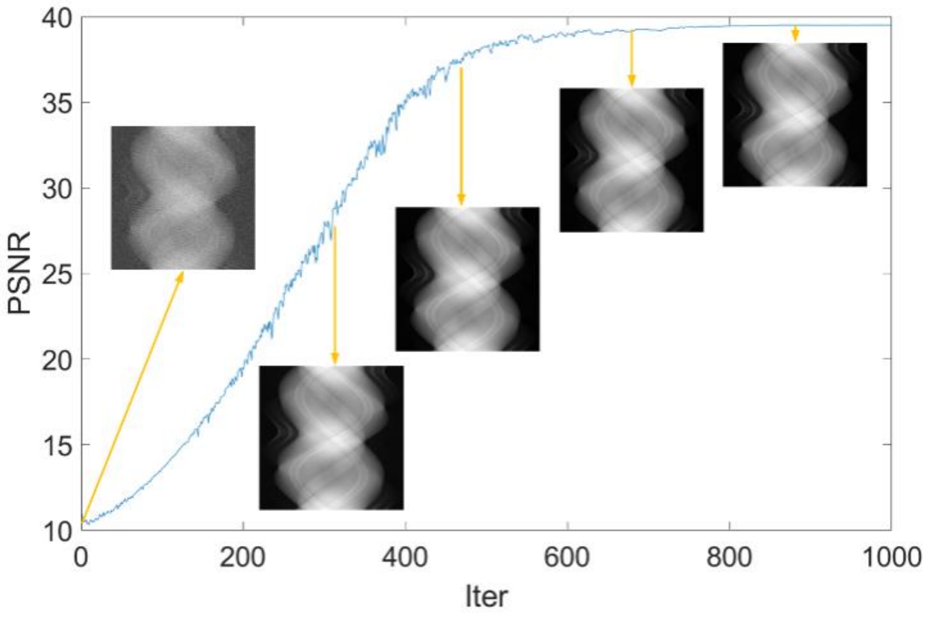
C. Yu, Y. Guan, Z. Ke, K. Lei, D. Liang, Q. Liu, Universal generative modeling in dual-domain for dynamic MR imaging, *NMR in Biomedicine*, 2023.

GMSD

Algorithm overview



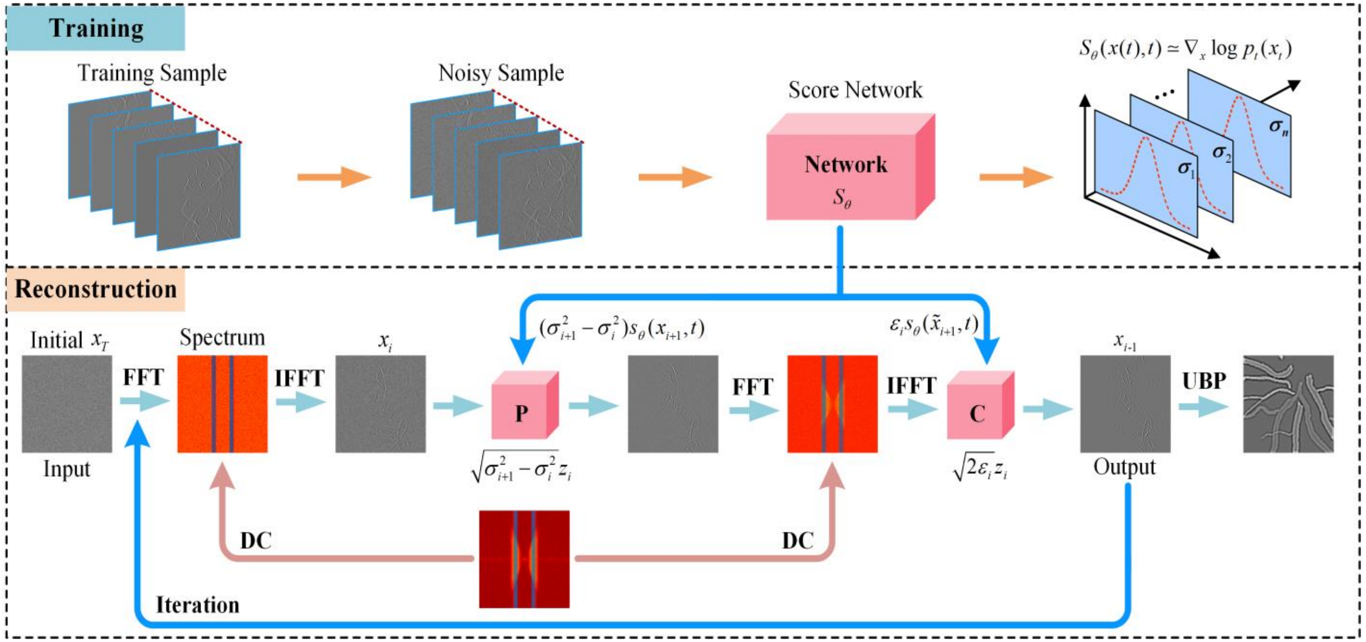




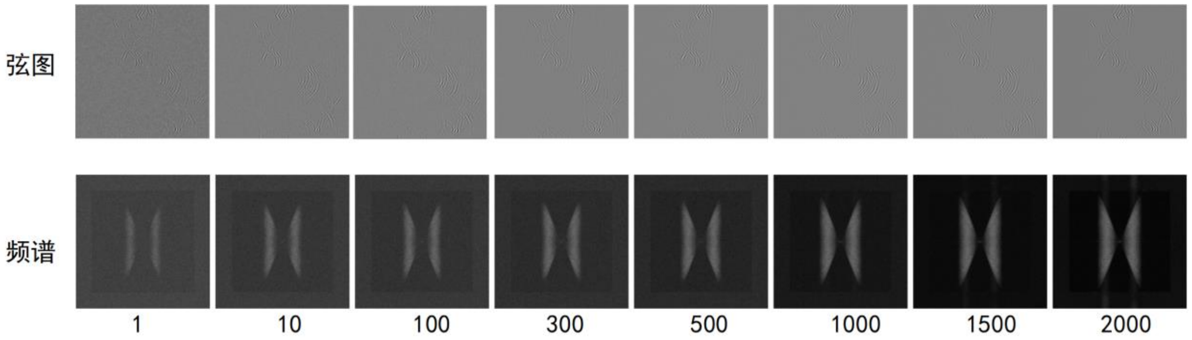
B. Guan, C. Yang, L. Zhang, S. Niu, M. Zhang, Y. Wang, W. Wu, Q. Liu, Generative modeling in sinogram domain for sparse-view CT reconstruction, IEEE Transactions on Radiation and Plasma Medical Sciences, 2023.

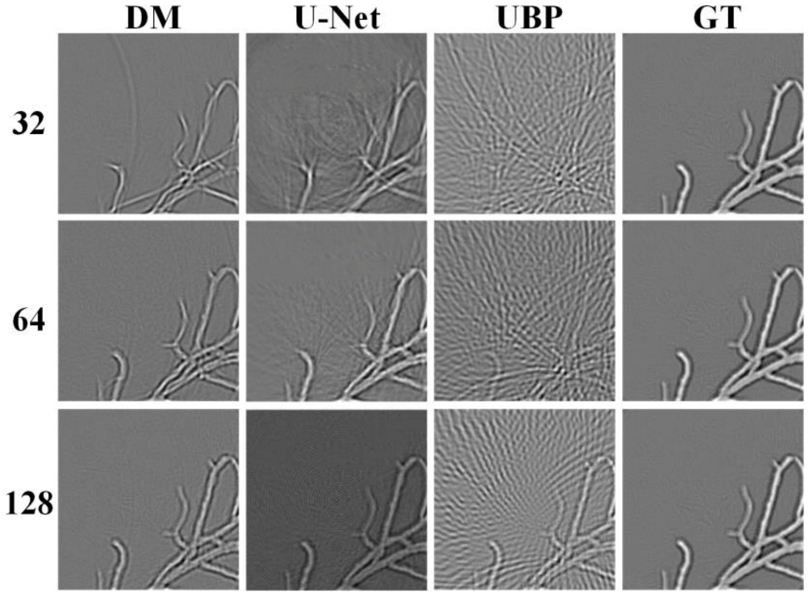
Algorithm overview

基于扩散模型的光声断层弦图域的稀疏重建和带宽增强

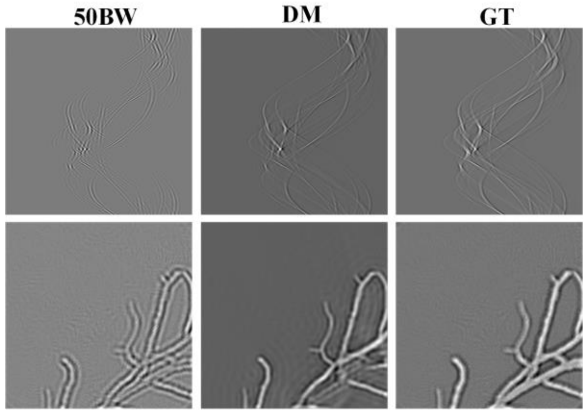


迭代过程





稀疏重建结果



带宽增强结果

Z. Li, J. Lin, Y. Wang, J. Li, Y. Cao, X. Liu, W. Wan, Q. Liu, X. Song. Ultra-sparse reconstruction for photoacoustic tomography: Sinogram domain prior-guided method exploiting enhanced score-based diffusion model, Photoacoustics, 2025, 41: 100670.

面向原始数据域的生成式智能成像

1. Background: From CS to AI

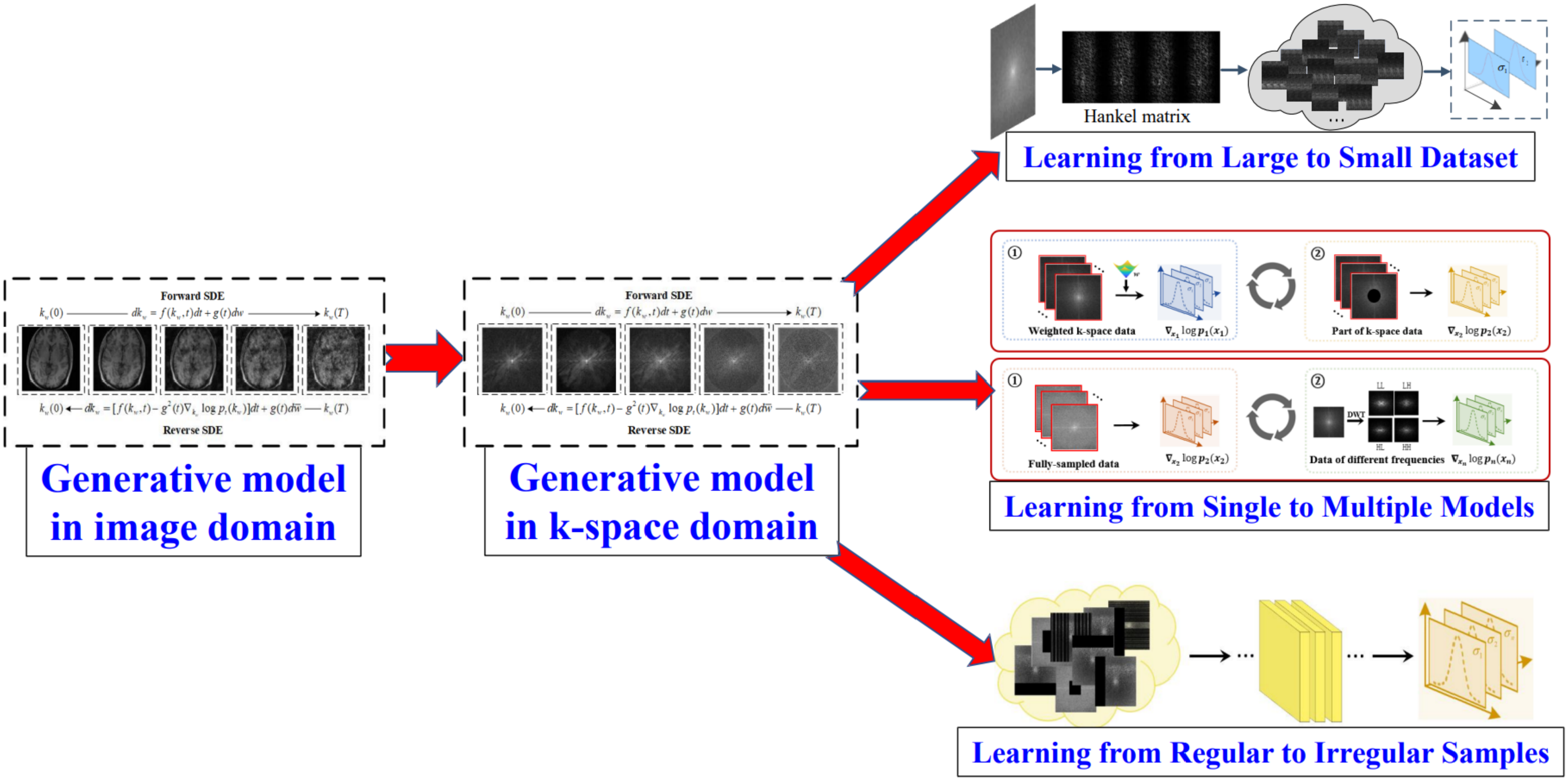
2. Part1: Diffusion Model (DM)

