Accelerated Multi-Modal Magnetic Resonance (MR) Imaging

Huazhu Fu

Senior Scientist,
IHPC, A*STAR, Singapore
hzfu@ieee.org

Institute of High Performance Computing
IHPC

Agenda

- **Background of Accelerated MRI Reconstruction.**
- **Multi-modal MRI Reconstruction.**
  - “Multi-modal Aggregation Network for MR Image Reconstruction”, *arXiv*, 2021.
  - "Multi-Contrast MRI Super-Resolution via a Multi-Stage Integration Network", *MICCAI*, 2021.
- **Multi-Modal MRI Reconstruction with Transformers.**
  - "Task Transformer Network for Joint MRI Reconstruction and Super-Resolution", *MICCAI*, 2021.
  - "Accelerated Multi-Modal MR Imaging with Transformers", *arXiv*, 2021.
- **Conclusion.**

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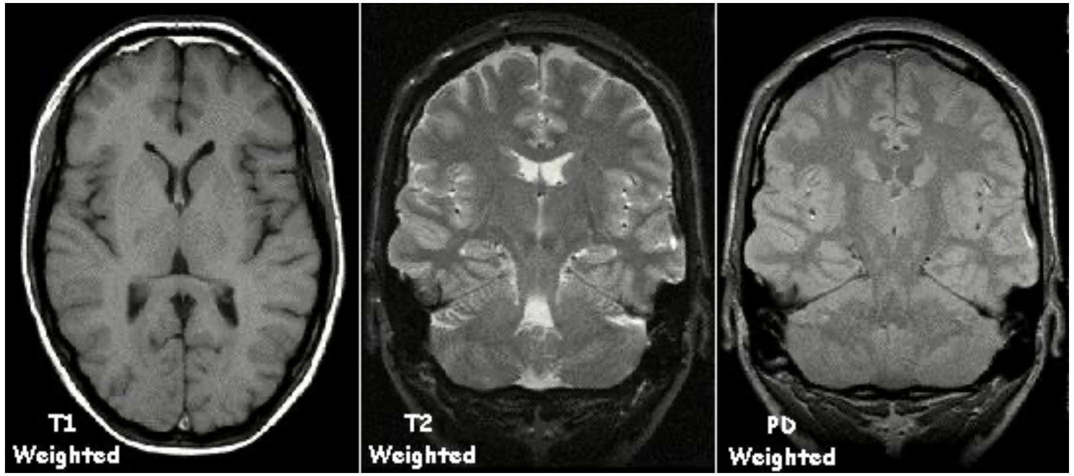
Background – MR Imaging

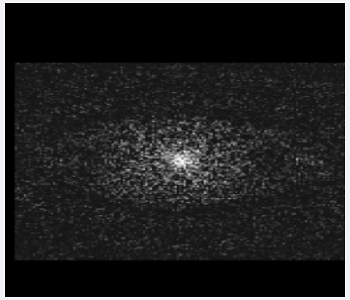


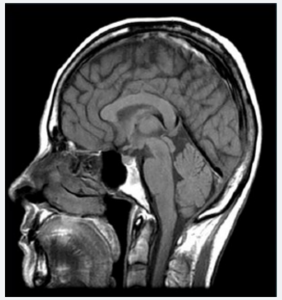
- Magnetic Resonance Imaging (MRI)
  - 1882-Nichola Tesla
  - Discovered rotating magnetic field
  - 1971-Paul Lauterbur NOBEL PRIZE
  - First invented MRI
  - Late 1970-Sir Peter Mansfield (Nottingham) NOBEL PRIZE
  - Developed mathematical techniques to create clearer images and also in minutes rather than hours as Lauterbur did.

1. CT is more widely used than MRI.
2. MRI does not have ionizing-radiation.
3. MRI has excellent soft tissue contrast, while CT is preferred for lung and bone imaging.
4. CT is fast (few seconds), while MRI is slow (sparse MRI ~5-10 mins, abdomen or brain may take 30-40 mins).

