Symposium on AI and Reconstruction for Biomedical Imaging

London, UK

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Physics-Informed Synthetic Data Learning: Boosting Multi-Scenario Fast MRI Reconstruction with Only One Model

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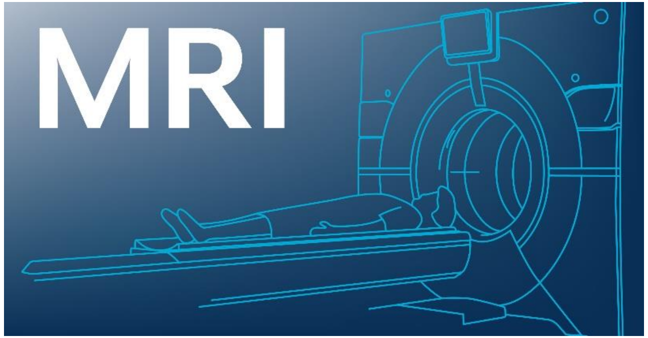
1 Deep Learning for Fast MRI

◻ Fast sampling

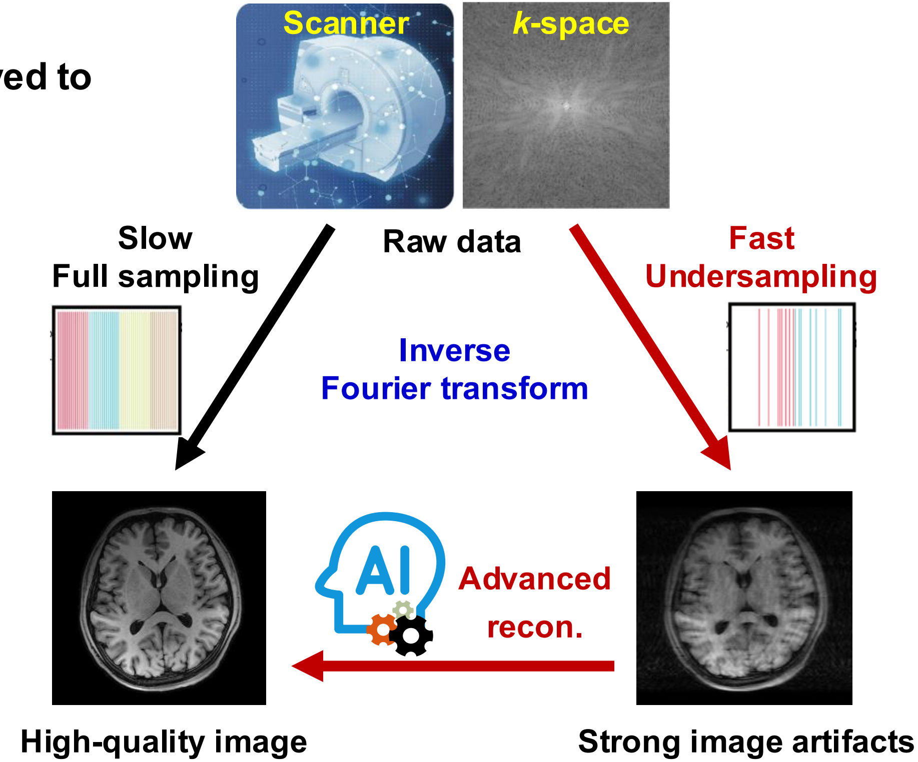
- MRI scans usually require long acquisition time
- Parallel imaging and sparse sampling are employed to accelerate MRI through *k*-space undersampling

◻ Deep learning reconstruction

- High-quality reconstructed image
- Short reconstruction time
- Patient-friendly scanning