DM from Image to Projection Domain

3. Part2: DM from Large to Small Dataset

DM from Single to Multiple Models

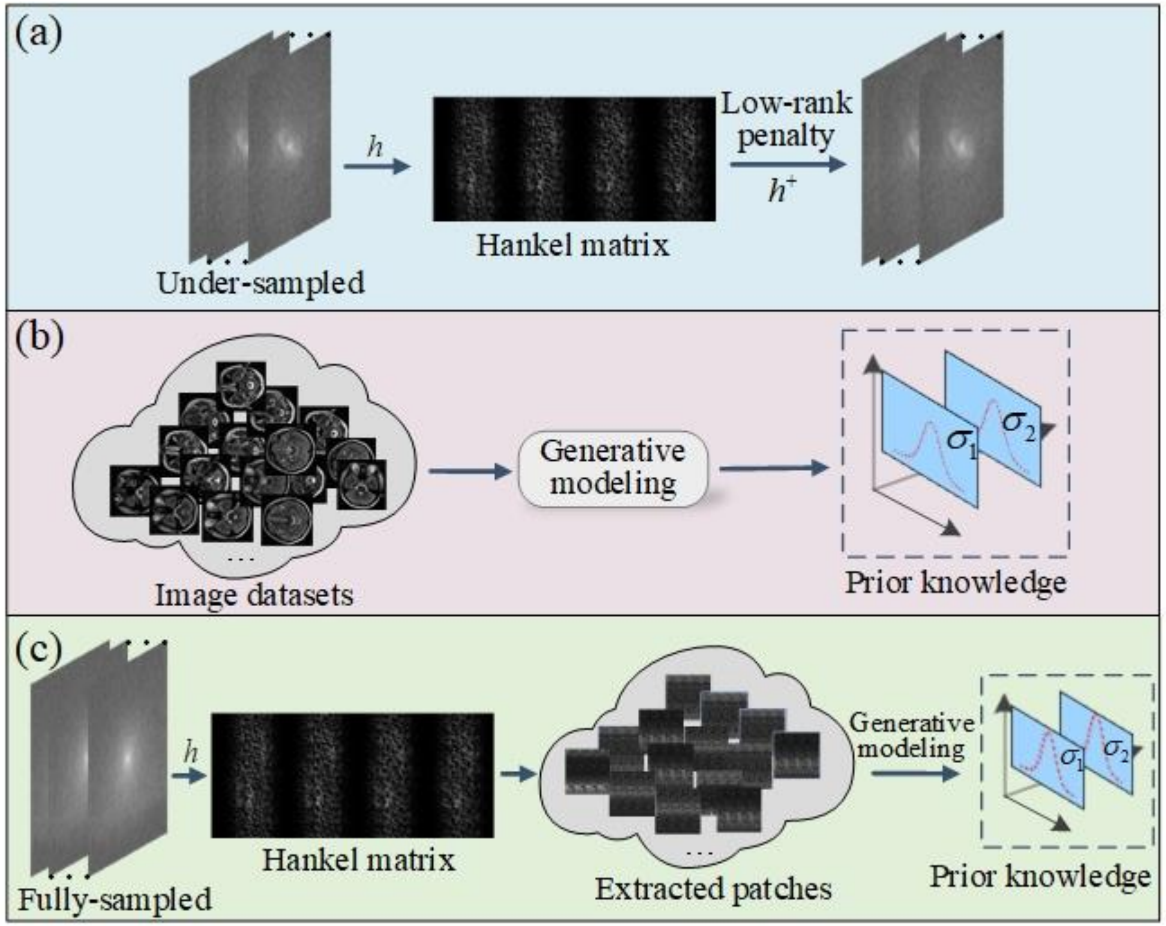
DM from Regular to Irregular Samples



Forward SDE
$k_w(0) \longrightarrow dk_w = f(k_w,t)dt + g(t)dw \longrightarrow k_w(T)$
$k_w(0) \longleftarrow dk_w = [f(k_w,t) - g^2(t)\nabla_{k_w} \log p_t(k_w)]dt + g(t)d\bar{w} \longleftarrow k_w(T)$
Reverse SDE
Generative model in image domain
Forward SDE
$k_w(0) \longrightarrow dk_w = f(k_w,t)dt + g(t)dw \longrightarrow k_w(T)$
$k_w(0) \longleftarrow dk_w = [f(k_w,t) - g^2(t)\nabla_{k_w} \log p_t(k_w)]dt + g(t)d\bar{w} \longleftarrow k_w(T)$
Reverse SDE
Generative model in k-space domain
Hankel matrix
...
Learning from Large to Small Dataset
①
Weighted k-space data
$\nabla_{x_1} \log p_1(x_1)$
②
Part of k-space data
$\nabla_{x_2} \log p_2(x_2)$
①
Fully-sampled data
$\nabla_{x_2} \log p_2(x_2)$
②
LL
LH
DWT
HL
HH
Data of different frequencies
$\nabla_{x_n} \log p_n(x_n)$
Learning from Single to Multiple Models
...
...
Learning from Regular to Irregular Samples

Algorithm overview

Learning from Large to Small Dataset



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.

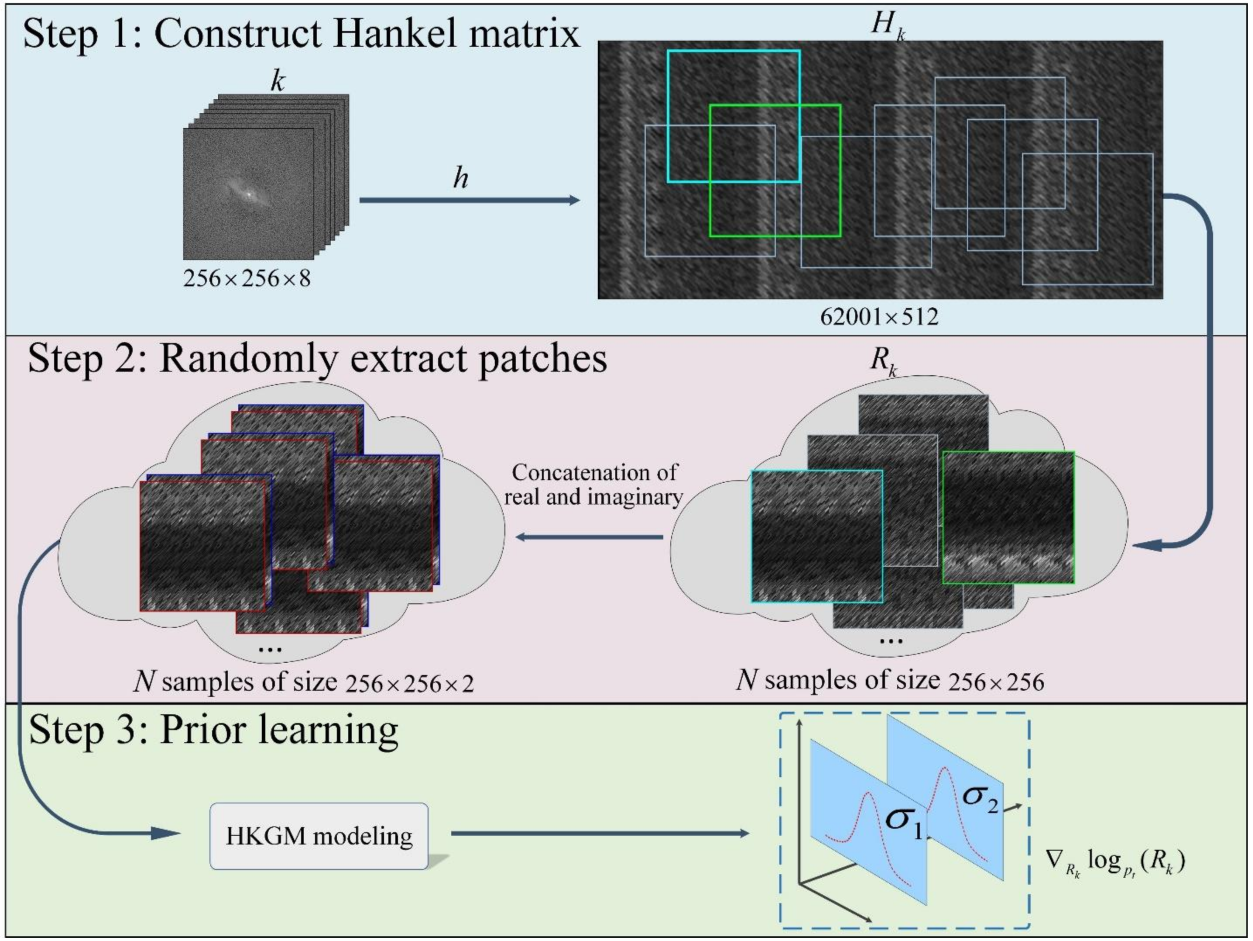
HKGM on a single k-space measurement that condu cted on dataset of low-rank patches.

Prior learning in a single k-space measurement !

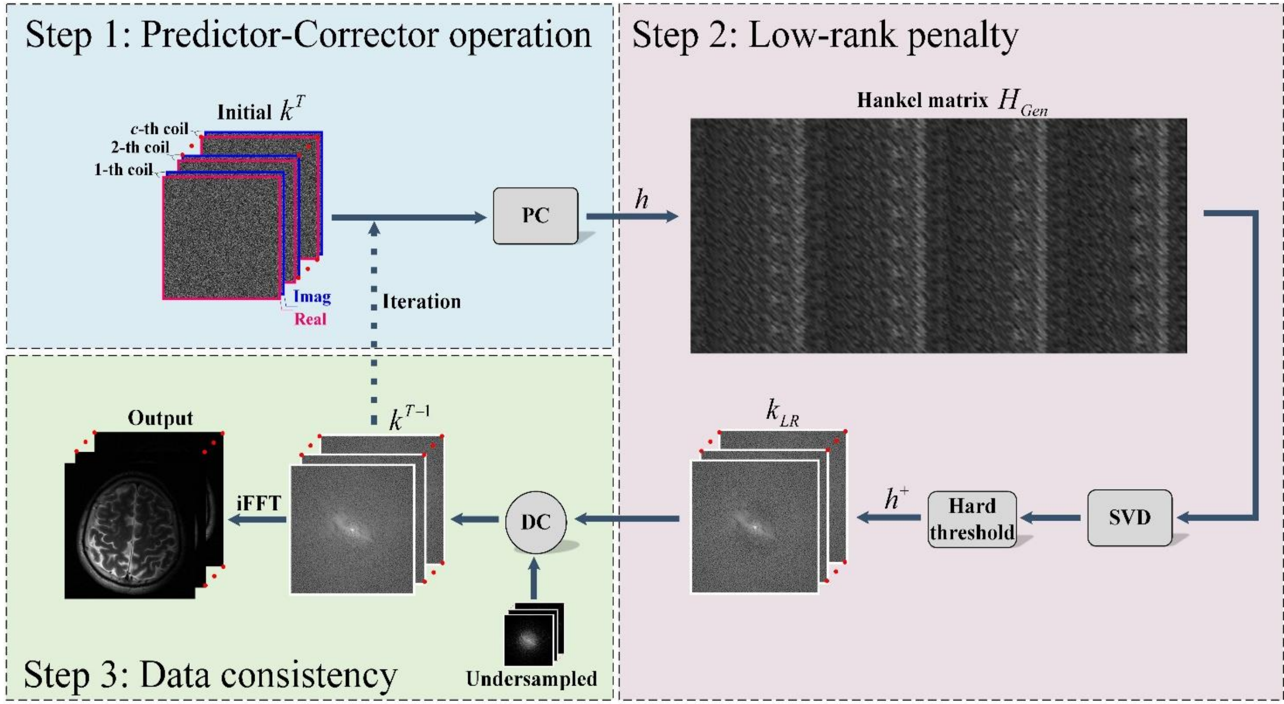
H. Peng, C. Jiang, X. Guan, C. Jiang, M. Zhang, D. Liang, Q. Liu. One-shot generative prior learned from Hankel-k-space for parallel imaging reconstruction, *IEEE Trans. Med. Imag.*, 2023.