Background – Accelerated MR Imaging

传统 MRI 扫描
和诊断过程





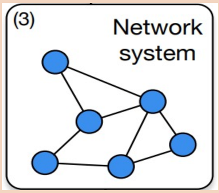
扫描 重建 诊断

挑战：长时间的线上扫描会给患者造成不良体验，以及不自主呼吸等造成运动伪影！简单缩短成像时间可能会导致低分辨率和信噪比等问题！

AI 辅助 MRI
快速成像

扫描

线下学习

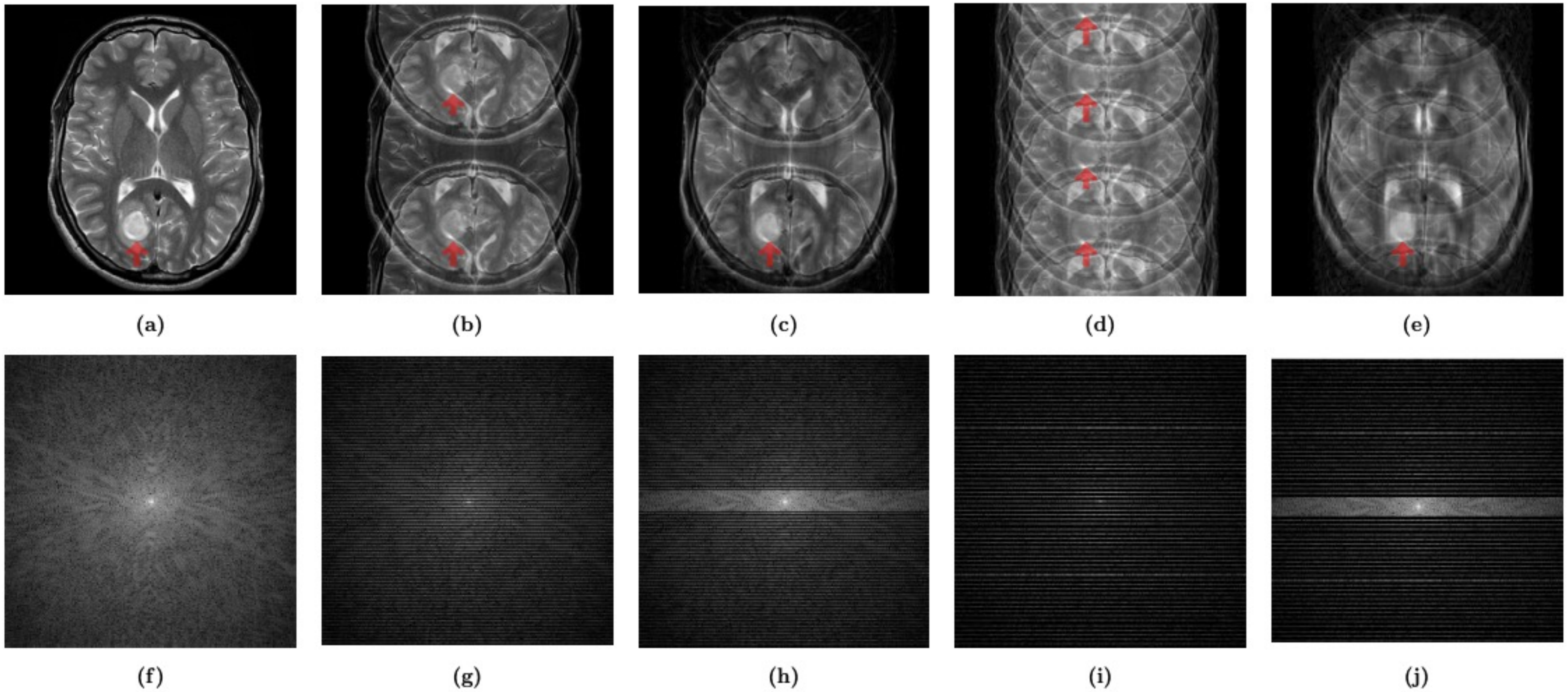


重建 诊断

技术：将线上扫描时间转移至线下网络训练，大大缩短扫描成像时间！

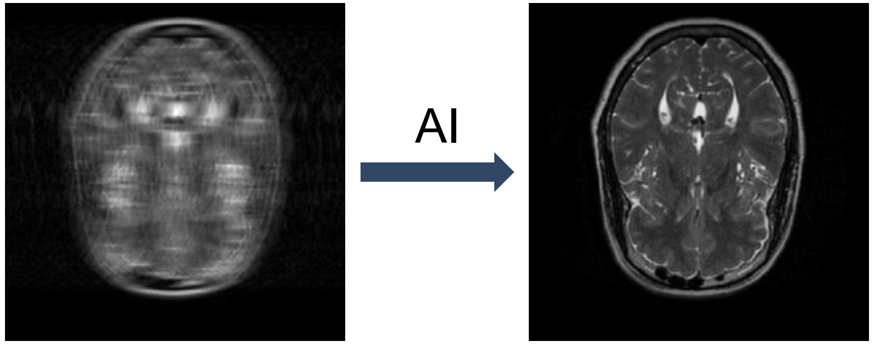
Background – Accelerated MR Imaging

欠采样模式



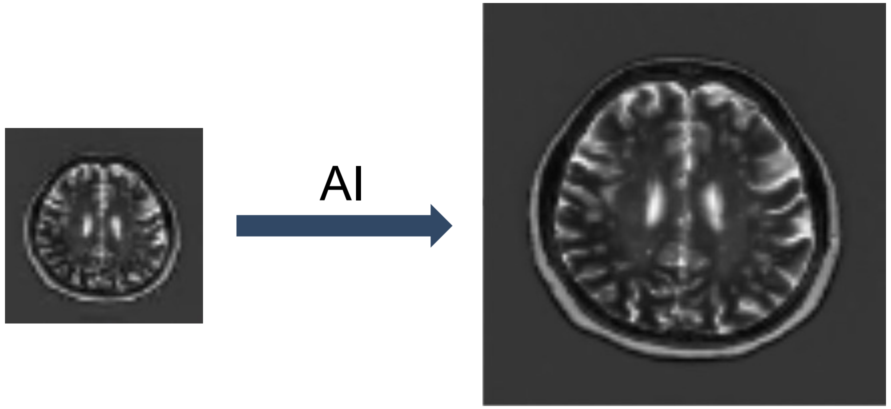
Background – Accelerated MRI Reconstruction

1. 前端快速重建



零填充/伪影图像　　重建干净图像

2. 后端图像增强



低分辨率图像　　高分辨率图像

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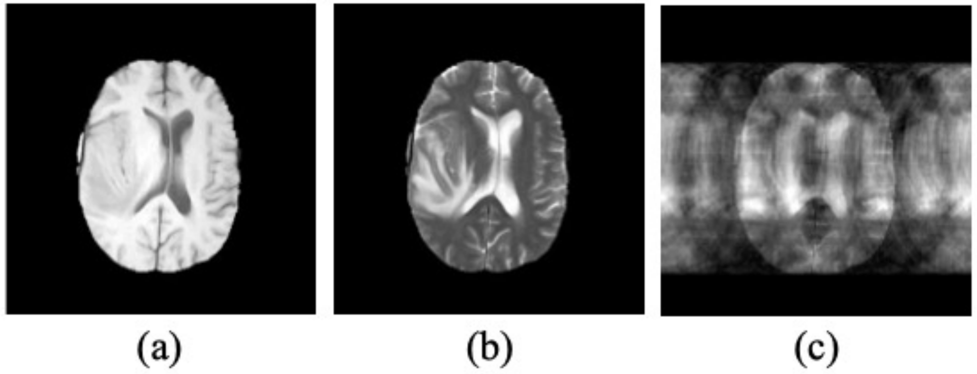
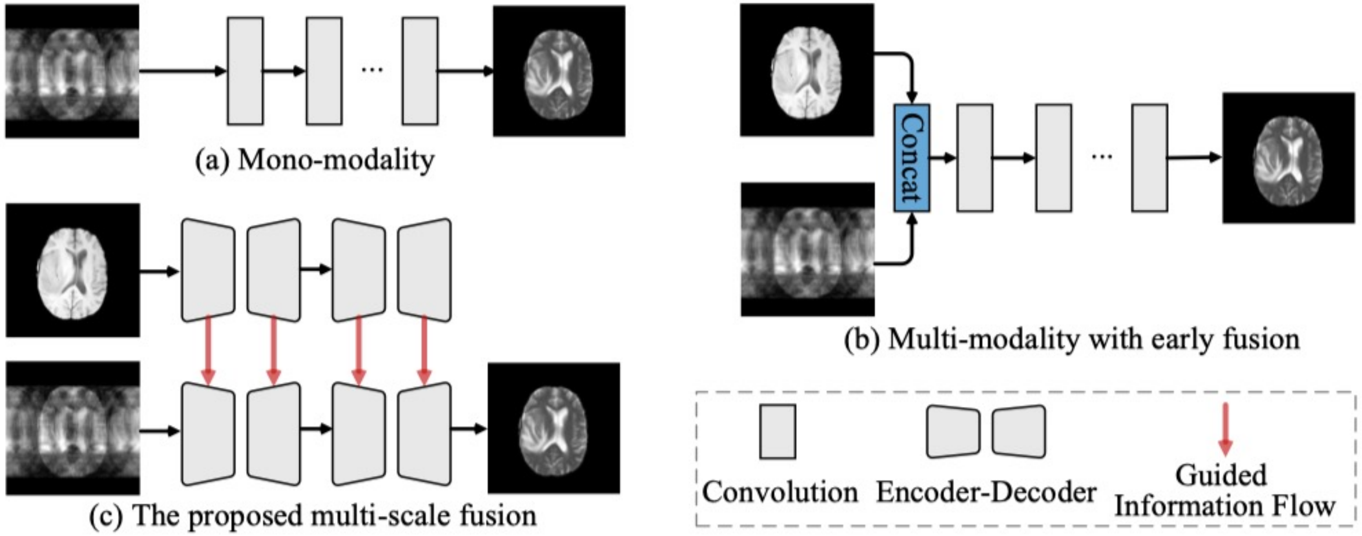
2.1 Multi-modal Aggregation Network for MR Image Reconstruction