Fast MRI

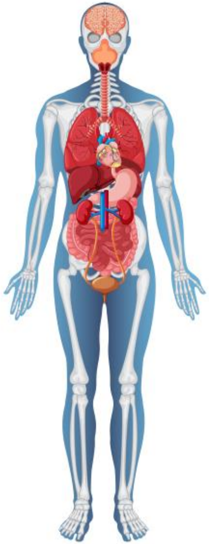


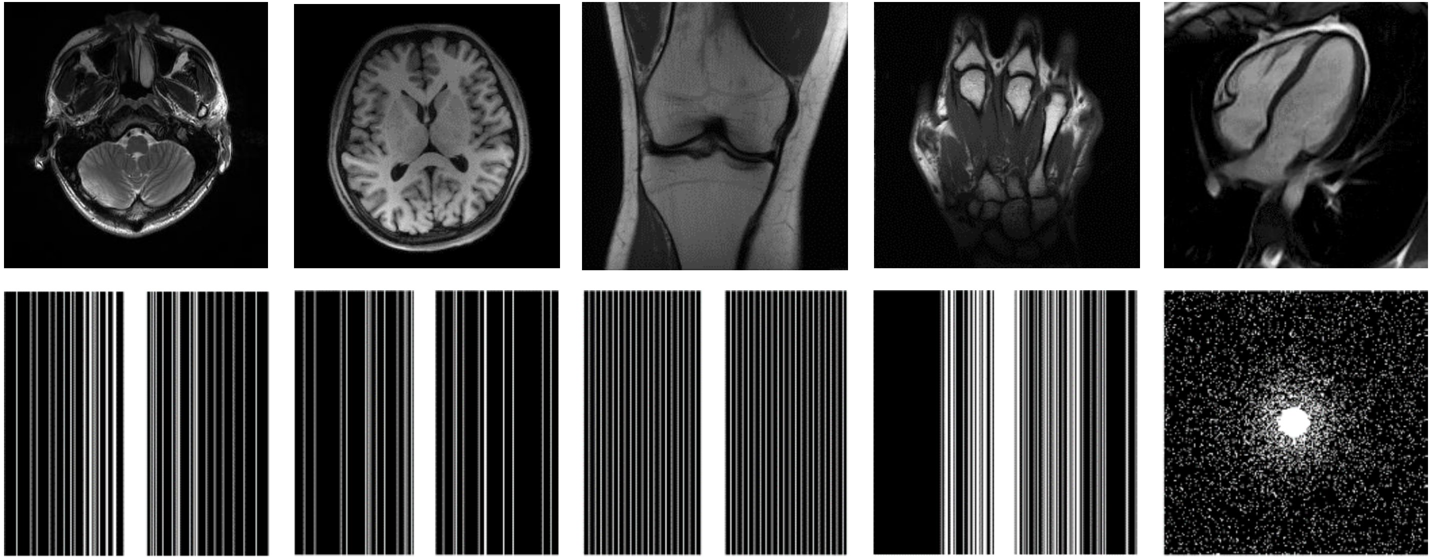
2 Big Challenge

- **Multi-scenario imaging** (anatomy /orientation / contrast / vendor / center / sampling)

How to obtain large-scale *k*-space training datasets for AI? How to achieve robust recon.?

It is impractical to collect datasets which cover all imaging scenarios





SIEMENS Healthineers

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UNITED 联影 IMAGING

3 Physics-Informed AI for Fast MRI (PISF)

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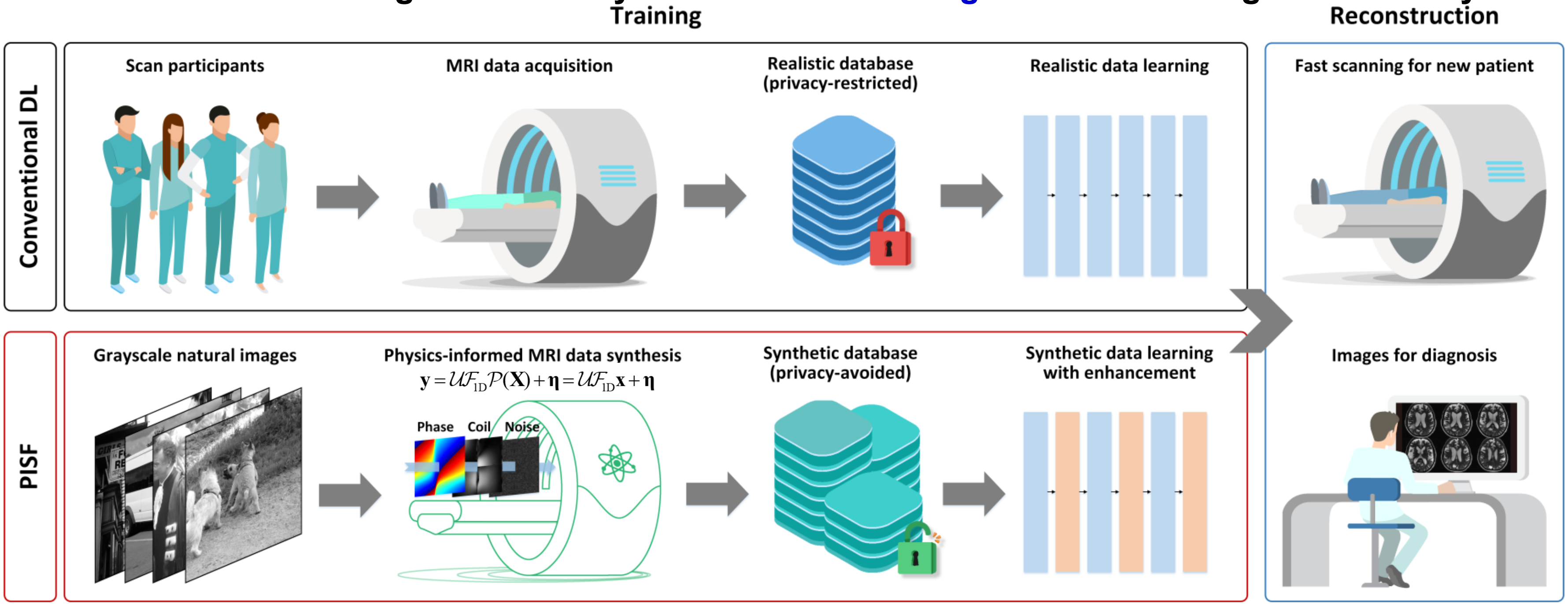
Conventional AI

- Realistic raw data learning
- Train multiple expert models
- Poor robustness and generalizability