HKGM

Algorithm overview

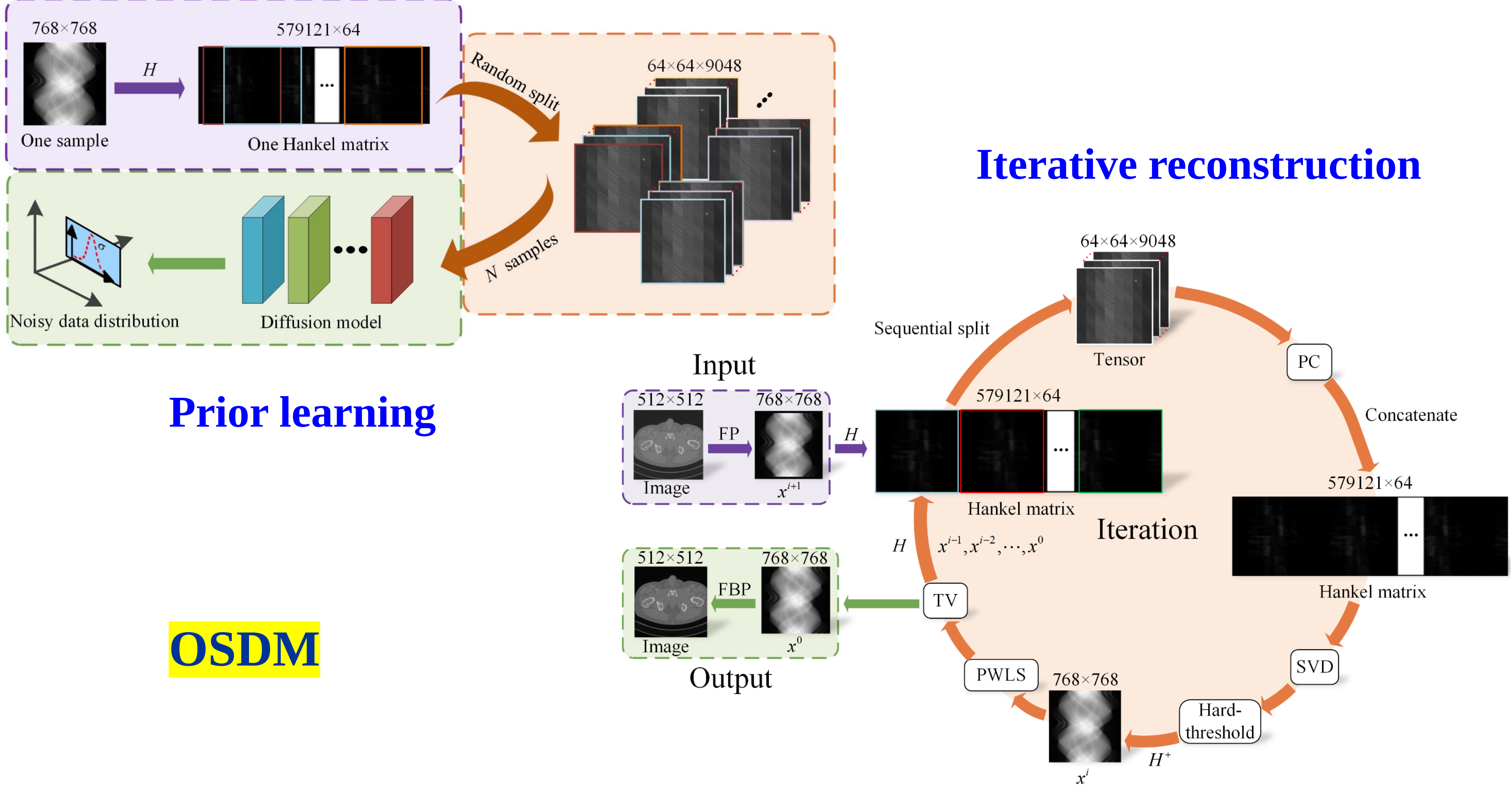


Prior learning



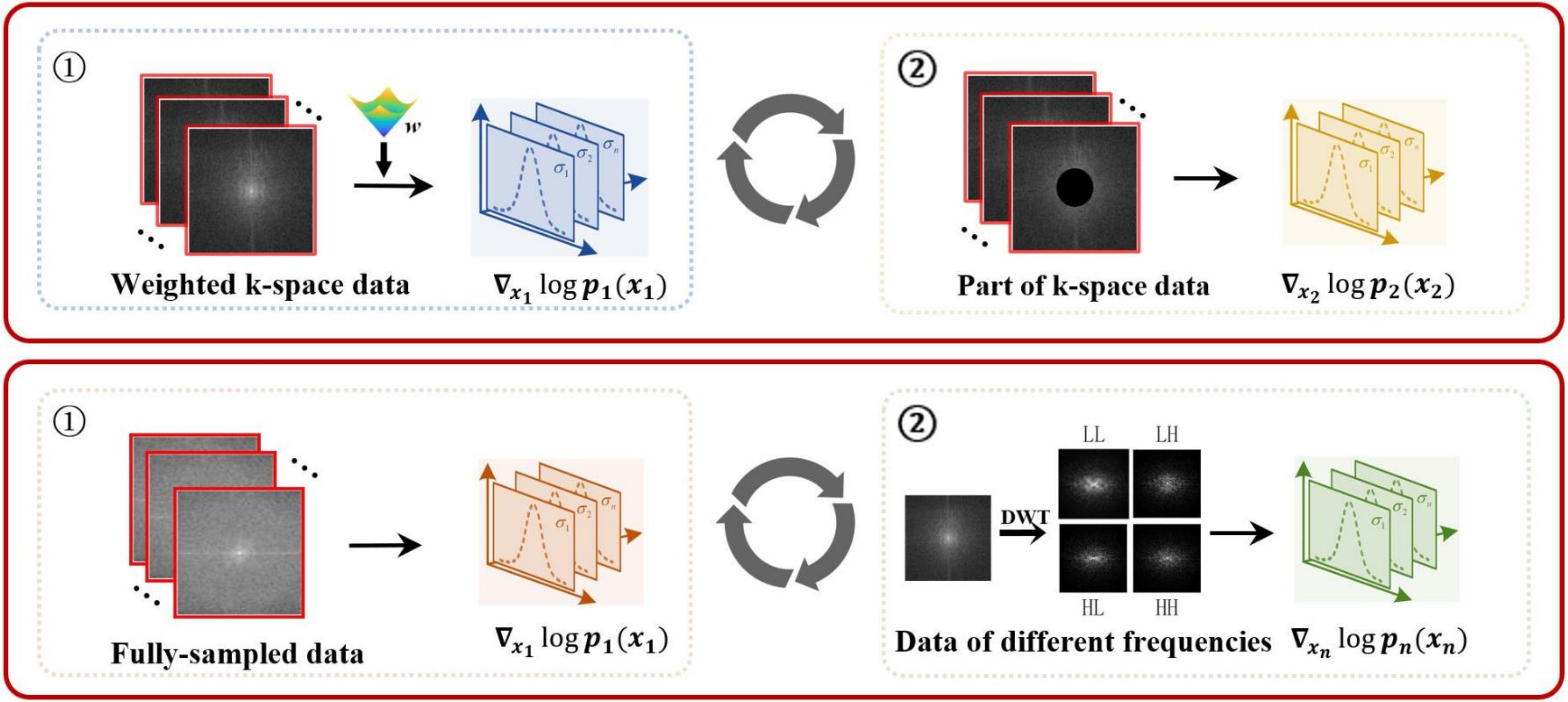
MRI reconstruction

H. Peng, C. Jiang, X. Guan, C. Jiang, M. Zhang, D. Liang, Q. Liu. One-shot generative prior learned from Hankel-k-space for parallel imaging reconstruction, *IEEE Trans. Med. Imag.*, 2023.



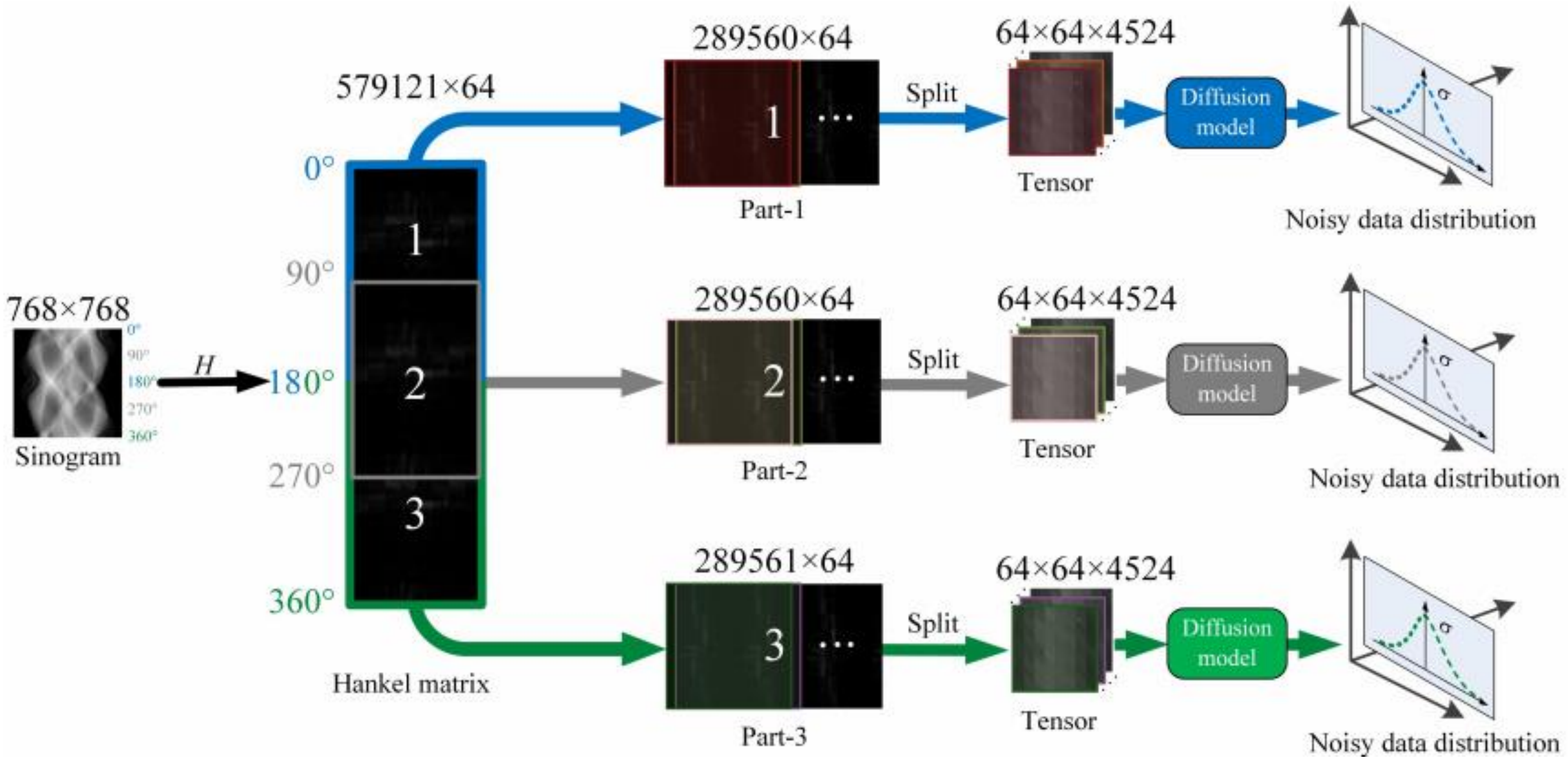
B. Huang, L. Zhang, S. Lu, B. Lin, W. Wu, Q. Liu. One sample diffusion modeling in projection domain for low-dose CT imaging, *IEEE Trans. Radiat. Plasma Med. Sci.*, 2024.

Learning from Single to Multiple Models



RAP

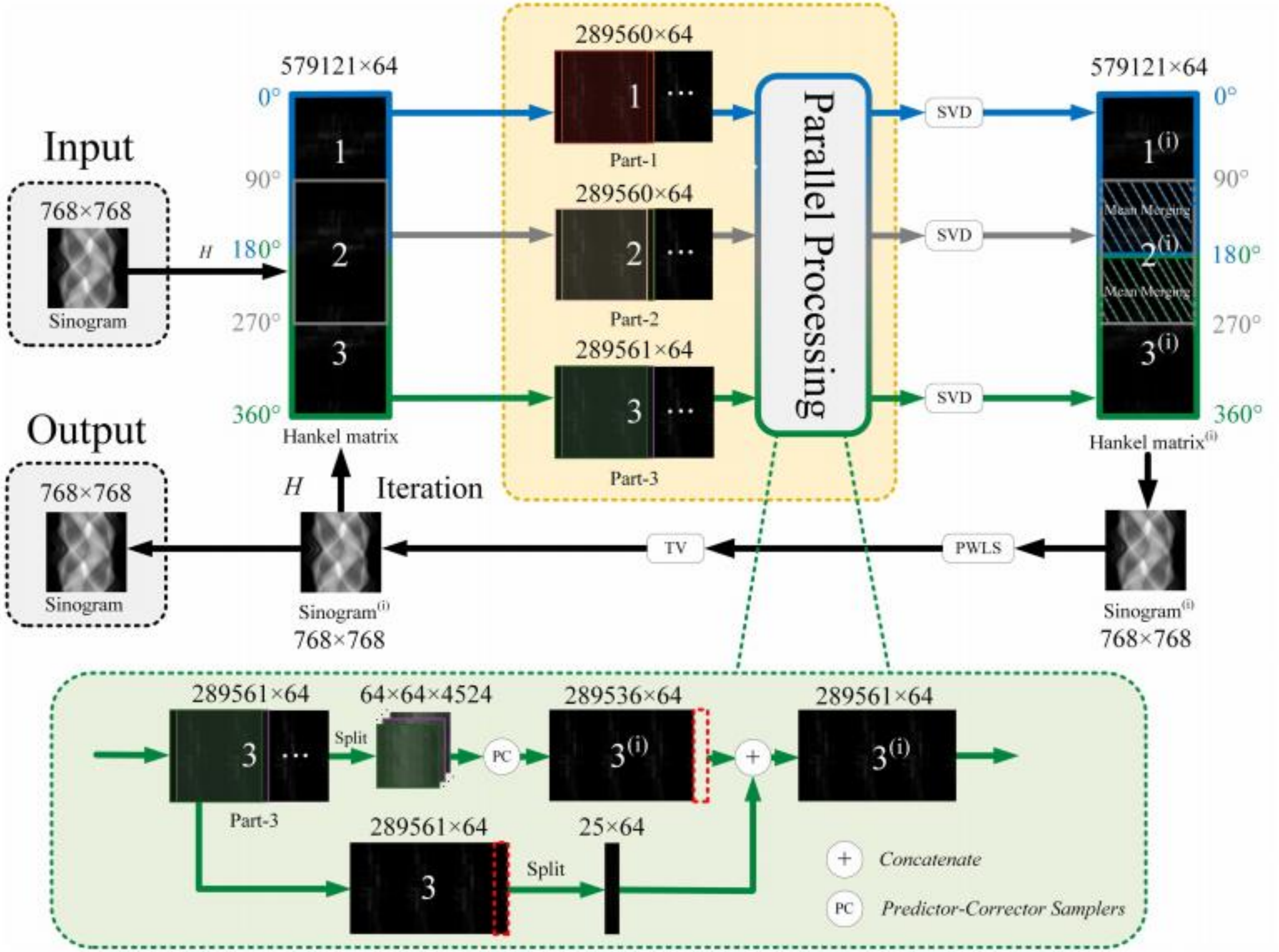
Algorithm overview



W. Zhang, B. Huang, S. Chen, X. Xu, W. Wu, Q. Liu, Low-rank angular prior guided multi-diffusion model for few-shot low-dose CT reconstruction, *IEEE Trans. Comput. Imag.*, 2024.