前端加速方式，重建欠采样数据

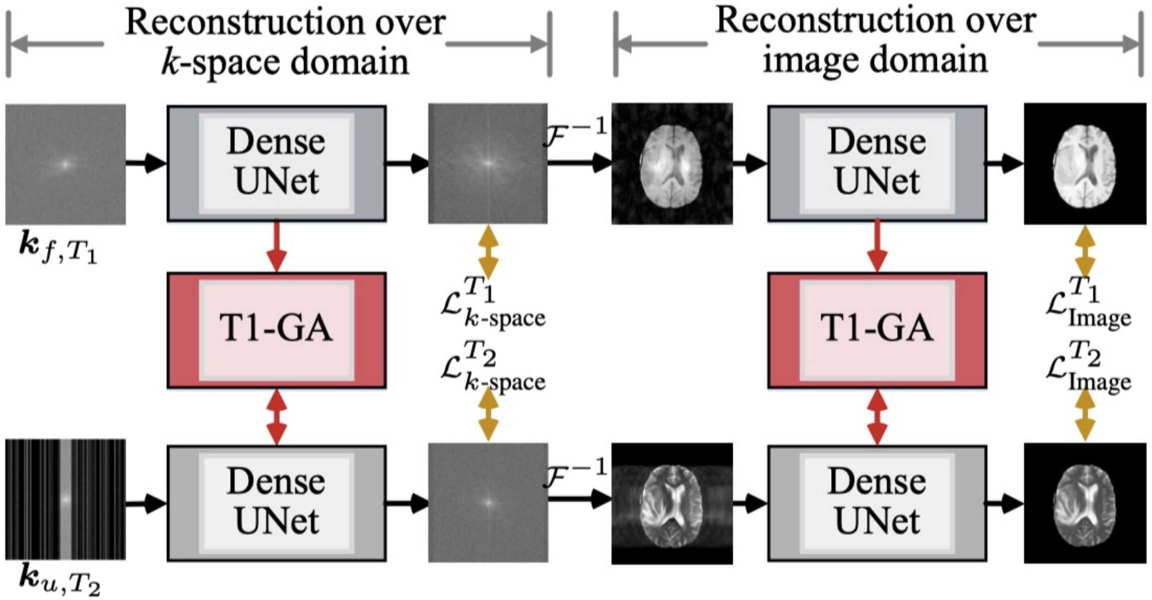
- T1 and T2 weighted images are two closely related MR sequences, but T2 weighted imaging is slower than T1 weighted due to its relatively longer repetition time (TR) and echo time (TE).

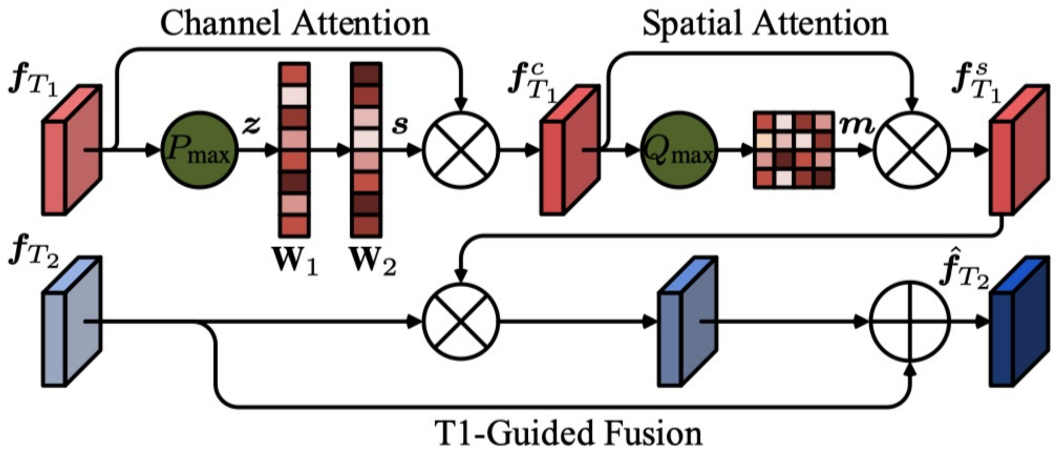


(a) The fully-sampled T1WI MR image. (b) The fully-sampled T2WI MR image. (c) The undersampled T2WI image under a 1D random sampling mask with 3× acceleration.



2.1 Multi-modal Aggregation Network for MR Image Reconstruction





左图是多模态重建框架。采用**混合域重建**方案，输入为**全采样的T1模态和欠采样的T2模态的k-space数据**。经过**第一阶段恢复k-space信号**后，逆傅里叶变换得到图像后传送到**第二阶段，对图像进行重建**，最终输出重建图像。在**每个域的不同层都引入了T1指导机制**来获得多尺度的融合信息。**右图**为T1指导机制，由级联的**通道和空间注意力机制**来有机的融合T1模态中的结构信息，从而指导T2模态的重建。

2.1 Multi-modal Aggregation Network for MR Image Reconstruction

TABLE I: Average (with standard deviation) results on the IXI dataset under different undersampling patterns, in terms of SSIM, and PSNR. The best and second-best results are marked in red and blue, respectively.