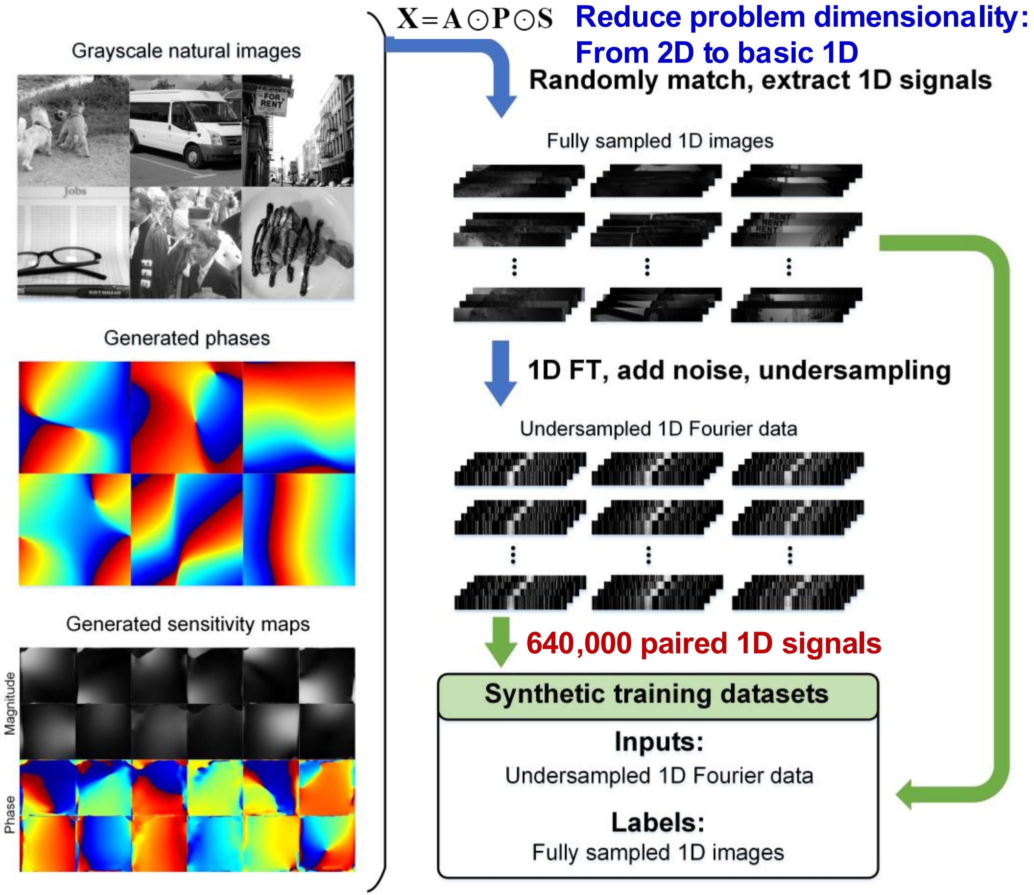
Physics-informed AI

- Physics-informed synthetic data learning
- Train only one versatile model
- Strong robustness and generalizability



Z. Wang, *et al.*, ***Med. Image Anal.***, 103: 103616, 2025.

4.1 Physics-Informed Synthetic Data Generation



Physics-based forward model

$$\boxed{\mathbf{y} = \mathcal{U}\mathcal{F}_{1\mathrm{D}}\mathcal{P}(\mathbf{X}) + \boldsymbol{\eta} = \mathcal{U}\mathcal{F}_{1\mathrm{D}}\mathbf{x} + \boldsymbol{\eta}}$$

- **5 key components:** $\mathbf{X} = \mathbf{A} \odot \mathbf{P} \odot \mathbf{S}$
  - ✓ Magnitude **A**, phase **P**, coil sensitivities **S**
  - ✓ Noise **η**, undersampling operation $\mathcal{U}$
- **Data engine for signal generation:**
  - ✓ **Diverse image contrasts**
    Select 4,000 natural images from ImageNet and convert them to grayscale
  - ✓ **Different experimental conditions**
    Generate varied phase, add varied complex white Gaussian noise, do undersampling
  - ✓ **Simulate multi-coil acquisitions:**
    Estimate sensitivity maps from six cases of realistic data in fastMRI dataset

Z. Wang, *et al.*, ***Med. Image Anal.***, 2025; Z. Wang, *et al.*, ***IEEE Trans. Med. Imaging***, 2023; J. P. Haldar, ***IEEE Trans. Med. Imaging***, 2014; J. Zbontar, *et al.*, arXiv: 1811.08839, 2019.