RAP

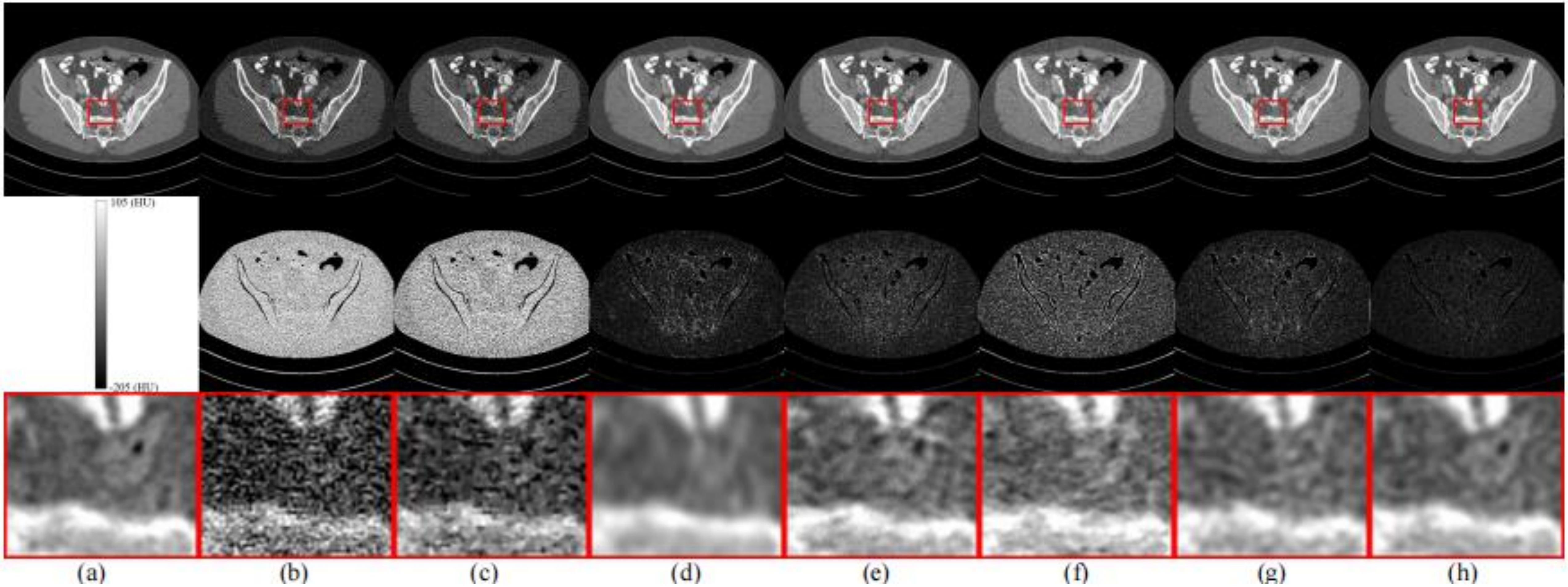
Algorithm overview



W. Zhang, B. Huang, S. Chen, X. Xu, W. Wu, Q. Liu, Low-rank angular prior guided multi-diffusion model for few-shot low-dose CT reconstruction, *IEEE Trans. Comput. Imag.*, 2024.

RAP

Algorithm overview

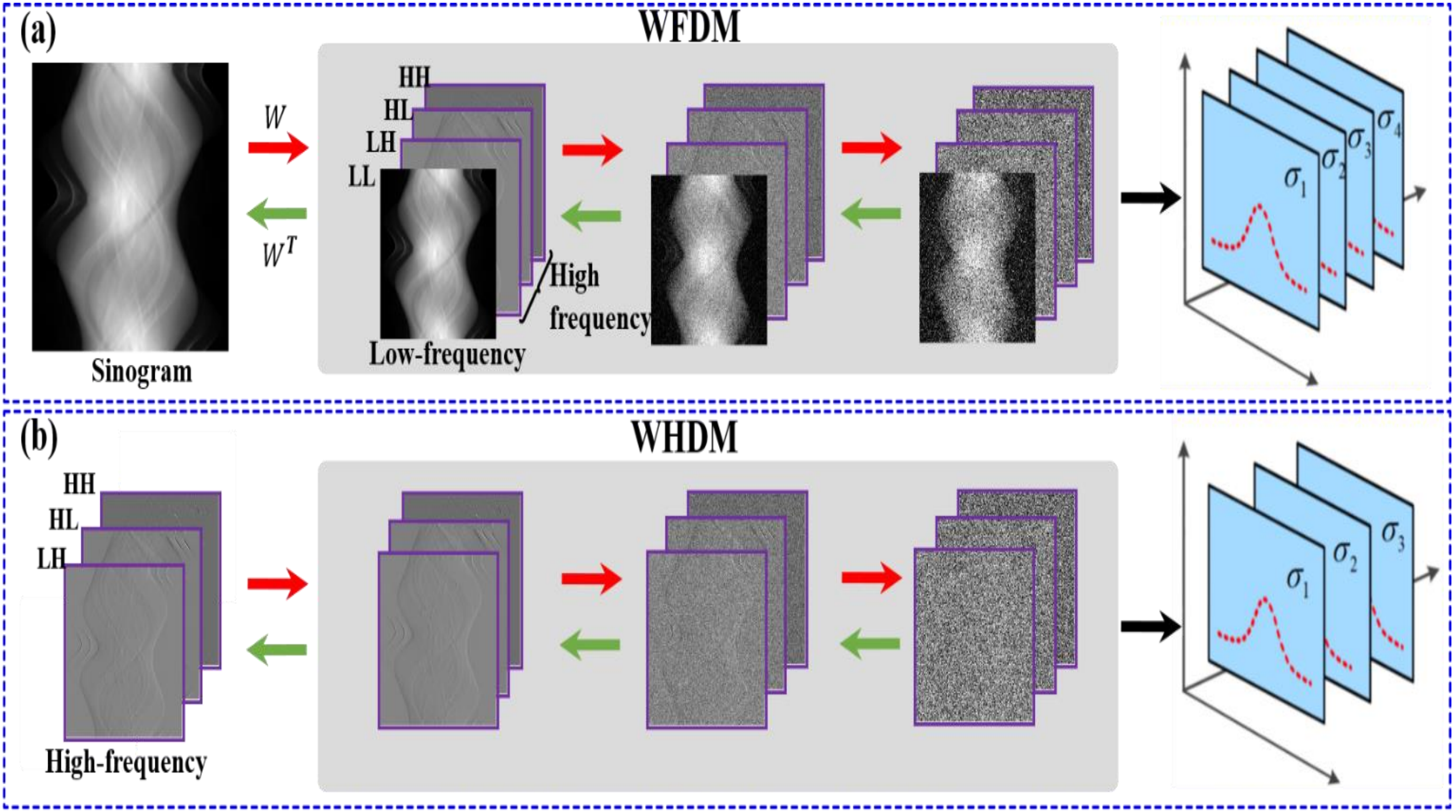


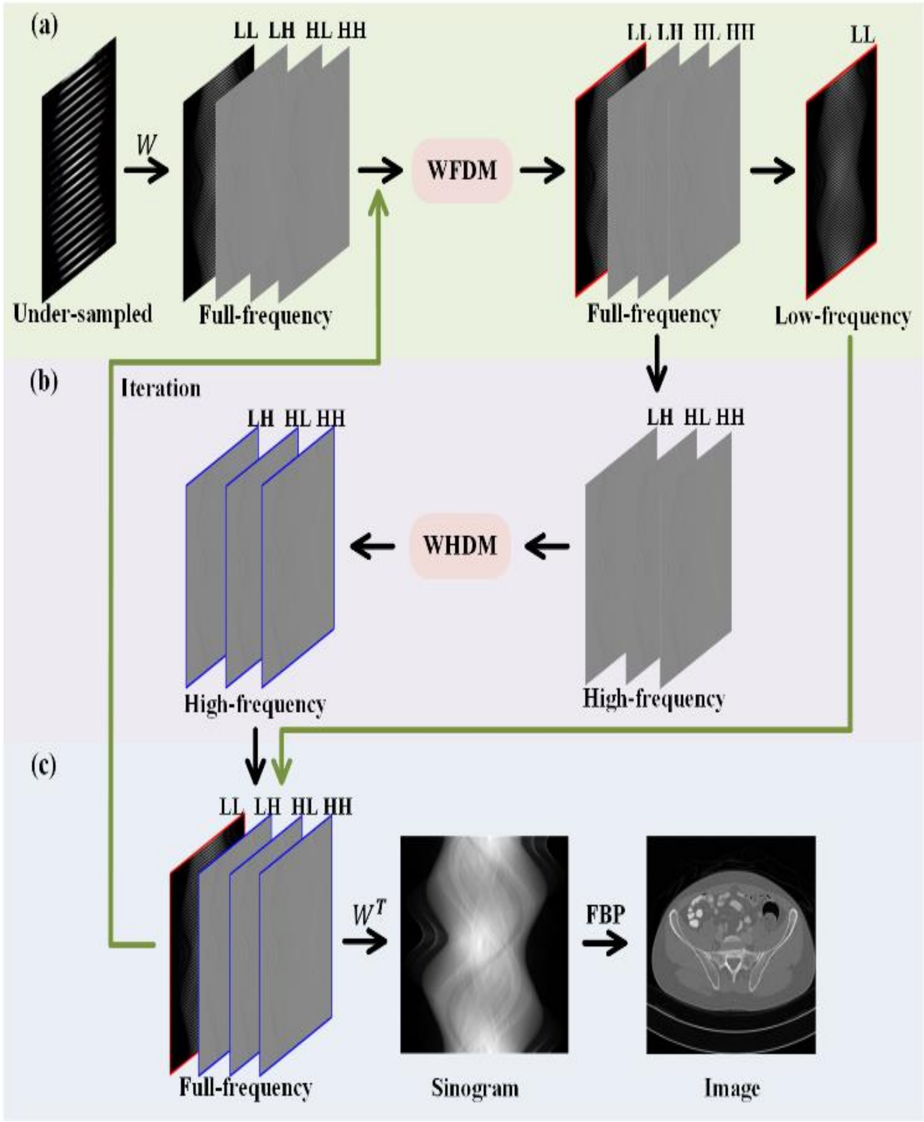
(a) Reference (b) FBP (c) SART-TV (d) CNN (e) NCSN++ (f) U-ViT (g) OSDM (h) RAP

W. Zhang, B. Huang, S. Chen, X. Xu, W. Wu, Q. Liu, Low-rank angular prior guided multi-diffusion model for few-shot low-dose CT reconstruction, *IEEE Trans. Comput. Imag.*, 2024.

SWORD

Algorithm overview

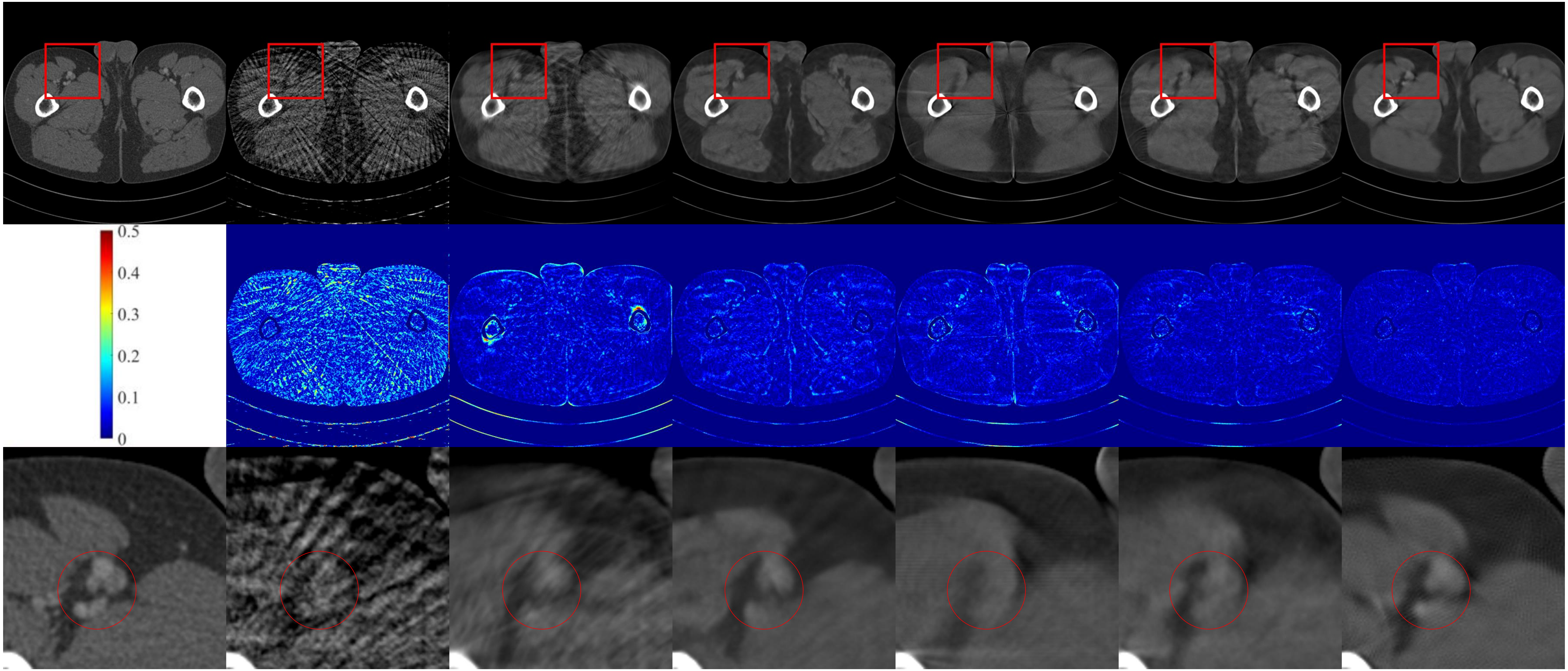




K. Xu, S. Lu, B. Huang, W. Wu, Q. Liu, Stage-by-stage wavelet optimization refinement diffusion model for sparse-view CT reconstruction, *IEEE Trans. Med. Imag.*, 2024.