Method	1D-Uniform-6×		1D-Uniform-9×	
	SSIM↑	PSNR↑	SSIM↑	PSNR↑
ZF	0.756±0.06	25.9±1.93	0.703±0.08	25.9±2.11
UNet-T2	0.897±0.03	29.5±1.01	0.880±0.05	28.3±1.01
Xiang *et al.*	0.935±0.04	31.5±1.52	0.955±0.08	31.0±1.47
DuDoRNet	0.937±0.04	32.6±1.72	0.930±0.08	31.8±1.38
MANet	0.944±0.02	32.9±1.02	0.947±0.04	32.4±1.16

Method	1D-Random-3×		1D-Random-6×	
	SSIM↑	PSNR↑	SSIM↑	PSNR↑
ZF	0.747±0.10	27.8±1.73	0.694±0.12	25.9±2.28
UNet-T2	0.926±0.14	32.6±1.02	0.882±0.07	29.3±1.28
Xiang *et al.*	0.932±0.08	32.5±1.21	0.920±0.04	31.6±1.09
DuDoRNet	0.945±0.07	33.9±1.09	0.926±0.07	31.9±1.29
MANet	0.969±0.06	36.9±1.18	0.949±0.04	33.1±1.02

Method	2D-Radial-6×		2D-Radial-9×	
	SSIM↑	PSNR↑	SSIM↑	PSNR↑
ZF	0.487±0.08	27.1±1.86	0.414±0.07	25.2±1.28
UNet-T2	0.894±0.06	31.3±1.09	0.853±0.06	28.8±1.17
Xiang *et al.*	0.905±0.08	32.3±1.68	0.890±0.08	30.5±1.72
DuDoRNet	0.931±0.06	33.3±1.02	0.912±0.06	31.5±1.27
MANet	0.947±0.07	34.3±1.31	0.927±0.05	32.9±1.11

Method	2D-Spiral-6×		2D-Spiral-9×	
	SSIM↑	PSNR↑	SSIM↑	PSNR↑
ZF	0.617±0.06	28.1±1.28	0.638±0.07	27.6±2.12
UNet-T2	0.894±0.06	31.2±1.42	0.883±0.04	30.4±1.08
Xiang *et al.*	0.905±0.05	31.8±1.07	0.890±0.03	30.6±1.21
DuDoRNet	0.942±0.04	34.1±1.27	0.939±0.05	33.1±1.65
MANet	0.951±0.04	34.5±1.17	0.940±0.03	33.0±1.20

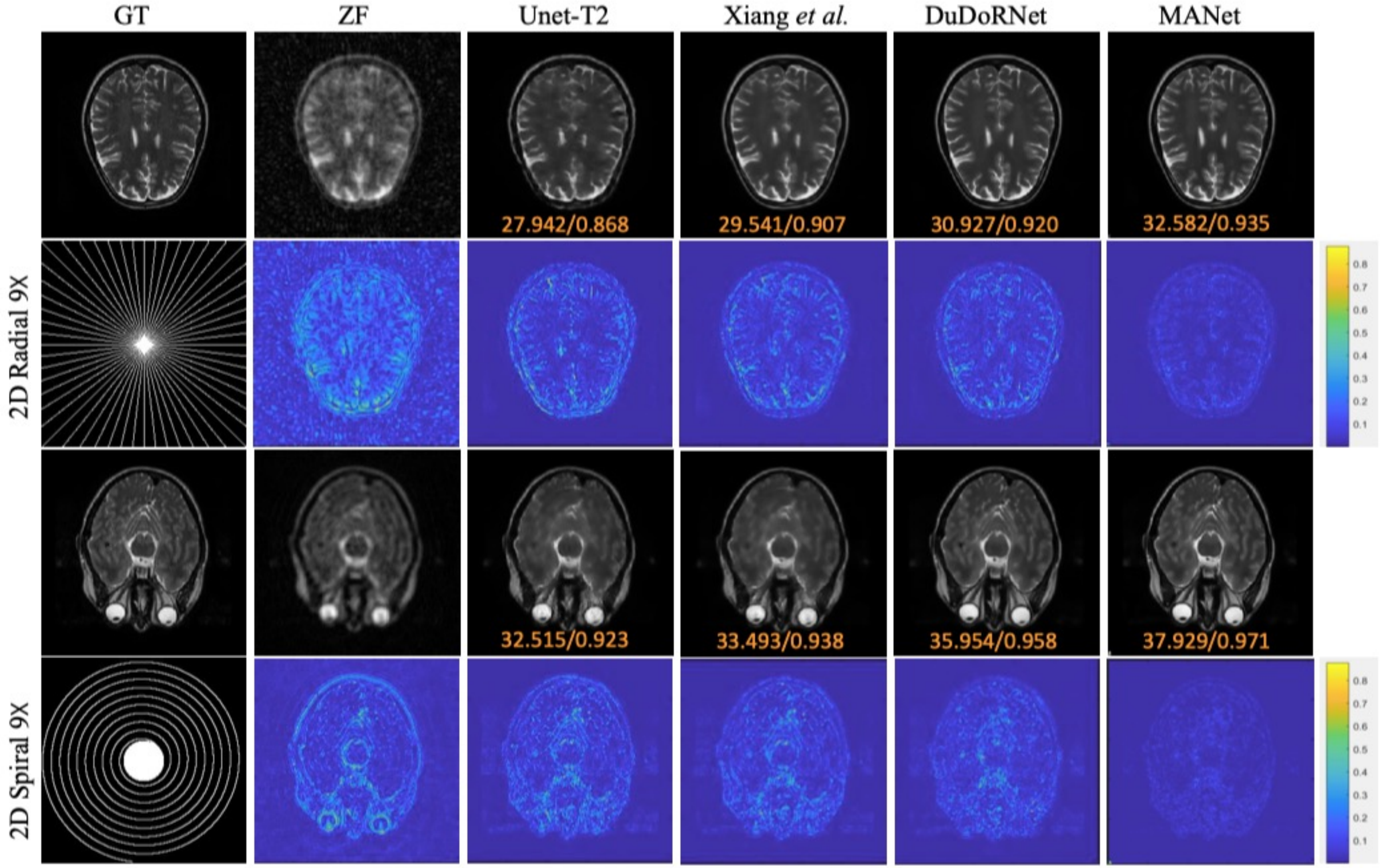
TABLE II: Average (with standard deviation) results on the fastMRI dataset under different undersampling patterns, in terms of SSIM, and PSNR. The best and second-best results are marked in red and blue, respectively.

Method	Random-4×		Random-8×	
	SSIM↑	PSNR↑	SSIM↑	PSNR↑
UNet-PDFS	0.630±0.04	29.2±1.55	0.550±0.02	28.1±1.07
Xiang *et al.*	0.600±0.05	29.3±1.54	0.562±0.06	28.4±1.25
DuDoRNet	0.640±0.02	29.5±1.33	0.571±0.05	28.7±1.38
MANet	0.652±0.02	30.3±1.12	0.604±0.05	29.4±1.09

Method	Equispaced-4×		Equispaced-8×	
	SSIM↑	PSNR↑	SSIM↑	PSNR↑
UNet-PDFS	0.600±0.06	29.2±1.52	0.553±0.06	28.2±1.15
Xiang *et al.*	0.621±0.05	29.4±1.71	0.567±0.03	28.6±1.10
DuDoRNet	0.641±0.05	29.6±1.39	0.577±0.05	28.8±1.29
MANet	0.646±0.03	30.4 ±1.22	0.588±0.04	29.6±1.19

Xiang et al.: "Deep-learning-based multi-modal fusion for fast mr reconstruction," IEEE TBME, 2018.
DuDoRNet: "Dudornet: Learning a dual-domain recurrent network for fast mri reconstruction with deep t1 prior," in CVPR, 2020.