4.2 Why It Works? Diverse Data Synthesis

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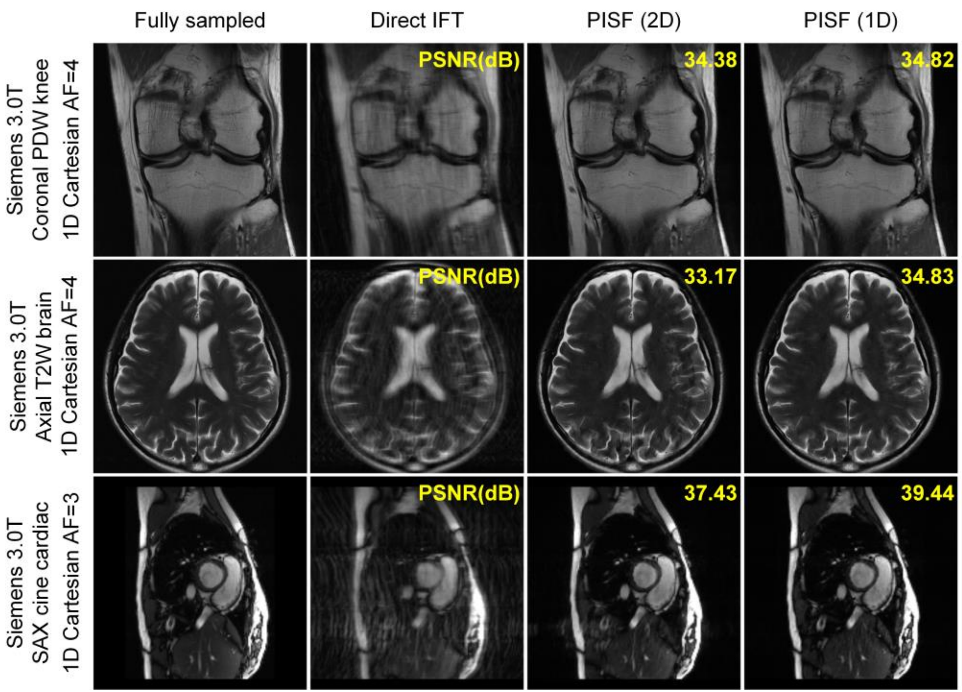
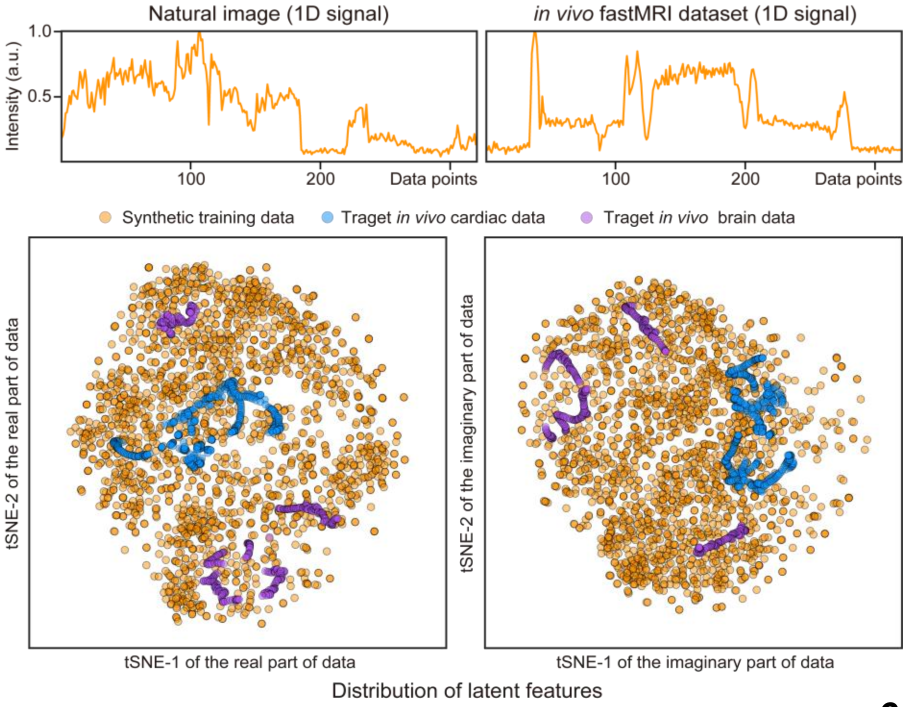
- **1D learning:** Reduce dimensionality of solution space (More similar signal, better performance than 2D)
- tSNE visualization: Cover most latent features of target *in vivo* MRI data
- To learn the versatile mapping between images with and without artifacts