SWORD

Algorithm overview

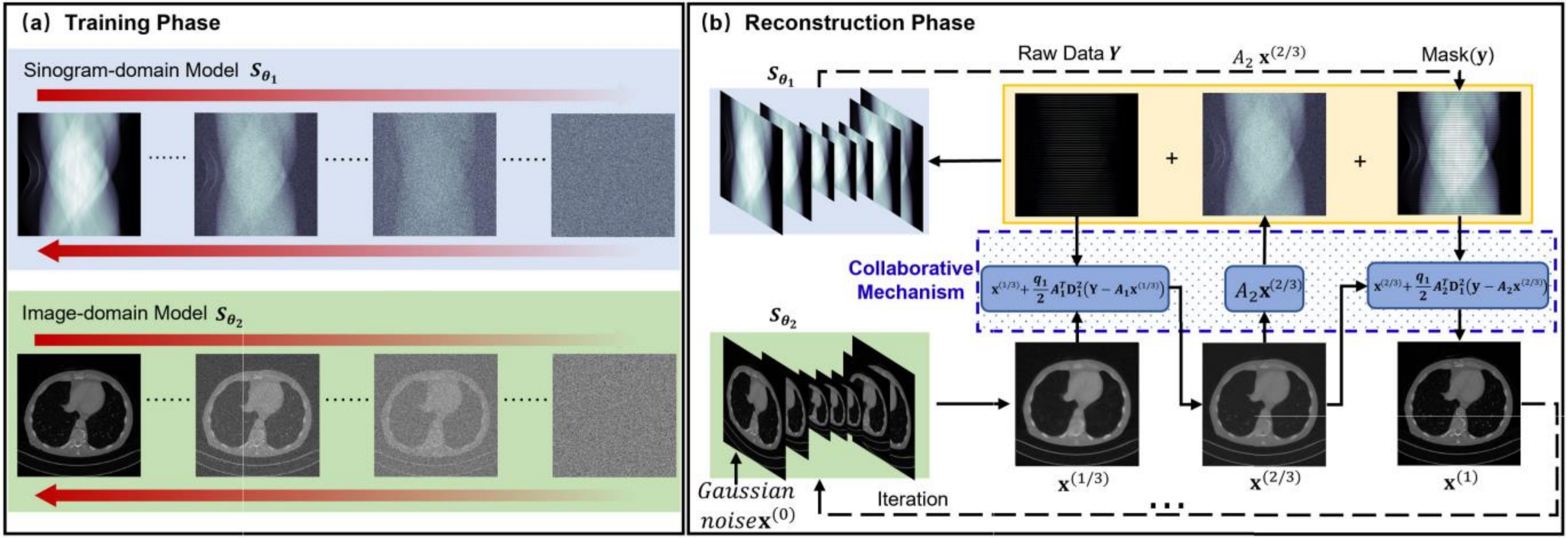


FBP U-Net FBPConvNet Patch-based DDPM GMSD SWORD

K. Xu, S. Lu, B. Huang, W. Wu, Q. Liu, Stage-by-stage wavelet optimization refinement diffusion model for sparse-view CT reconstruction, *IEEE Trans. Med. Imag.*, 2024.

Algorithm overview

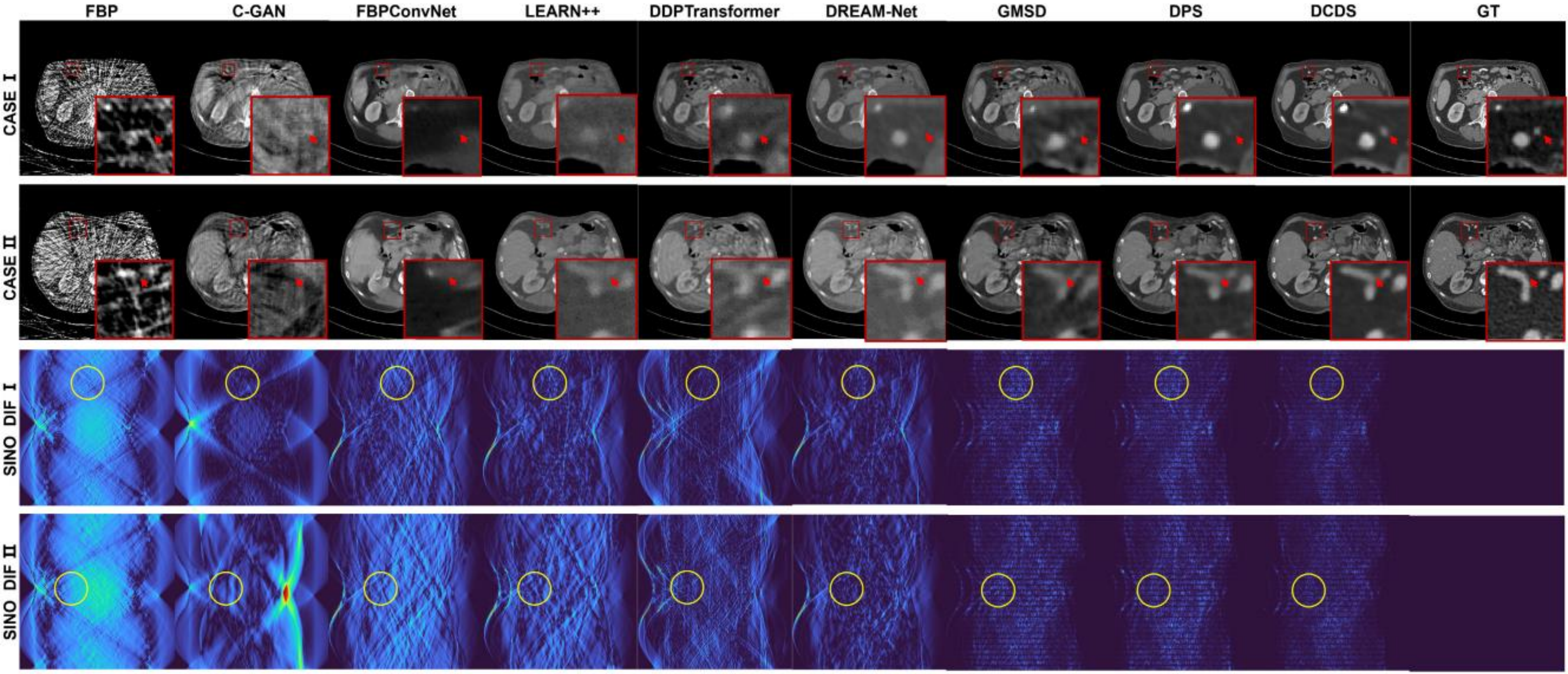
DCDS



Z. Li, D. Chang, Z. Zhang, F. Luo, Q. Liu, J. Zhang, G. Yang, W. Wu, Dual-domain collaborative diffusion sampling for multi-source stationary computed tomography reconstruction, *IEEE Trans. Med. Imag.*, 2024.

Algorithm overview

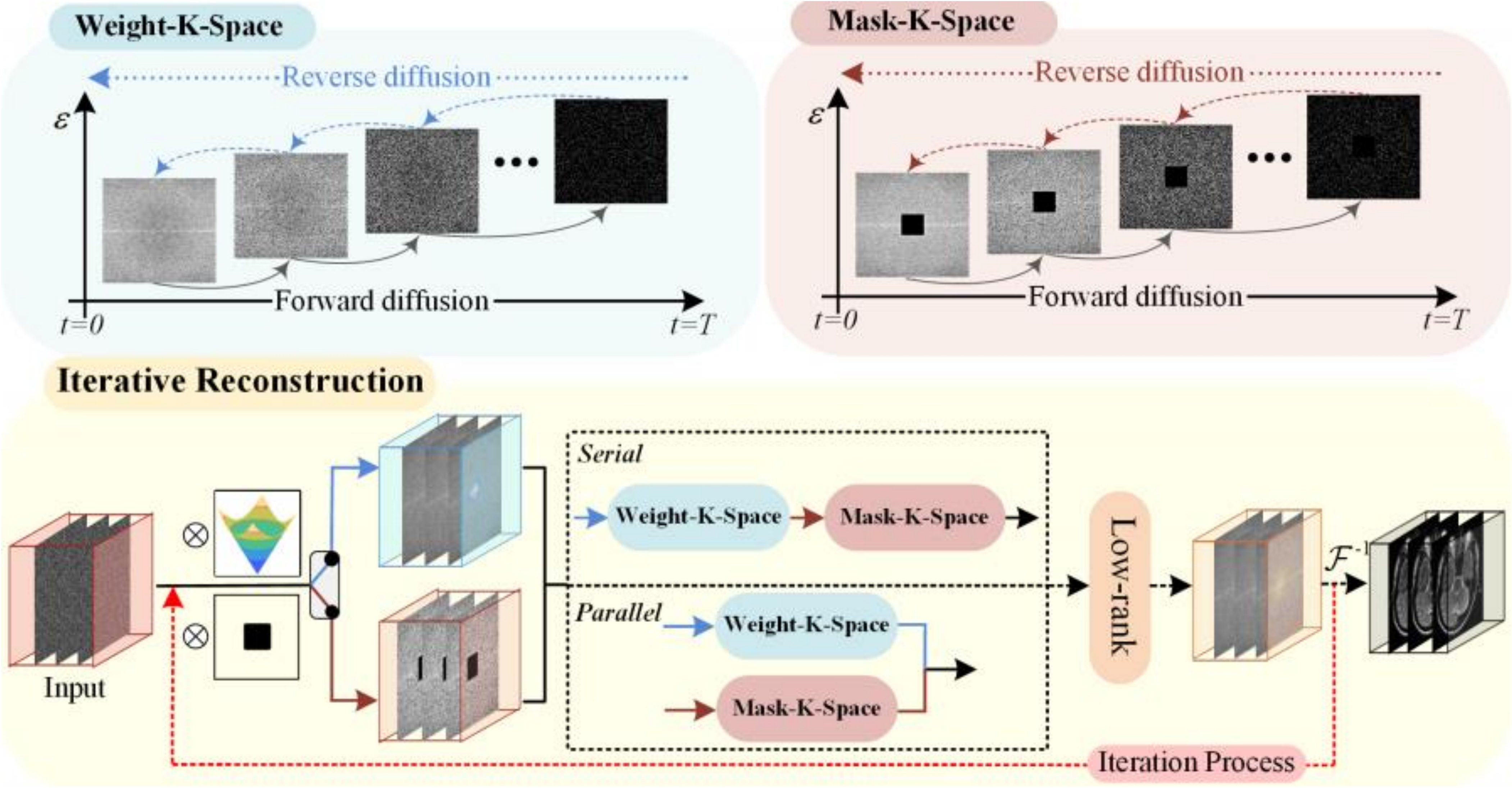
DCDS



Z. Li, D. Chang, Z. Zhang, F. Luo, Q. Liu, J. Zhang, G. Yang, W. Wu, Dual-domain collaborative diffusion sampling for multi-source stationary computed tomography reconstruction, *IEEE Trans. Med. Imag.*, 2024.

CM-DM

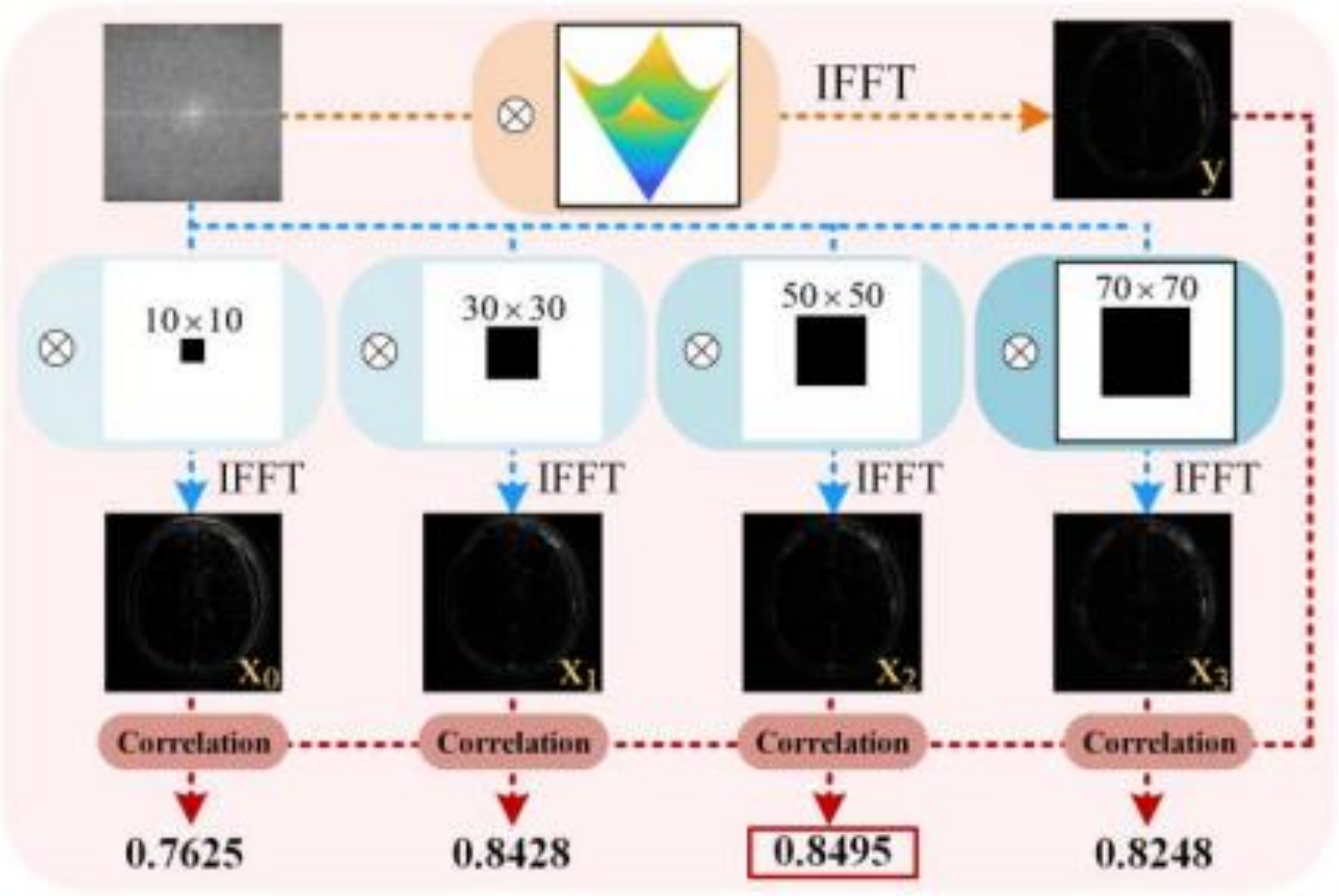
Algorithm overview



Y. Guan, C. Yu, Z. Cui, H. Zhou, Q. Liu, Correlated and multi-frequency diffusion modeling for highly under-sampled MRI reconstruction, *IEEE Trans. Med. Imag.*, 2024.