2.1 Multi-modal Aggregation Network for MR Image Reconstruction



Xiang et al.: "Deep-learning-based multi-modal fusion for fast mr reconstruction," IEEE TBME, 2018.
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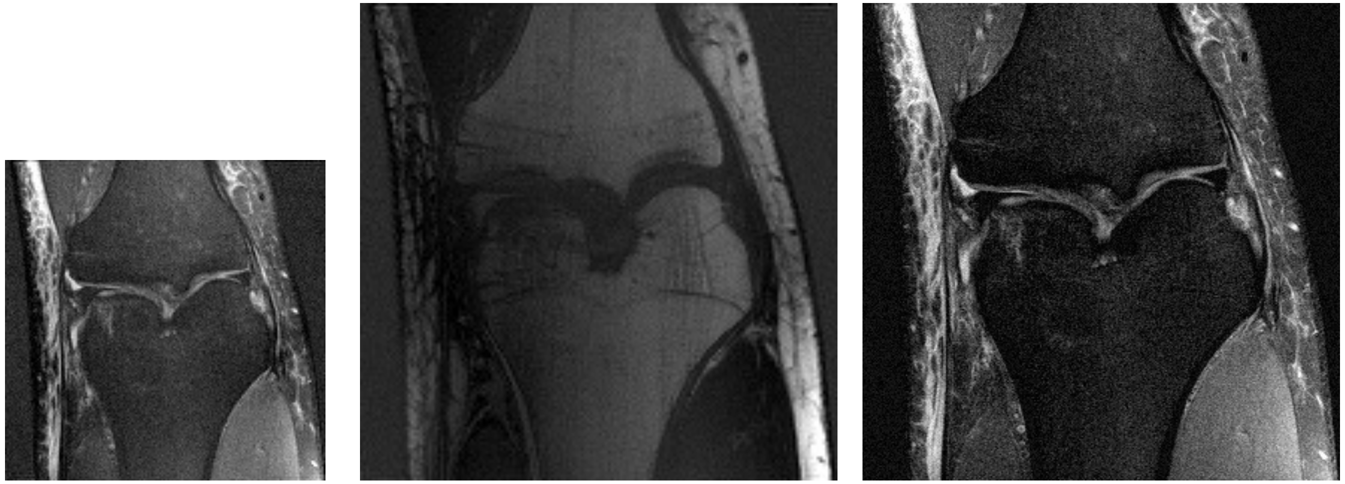
2.2 Multi-Contrast MRI Super-Resolution via a Multi-Stage Integration Network

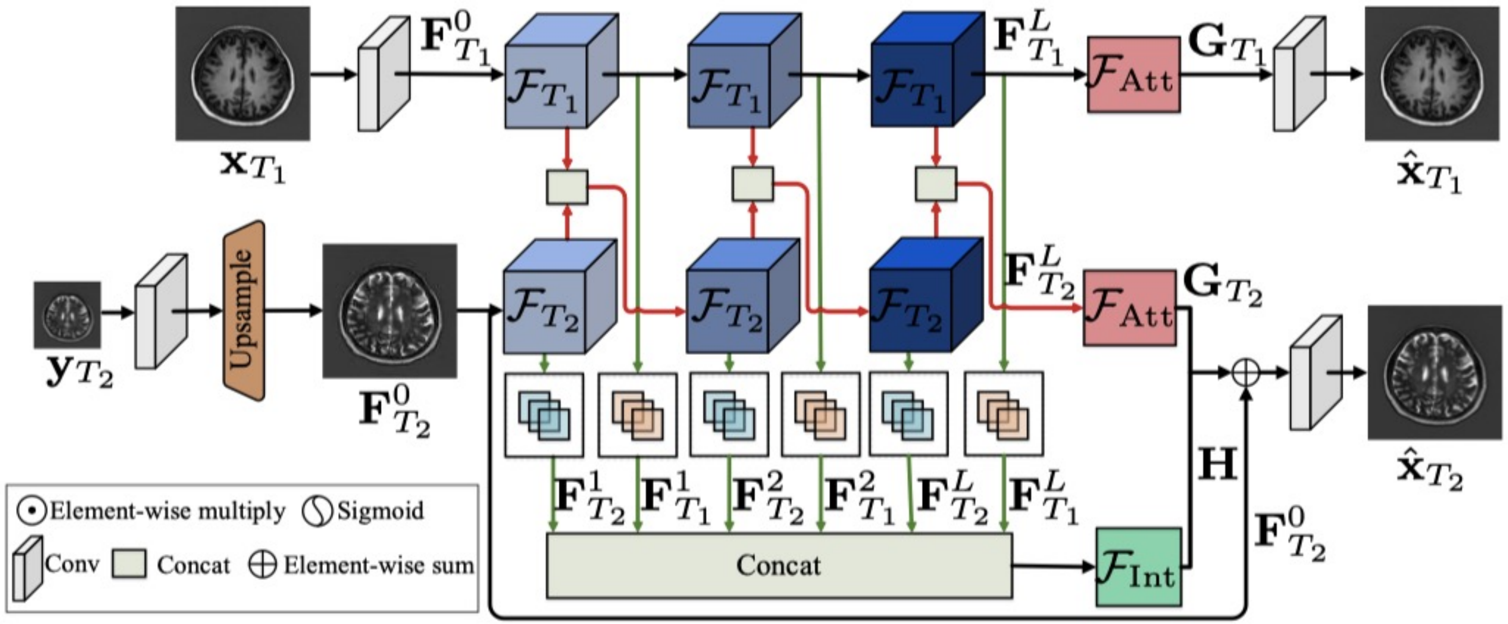
后端加速方式，超分辨率增强图像

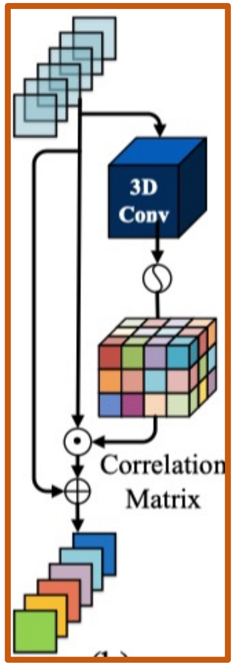


(a) (b) (c)