Z. Wang, *et al.*, ***Med. Image Anal.***, 2025; Z. Wang, *et al.*, ***IEEE Trans. Med. Imaging***, 2023.

5.1 Physics-Informed Deep Unrolled Network

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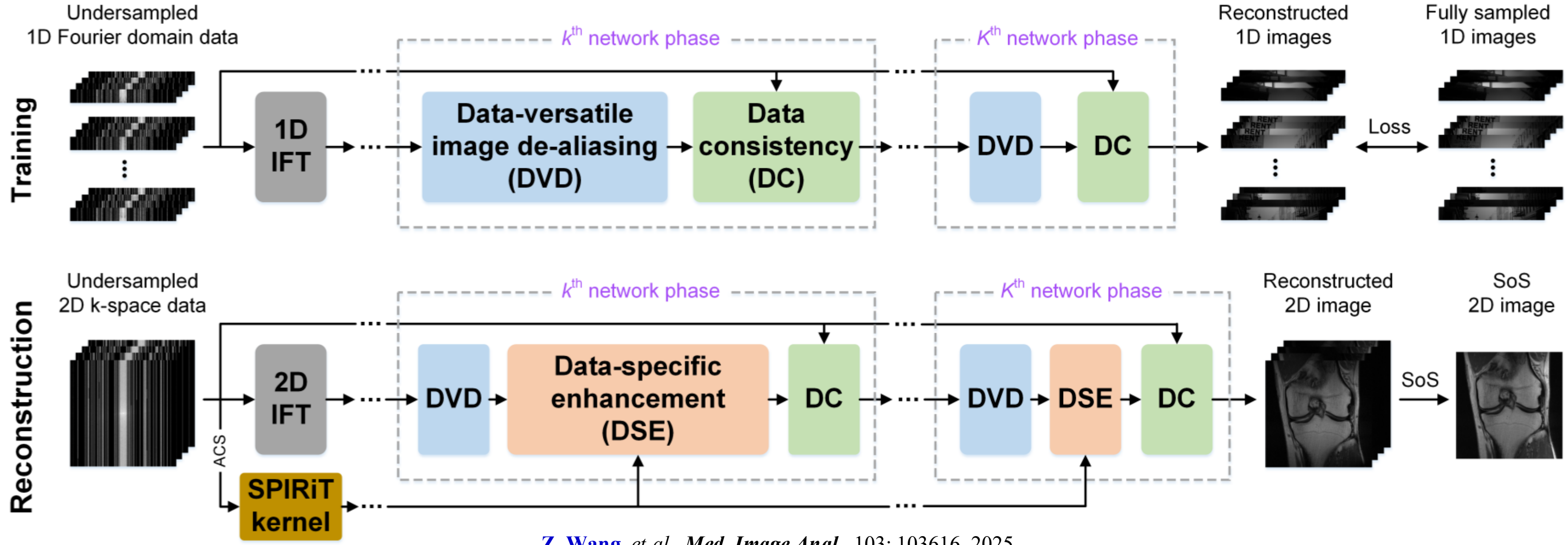
- Key idea: Separate-first-enhance-then
- Synthetic data training: Data-versatile 1D foundation network
- Target self-consistency recon.: Data-specific 2D enhancement
- Naturally extend to 2D undersampling in 3D imaging

Recon. with physics operators

$$
\begin{cases}
\mathbf{D}^{(k)} = \sum_{m=1}^{M} \mathcal{P}_m^*(\mathcal{D}(\mathcal{P}_m(\mathbf{X}^{(k-1)}))) = \sum_{m=1}^{M} \mathcal{P}_m^*(\mathbf{d}_m^{(k)}) \\
\mathbf{B}^{(k)} = \mathcal{F}_{2D}^* \mathcal{G}(\mathcal{F}_{2D} \mathbf{D}^{(k)}) \\
\mathbf{X}^{(k)} = \arg\min_{\mathbf{x}} \|\mathbf{Y} - \mathcal{U}\mathcal{F}_{2D}\mathbf{X}\|_2^2 + \lambda\|\mathbf{X} - \mathbf{B}^{(k)}\|_2^2 \\
\quad = (\mathcal{F}_{2D}^* \mathcal{U}^* \mathcal{U} \mathcal{F}_{2D} + \lambda^{(k)})^{-1} (\mathcal{F}_{2D}^* \mathcal{U}^* \mathbf{Y} + \lambda^{(k)} \mathbf{B}^{(k)})
\end{cases}
$$



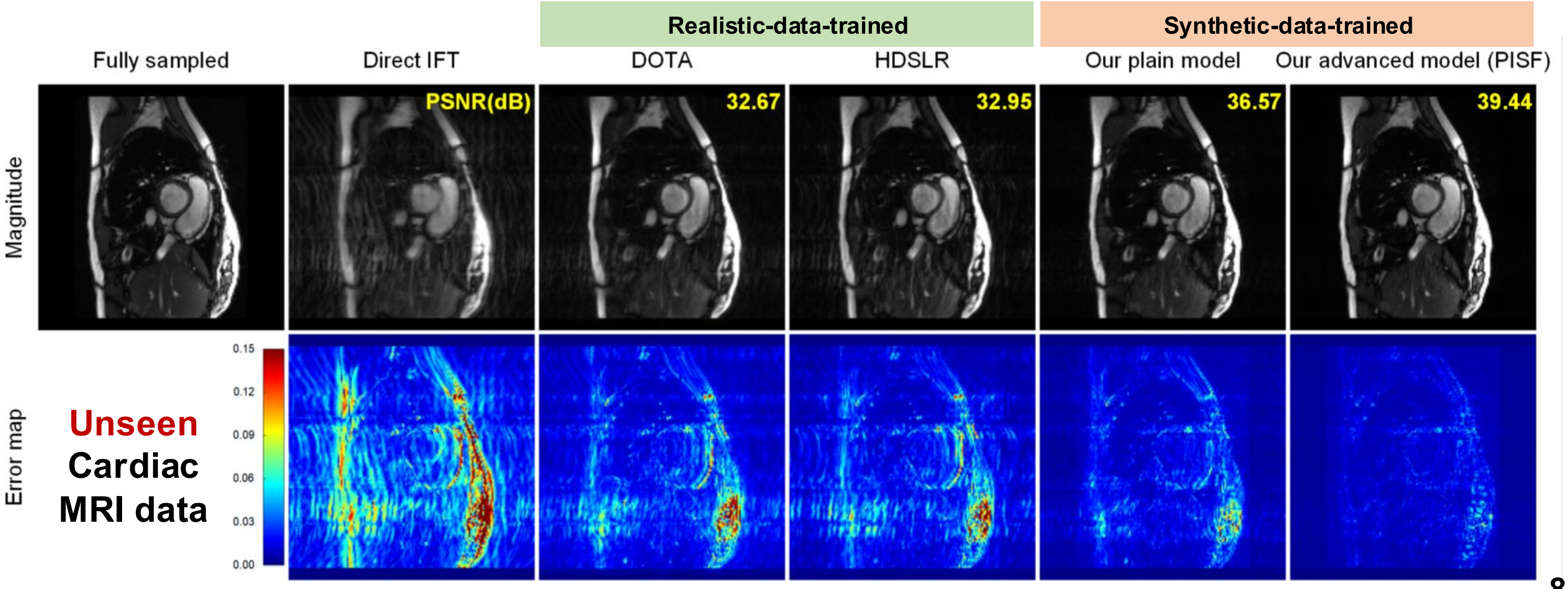
Z. Wang, *et al.*, ***Med. Image Anal.***, 103: 103616, 2025.