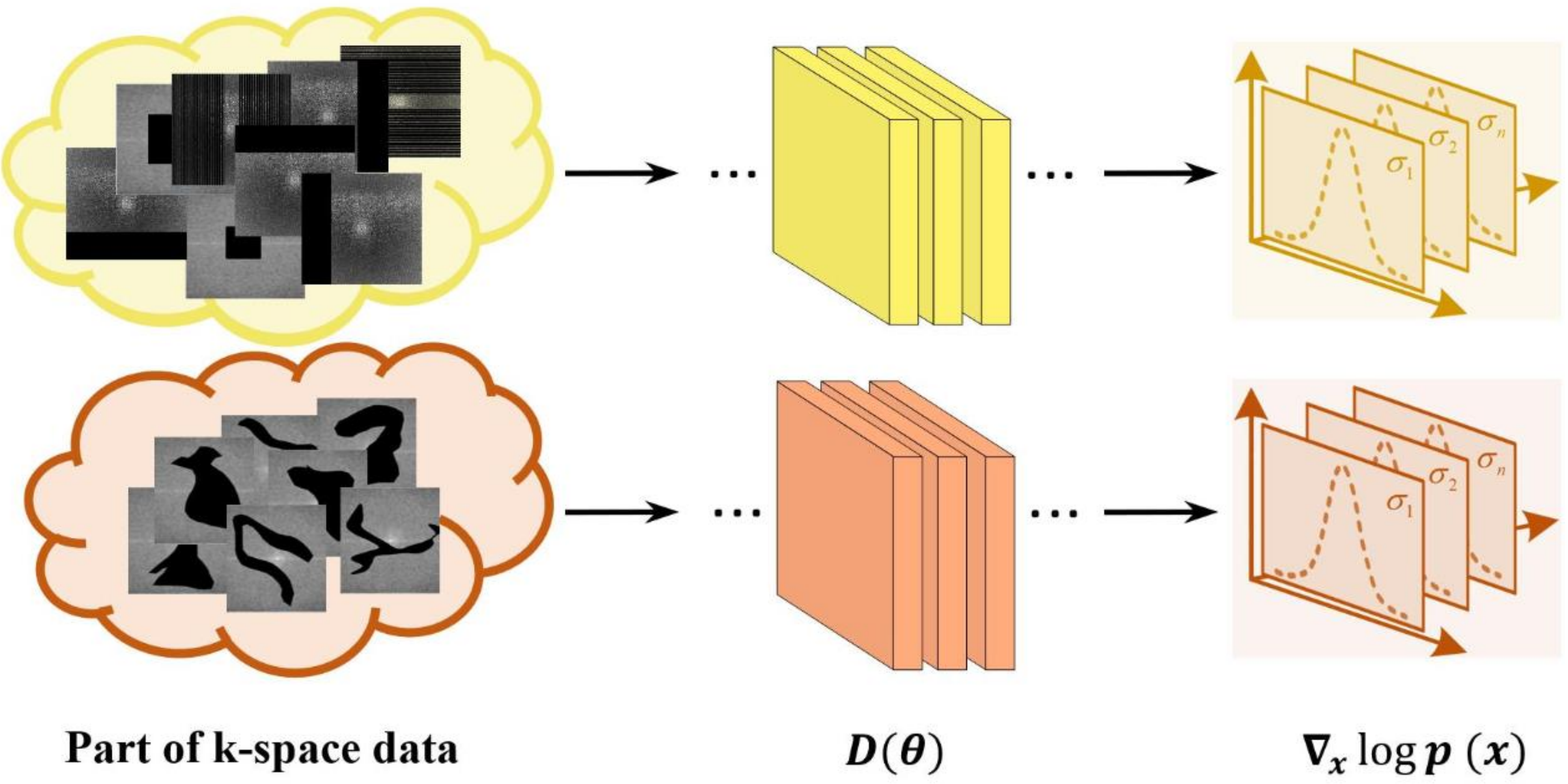
CM-DM

Algorithm overview



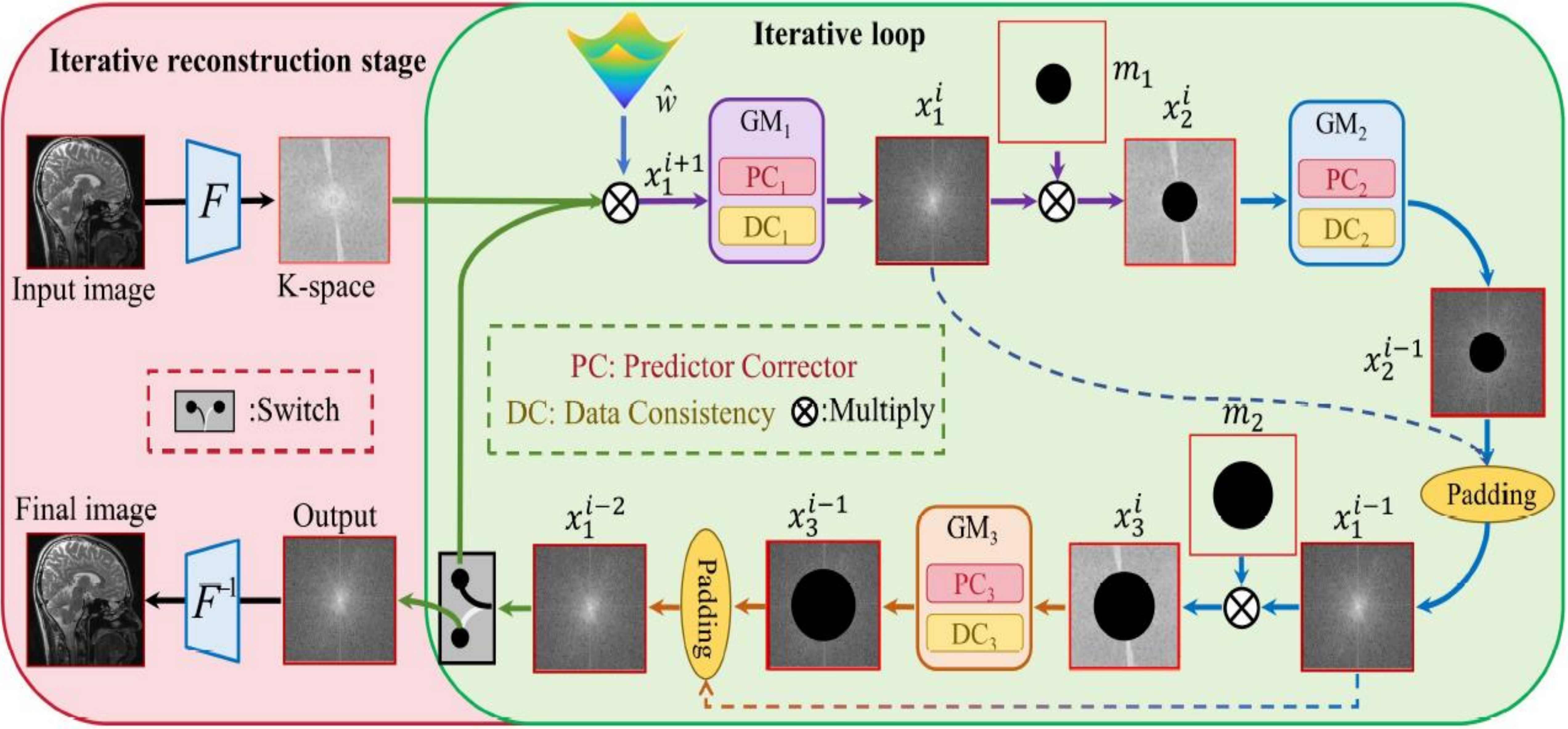
Y. Guan, C. Yu, Z. Cui, H. Zhou, Q. Liu, Correlated and multi-frequency diffusion modeling for highly under-sampled MRI reconstruction, *IEEE Trans. Med. Imag.*, 2024.

Learning from Regular to Irregular Samples



DP-MDM

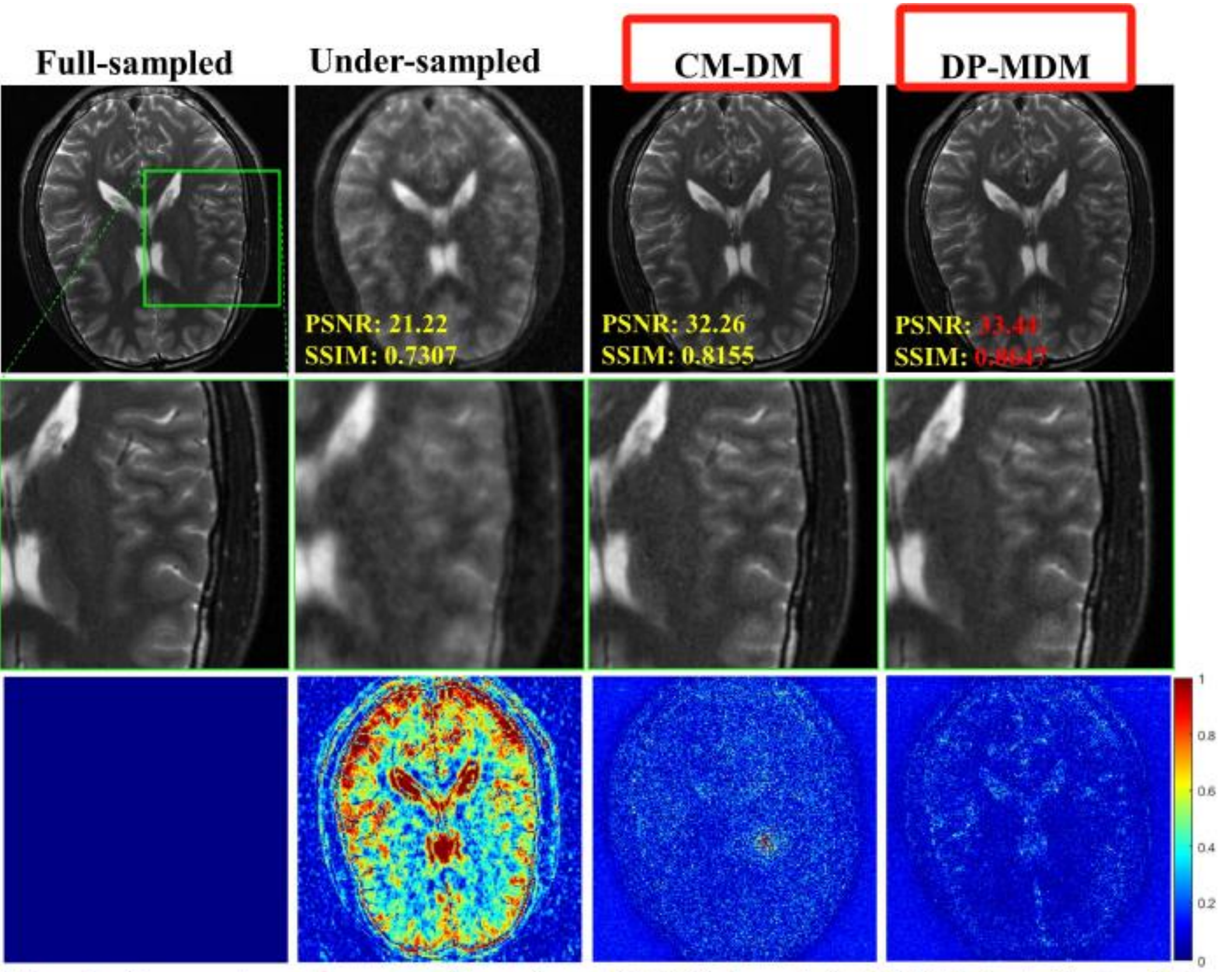
Algorithm overview



Geng M., Zhu J., et al., Multiple diffusion models for comprehensive detail preserving reconstruction, 2024.

DP-MDM

Algorithm overview



Fast-MRI	1-GM	2-GMs	3-GMs (DP-MDM)	4-GMs
Poisson *R*=8	29.59/0.7507	35.18/0.8990	38.05/0.9094	38.06/0.9104
Gap*	------	**5.59/0.1483**	**2.87/0.0104**	0.01/0.0010
Poisson *R*=10	29.16/0.7449	35.18/0.8995	37.62/0.9001	37.67/0.9033
Gap*	------	**6.02/0.1546**	**2.44/0.0006**	0.05/0.0032

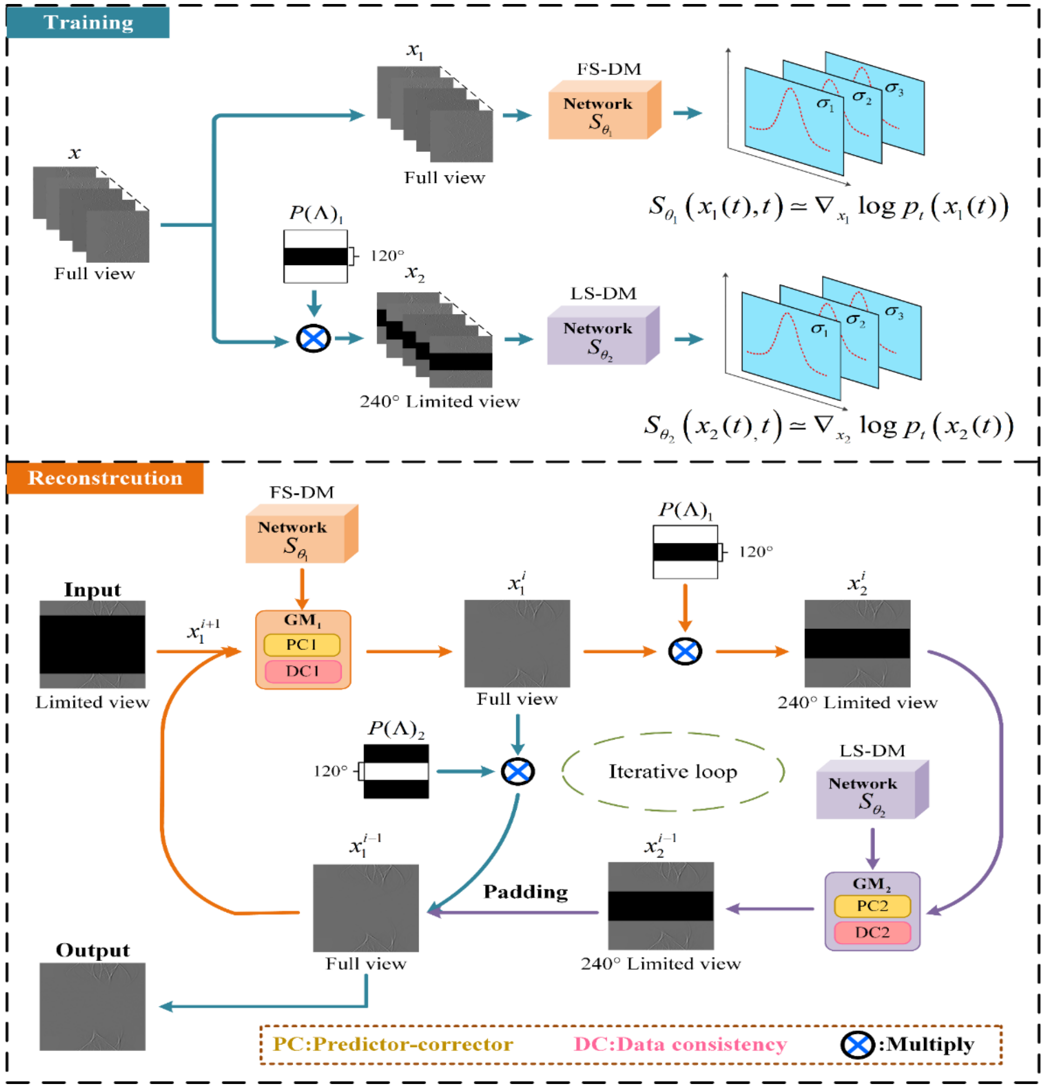
*Gap represents the difference between the corresponding indicator values of the current column and the subsequent column.