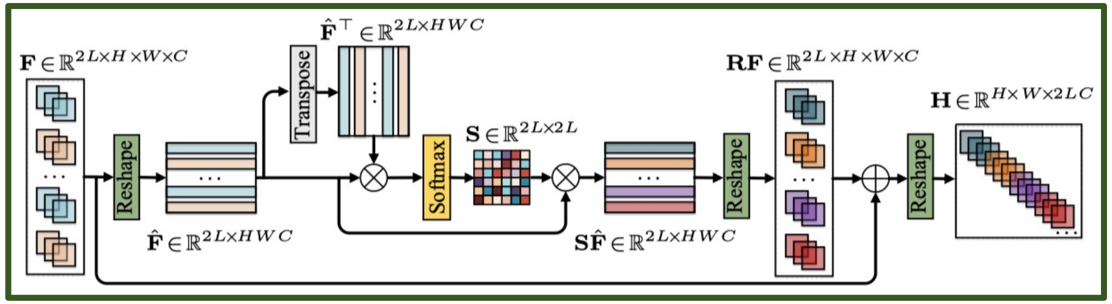
后端加速方式：从**退化了的图像**中超分辨率得到**增强图像**。(a)表示退化的PDFS模态图像，(b)表示全采样的PD模态图像，(c)表示超分辨率的PDFS模态图像。不同模态具有一致的结构，但是性质不同。**PD模态**提供了**关节软骨等结构**的信息，而**PDFS**可以**抑制脂肪信号**，并**突出软骨韧带**等组织结构的对比。物理采集特性导致PD模态的采集速度要快于PDFS，我们用成像速度快的PD来辅助速度慢的PDFS模态成像。

2.2 Multi-Contrast MRI Super-Resolution via a Multi-Stage Integration Network





第一个分支输入为**辅助模态（T1或者PD）**，**第二个分支**输入为**退化了的目标模态（T2或者PDFS）**。输出为超分辨率的图像。我们在两个分支的每个阶段中引入了**多阶段集成模块**，探究**多模态在不同阶段的响应**，得到**融合特征之间的依赖关系**。



2.2 Multi-Contrast MRI Super-Resolution via a Multi-Stage Integration Network

Table 1. Quantitative results on three datasets with different enlargement scales, in terms of SSIM and PSNR. The best and second-best results are marked in red and blue, respectively.

Dataset	fastMRI [23]				SMS				uMR			
Scale	2×		4×		2×		4×		2×		4×	
Metrics	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Bicubic	16.571	0.459	13.082	0.105	21.548	0.780	19.508	0.706	21.107	0.730	19.072	0.720
EDSR [12]	26.669	0.512	18.363	0.208	36.415	0.962	31.484	0.886	35.394	0.965	31.165	0.907
SMORE [26]	28.278	0.667	21.813	0.476	38.106	0.972	32.091	0.901	36.547	0.972	31.971	0.918
Zeng *et al.* [13]	28.870	0.670	23.255	0.507	38.164	0.973	32.484	0.912	36.435	0.971	31.859	0.921
Lyu *et al.* [24]	29.484	0.682	28.219	0.574	39.194	0.978	33.667	0.931	37.139	0.977	32.231	0.929
MINet	31.769	0.709	29.819	0.601	40.549	0.983	35.032	0.948	37.997	0.980	34.219	0.956

[12] "Enhanced deep residual networks for single image super-resolution", in CVPR workshop, 2017.
[13] "Multicontrast super-resolution mri through a progressive network", IEEE TMI, 2020.
[24] "Simultaneous singleand multi-contrast super-resolution for brain mri images based on a convolutional neural network", CIBM, 2018.
[26] "A deep learning based anti-aliasing self superresolution algorithm for mri.", in MICCAI, 2018.