5.2 Why It Works? Advanced Model Design

- Basic CNN (Plain) + Adaptive thresholding + Data-specific enhancement

Advanced Vs. Plain 8% ↑

PSNR (dB) in cardiac MRI



Unseen Cardiac MRI data

Z. Wang, *et al.*, ***IEEE Trans. Neural Netw. Learn. Syst.***, 2023; M. Lustig, *et al.*, ***Magn. Reson. Med.***, 2010; T. Eo, *et al.*, ***Med. Image Anal.***, 2020; A. Pramanik, *et al.*, ***IEEE Trans. Med. Imaging***, 2020.

6 SOTA Paradigm: One AI Model for Multi-Scenario Recon.

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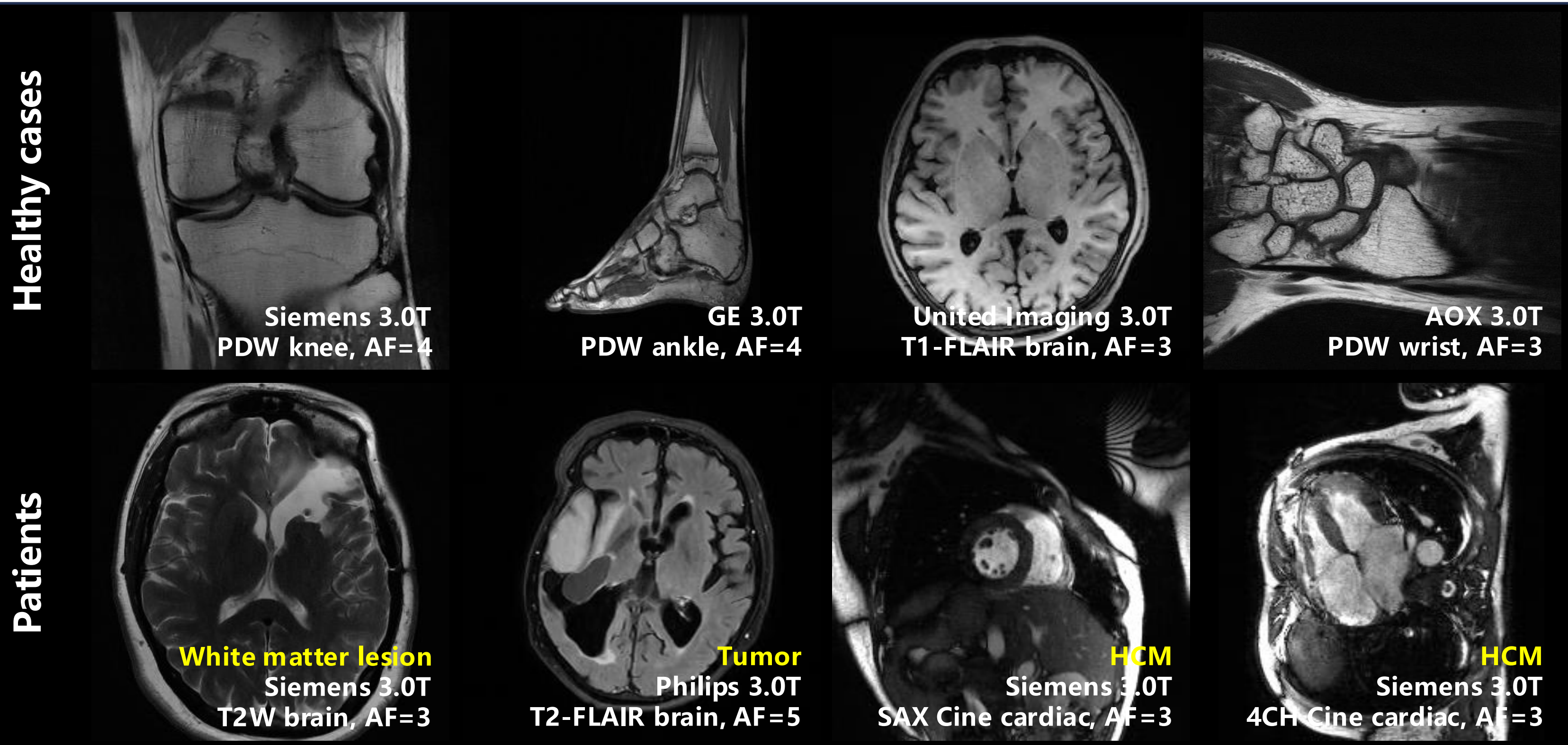
- PISF provides high-quality images in multiple anatomies/orientations/contrasts/vendors/centers/sampling settings
- Overall image quality steps into the excellent level for clinical diagnosis (Verified by 5 neuro + 5 cardiac radiologists)