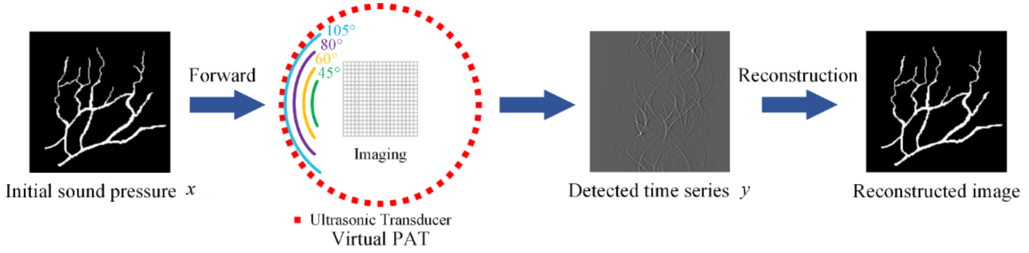
结果表明不同虚拟掩码以及不同模型个数对于保留MR图像细节都有影响

Geng M., Zhu J., et al., Multiple diffusion models for comprehensive detail preserving reconstruction, 2024.

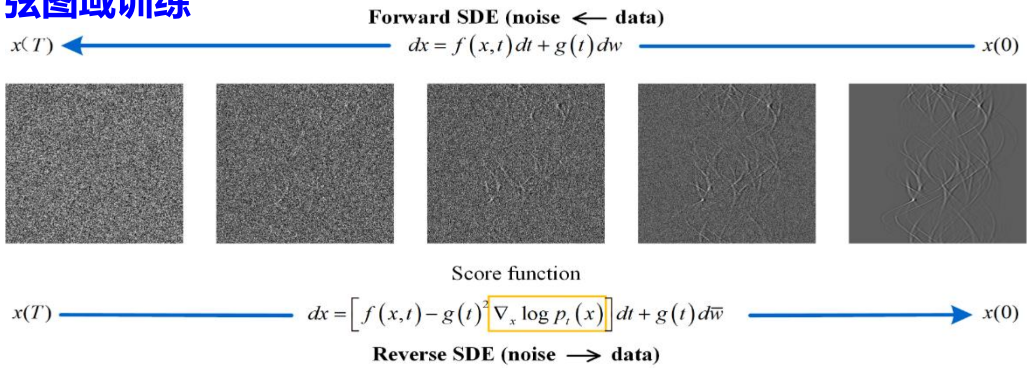
Algorithm overview

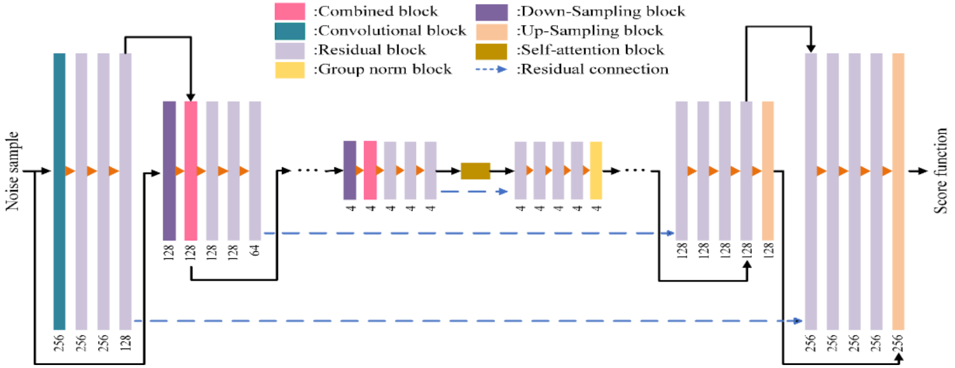
基于多扩散模型的光声断层弦图域的有限视角重建：多扩散模型+轮换迭代重建





弦图域训练



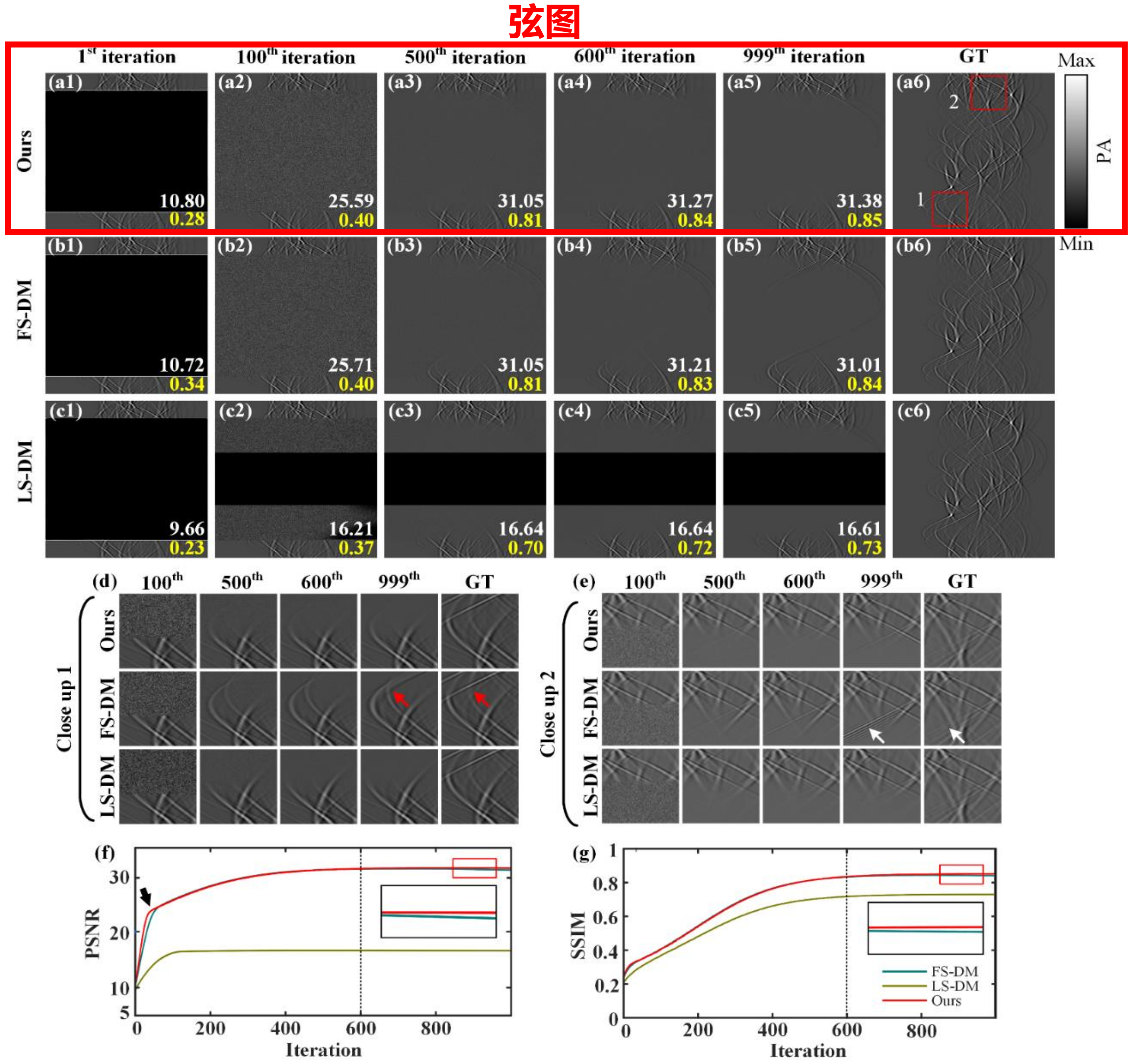


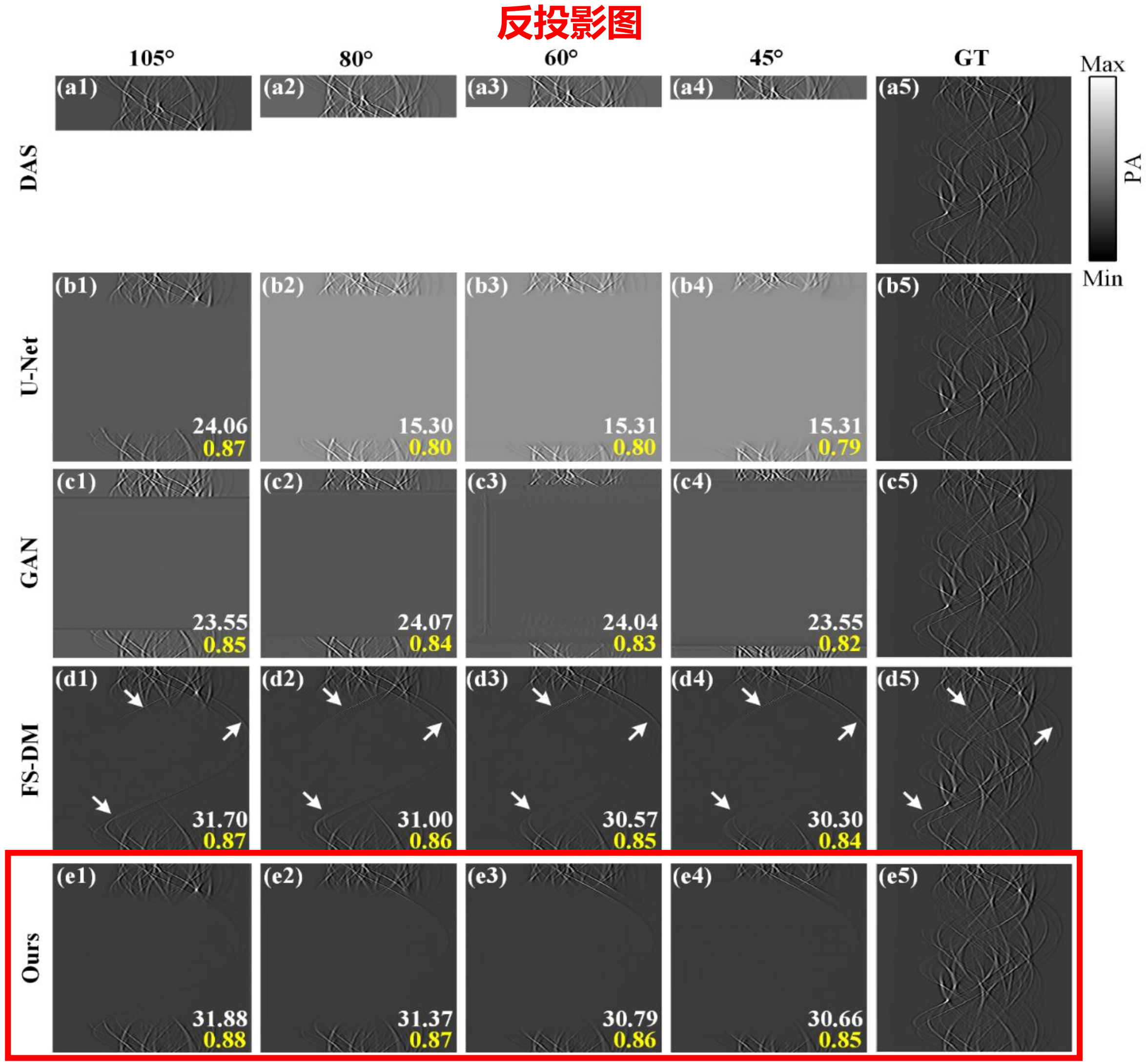
分数网络

X. Song, X. Zou, K. Zeng, J. Li, S. Hou, Y. Wu, Z. Li, C. Ma, Z. Zheng, K. Guo, Q. Liu. Multiple diffusion models-enhanced extremely limited-view reconstruction strategy for photoacoustic tomography boosted by multi-scale priors. Photoacoustics, 2024.