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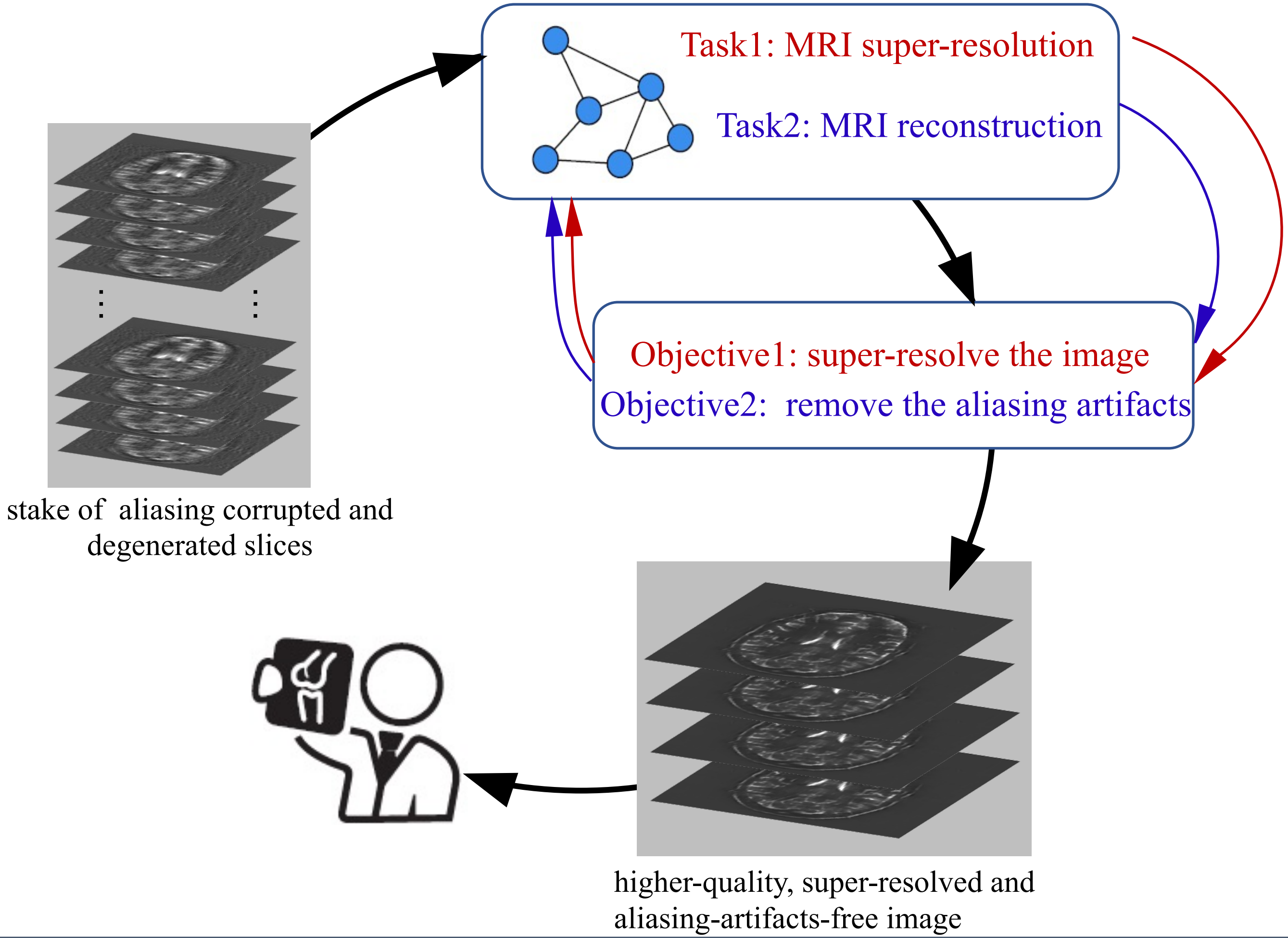
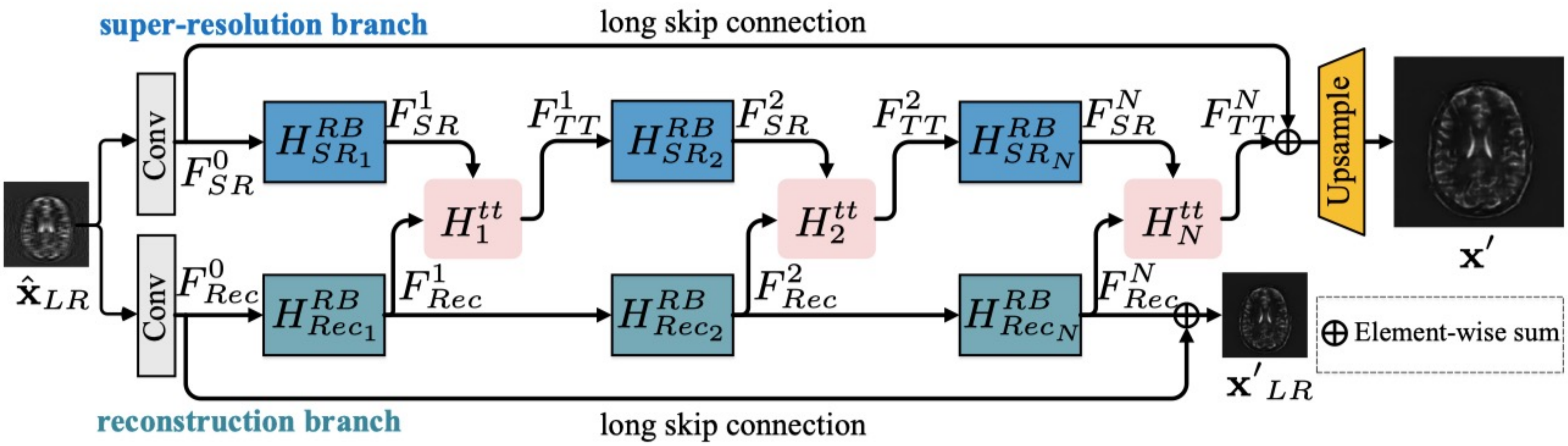
3.1 Task Transformer Network for Joint MRI Reconstruction and Super-Resolution



Multi-task MRI Reconstruction：

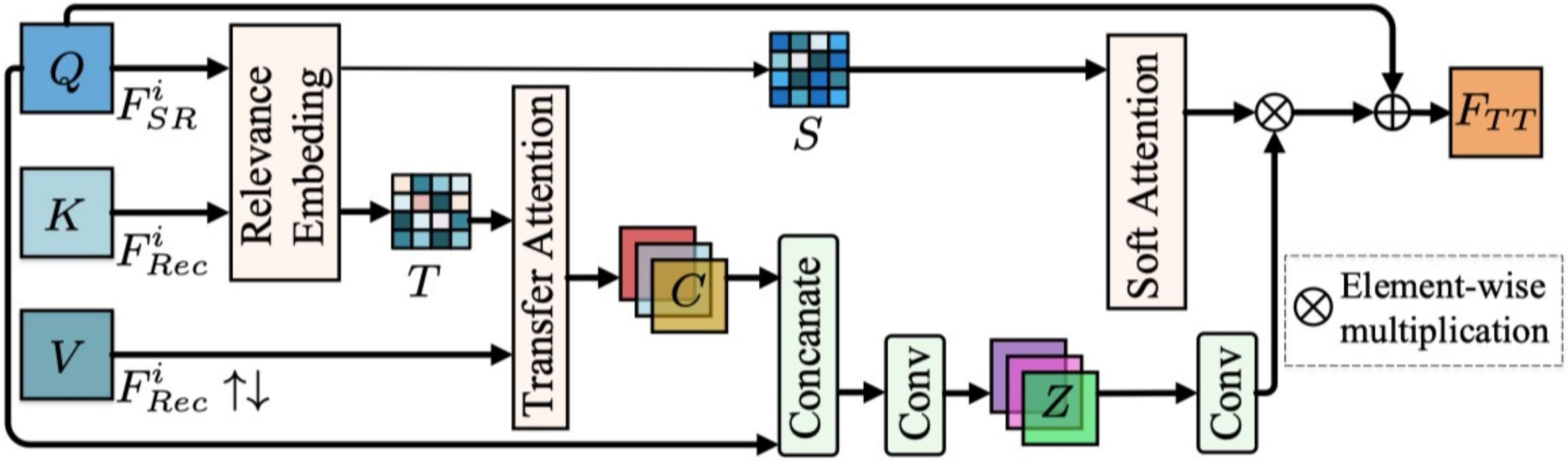
- 像目前的方法被设计成单独执行多个任务，忽略了它们之间的相关性。
- 我们的多任务方案：**首次实现MRI多任务建模**，从相关任务中转移相关特征，一步建模实现重建、超分辨率。
- 输入为混叠伪影且的退化MRI图像，框架分为两个子分支：重构和超分辨率(也就是同时从前端和后端加速MRI成像）。超分辨率的目的是对输入图像进行**超分辨增强**，而重建的目的是**去除混叠伪影**。

3.1 Task Transformer Network for Joint MRI Reconstruction and Super-Resolution



图示为多任务框架。输入为**退化**且欠采样而具有**混叠伪影**的MRI图像，输出为**超分辨率增强且去除混叠伪影**的MRI图像。该框架包括一个超分辨率分支（蓝色）、一个重建分支（绿色）和一个任务传输模块（粉色）。该模块允许在多个任务之间**共享表示和特征传输**。