Recon. time: 0.35s per slice (320×320, 8 coils)

Z. Wang, *et al.*, ***Med. Image Anal.***, 103: 103616, 2025.

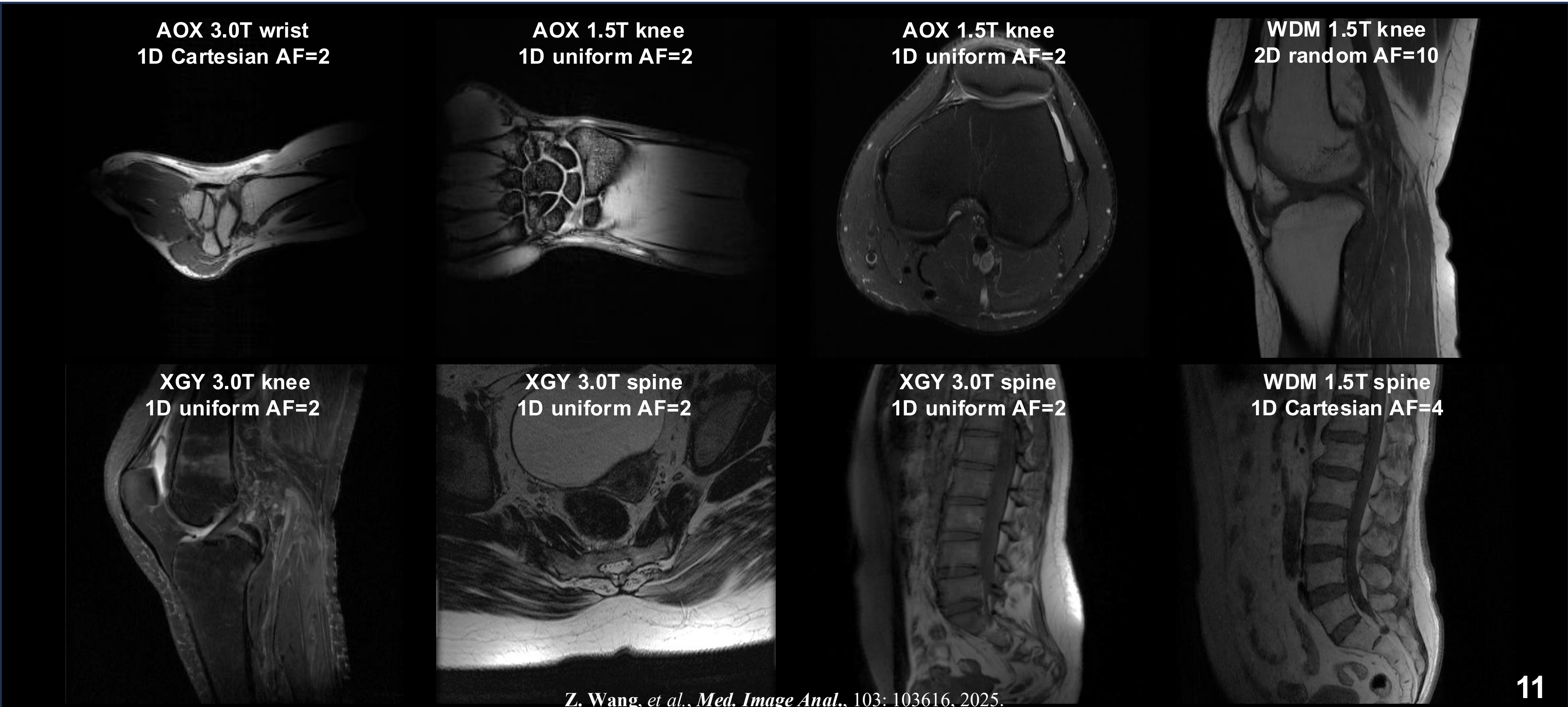
7 Conclusion

- Physics-informed synthetic data learning decreases the reliance of deep learning on large-scale realistic data and achieves the generalizable deep learning in multi-scenario fast MRI.
- With a single trained model, it supports high-quality and ultra-fast reconstructions under 4 sampling patterns, 5 anatomies, 6 contrasts, 5 vendors, and 7 centers.
- Provide a new insight: Realistic training data is not obligatory and can be effectively replaced by properly generated data.

Zi Wang, *et al.*, "One for Multiple: Physics-informed Synthetic Data Boosts Generalizable Deep Learning for Fast MRI Reconstruction", ***Medical Image Analysis***, 103: 103616, 2025.

8 Beyond Paper: Real-World Propspective Study

- PISF enables stable and reliable reconstruction across different MRI scanners in real-world applications



Z. Wang, *et al.*, *Med. Image Anal.*, 103: 103616, 2025.

Thanks for your attention !