Algorithm overview

基于多扩散模型的光声断层弦图域的有限视角重建：多扩散模型+轮换迭代重建

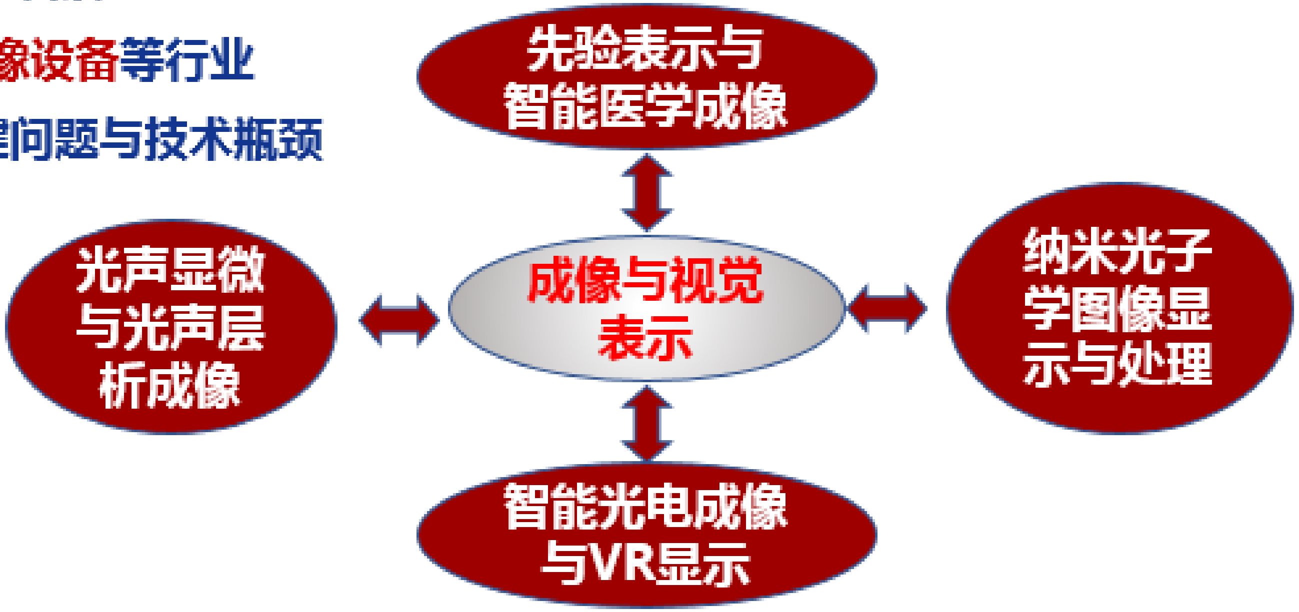


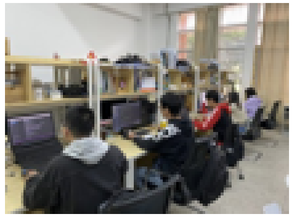


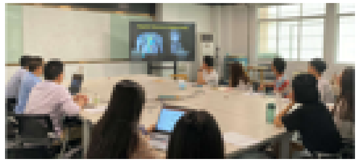
X. Song, X. Zou, K. Zeng, J. Li, S. Hou, Y. Wu, Z. Li, C. Ma, Z. Zheng, K. Guo, Q. Liu. Multiple diffusion models-enhanced extremely limited-view reconstruction strategy for photoacoustic tomography boosted by multi-scale priors. Photoacoustics, 2024.

成像与视觉表示实验室

- 立足**国家战略**需求和江西省**电子信息重点产业链**发展
- 聚焦**光电成像系统、VR/AR显示装置、医疗影像设备**等行业
- 围绕“**传感成像-信号处理-增强显示**”中的关键问题与技术瓶颈
- 实现关键技术突破与成果转化







刘且根 教授　张明辉 教授　徐晓玲 教授　宋贤林 副教授　万文博 讲师　姚爱萍 特聘研究员　肖书源 副研究员　刘婷婷 副教授

实验室网站：
https://github.com/yqx7150
https://www.labxing.com/lab/1018

研究方向1：先验表示与智能医学成像

大型医疗器械国产化替代需求

全球/中国医疗器械市场规模 （千亿元）

医疗器械细分市场国产品牌占比

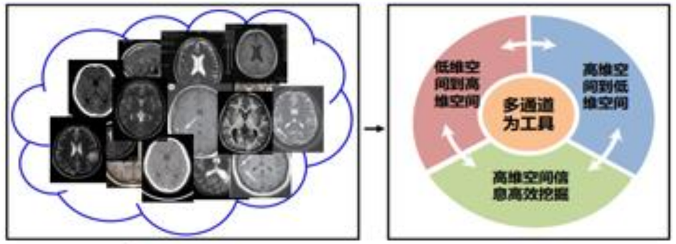
“企业-高校-医院”协同创新

医院

医疗器械

远程医疗

- 以高校为主要力量
- 联合企业力量为补充
- 结合医院提出目标任务
- 解决产业链痛点、难点、堵点



高维变量相关和多维空间分析新模式

优秀成果

✓ 转化应用

研究方向2：光声显微与光声层析成像

◆ **乳腺癌**检测主要难点

传统单模态成像精度低，仅实现解剖结构检测

- X光钼靶摄影有电离辐射，超声检测特异性低

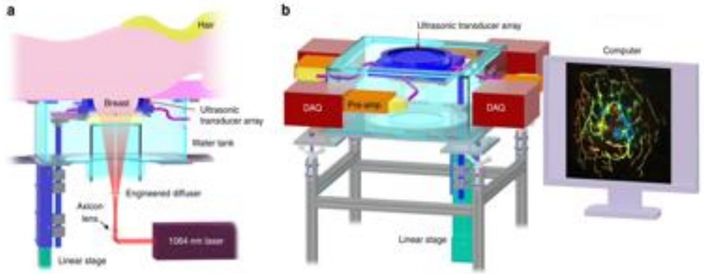
◆ 面向乳腺癌**早期**检测与诊断

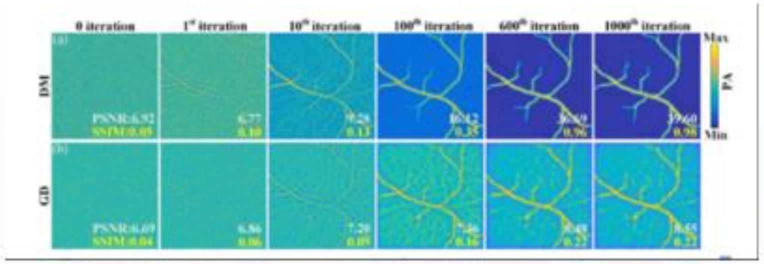
- 实现无损、高对比度、高分辨率深层智能成像
- 融合多模态信息，实现特异性诊断

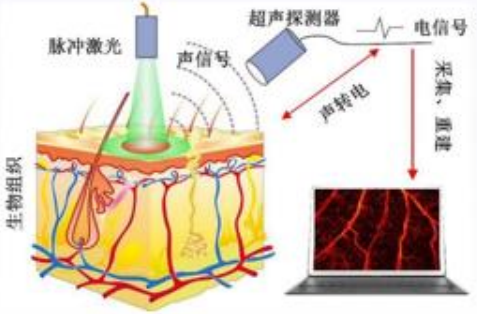
◆ **关键技术难题**

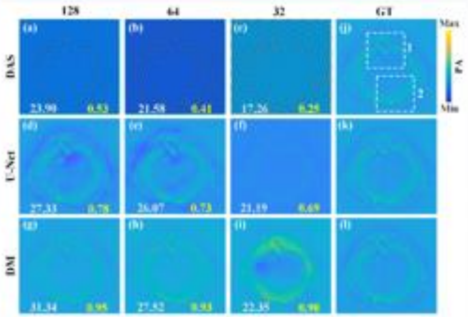
➤ 超声探测器数量有限、受到伪影干扰

➤ 光学参数背景先验信息缺失









研究方向3：智能光电成像与VR显示

产业需求牵引

HUAWEI

OFILM 欧菲光

ZETTAVR 境

复杂场景智能光电成像

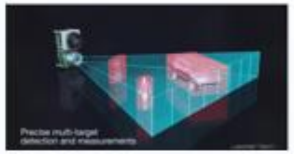
- 多相位菲涅尔孔径编码无透镜成像

多相位FZA编码板

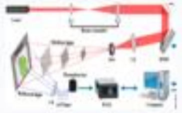
CMOS

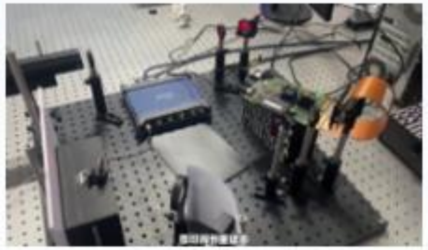
光学计算重建

- 直接飞行时间激光雷达模组



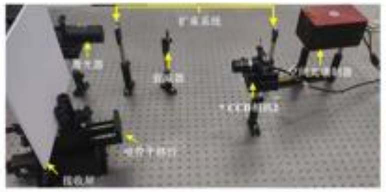
- 高速追踪单像素探测系统

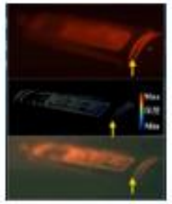




全息VR显示

- 三维场景快速采集与全息显示





  - 极简系统结构
  - 超快三维场景采集速度：~ 0.6 s

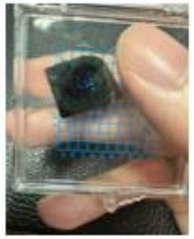
- 透过散射介质成像与全息显示

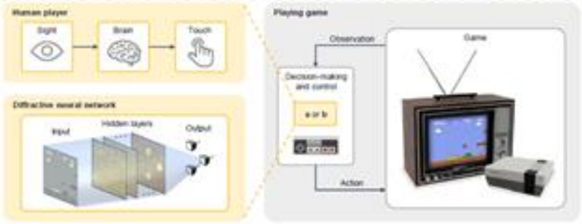
  - 透过散射介质实现高分辨率成像
  - 实现高质量全息显示

研究方向4：纳米光子学图像显示与信息处理

◆ 面向新一代信息技术产业的光学平面集成器件

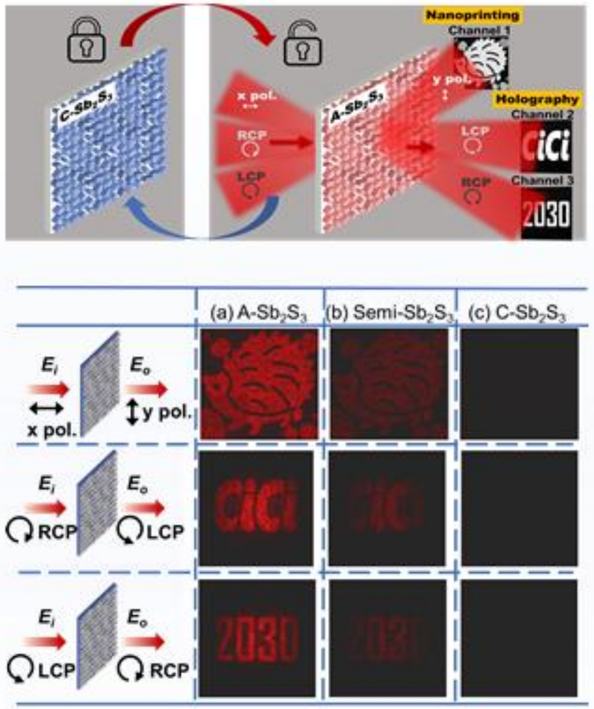
光子取代电子作为信息载体和能源介质





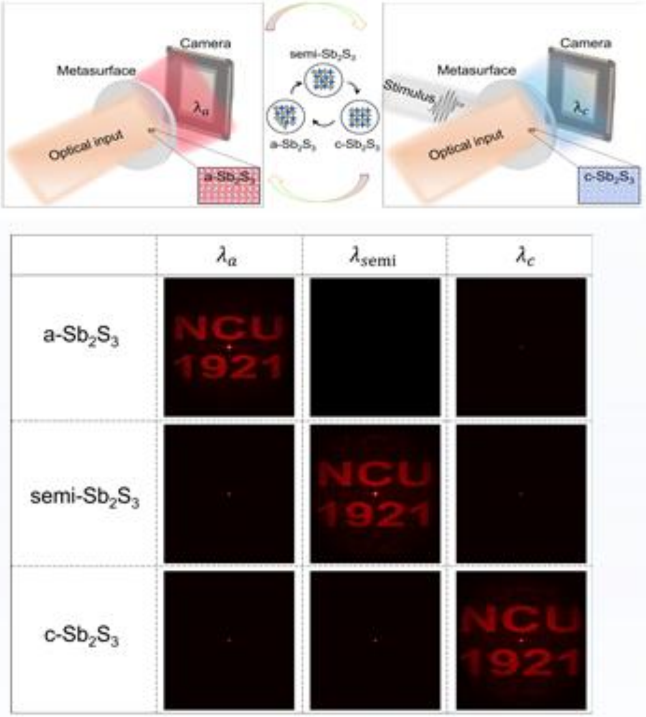
✓ 高速度、大带宽、低功耗、高集成

✓ 模拟人类的感知能力与控制行为



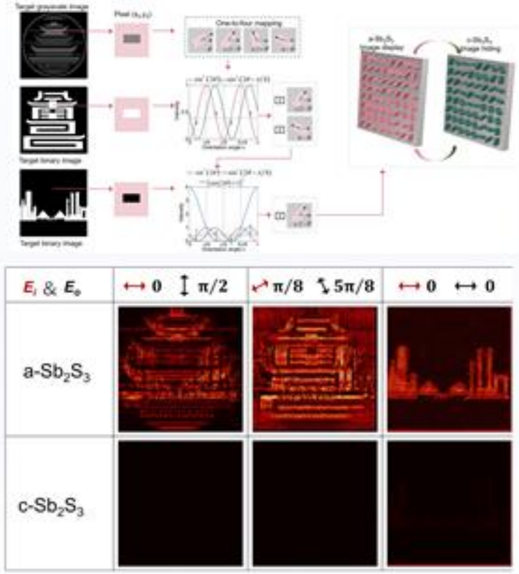
✓ 高容量、高集成度的片上信息存储

✓ 高空间分辨率的全息图像显示



✓ 光谱和空间调控的高自由度

✓ 可调谐波长的全息图像显示



✓ 信息复用超表面的极简设计

✓ 动态信息显示及加密编码