MEDIA paper: https://doi.org/10.1016/j.media.2025.103616

Github: https://github.com/wangziblake/PISF

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CMRxRecon Challenge & Foundation Model

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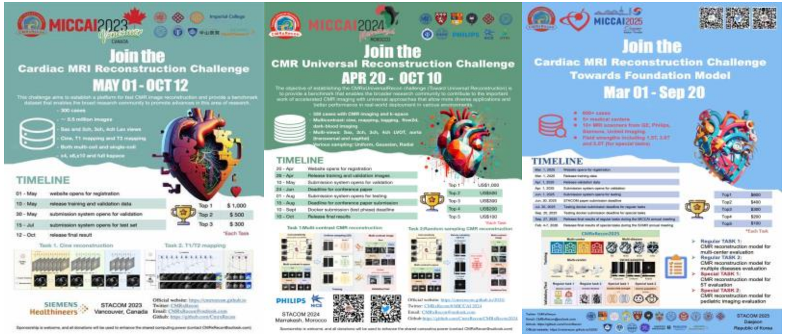
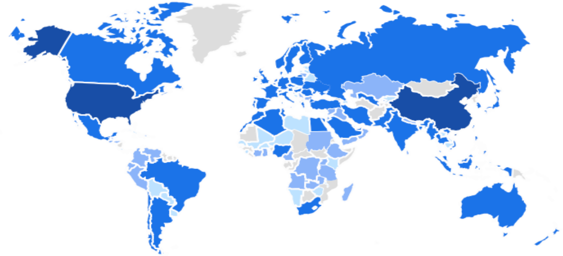
- **Our team:** Organizing the **MICCAI-SCMR CMRxRecon Challenges** (*2023, 2024, 2025*), **the world's largest** cardiovascular MR imaging and analysis benchmark series, with researchers from **over 20 international academic/industrial institutions**
- **Our impact:** 150,000+ website visits, 1,000+ dataset downloads, 11,000+ active users from **125 countries and regions,** reflecting **the broad and growing global interest** in next-generation CMR imaging technologies

Github: https://github.com/CmrxRecon

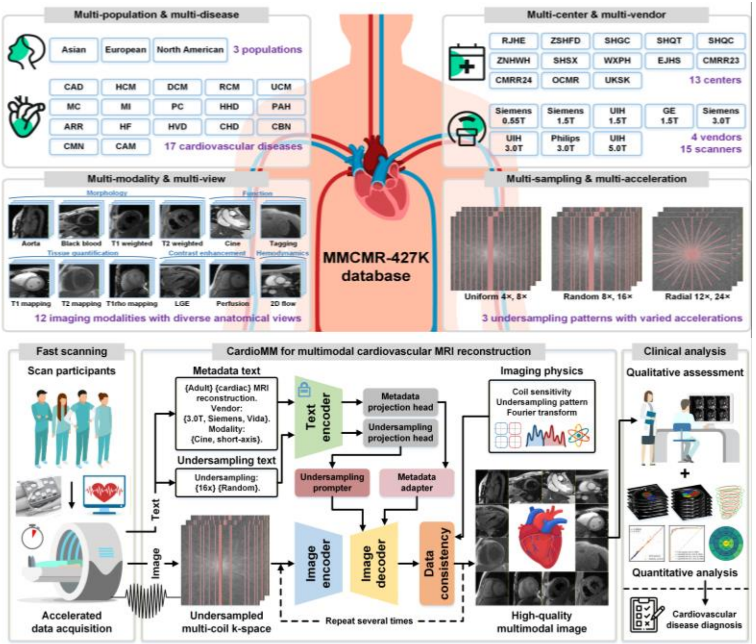


CMRxRecon Challenge series (*2023, 2024, 2025*)



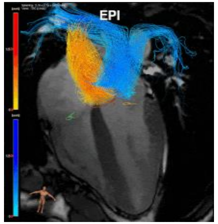
11,000+ active users from 125 countries and regions

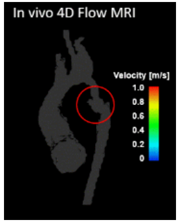
Github: https://github.com/wangziblake/CardioMM_MMCMR-427K



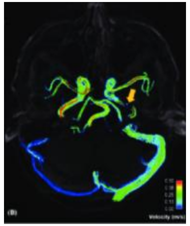
Multimodal database & reconstruction foundation model (CardioMM)

CMRx4DFlow2026 Challenge: Towards Clinical Adoption of 4D Flow

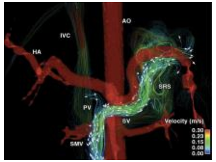
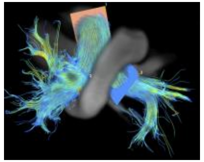




Heart Aorta




Intracranial Renal artery

Portal vein Pulmonary

Goal:

Github: https://github.com/CmrxRecon/CMRx4DFlow2026

- Build the world's largest standardized 4D Flow raw data collection
- Launch a challenge to gather the most outstanding reconstruction methods
- Establish an open benchmarking system to promote global algorithm development

Data Collection:

500+ k-space raw datasets:

- 10+ Centers
- 4+ Vendors
- 3 Field strength
- 6+ Regions
- N Pathologies
- 80 Children datasets

Tasks:

- Task 1: High quality recon under high acceleration factors (10x–50x)
- Task 2: Fast recon under limited computing resources (A6000 48G)
- Special Task 1: Generalizability across new sites and diseases
- Special Task 2: Generalizability across different anatomical regions

MEDIA paper: https://doi.org/10.1016/j.media.2025.103616

PISF Github: https://github.com/wangziblake/PISF

CardioMM Github: https://github.com/wangziblake/CardioMM_MMCMR-427K

CMRxRecon Challenge: https://github.com/CmrxRecon

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