3.1 Task Transformer Network for Joint MRI Reconstruction and Super-Resolution



图示为任务传输模块。**Q**为继承自**超分辨率分支**的特征，**K**和**V**是继承自**重建分支**的特征。首先通过一个**关联嵌入模块**估计Q和K之间的相似性来**嵌入来自重建分支的关联信息**，然后通过一个**传输注意力模块**将**解剖结构特征**从重建分支**转移到超分辨率分支**（因为重建的主要功能是去除混叠伪影，获得清晰的解剖结构），最后通过**软注意力模块**有机的融合两个任务的特征。

3.1 Task Transformer Network for Joint MRI Reconstruction and Super-Resolution

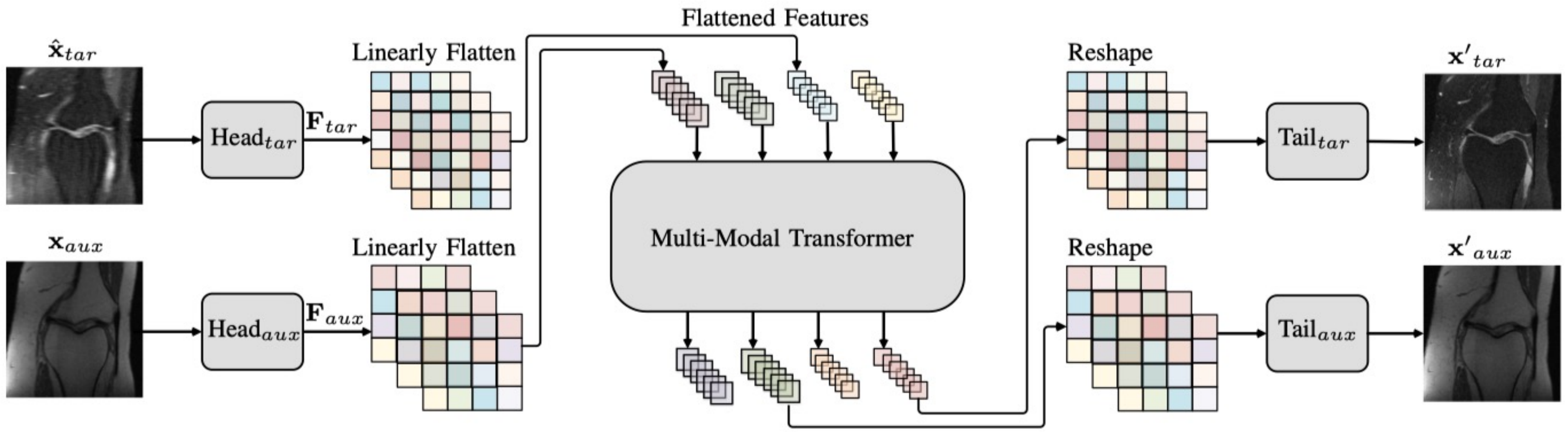
Table 1. Quantitative results on the two datasets under different enlargement scales.

Dataset	IXI dataset						clinical dataset					
Scale	2×			4×			2×			4×		
	PSNR	SSIM	NMSE	PSNR	SSIM	NMSE	PSNR	SSIM	NMSE	PSNR	SSIM	NMSE
Com-A	27.541	0.801	0.041	21.111	0.705	0.178	27.031	0.764	0.065	26.169	0.742	0.079
Com-B	28.439	0.847	0.033	21.323	0.687	0.170	28.750	0.816	0.044	27.539	0.803	0.058
Com-C	27.535	0.802	0.041	21.696	0.731	0.156	28.781	0.765	0.064	26.197	0.751	0.079
Com-D	28.426	0.847	0.033	21.895	0.710	0.149	28.839	0.817	0.043	27.700	0.815	0.056
w/o Rec	28.400	0.809	0.035	25.952	0.789	0.091	28.932	0.802	0.045	28.601	0.819	0.044
w/o H^{tt}	28.700	0.856	0.031	26.692	0.7730	0.089	29.510	0.817	0.037	29.528	0.821	0.037
T^2Net	**29.397**	**0.872**	**0.027**	**28.659**	**0.850**	**0.032**	**30.400**	**0.841**	**0.030**	**30.252**	**0.840**	**0.031**

Com-A: ADMMNet [29]+[24], Com-B: ADMMNet [29]+[16], Com-C: MICCAN[11]+[24], Com-D: MICCAN[11]+[16].

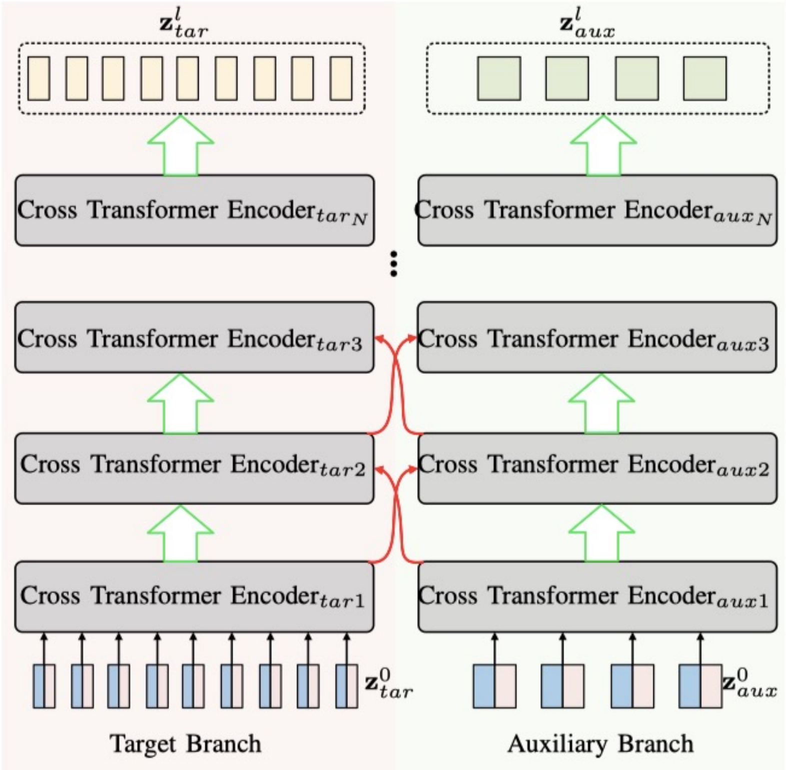
[11] "MRI reconstruction via cascaded channel-wise attention network", in ISBI, 2019.
[16] "MRI super-resolution with ensemble learning and complementary priors", IEEE TCI, 2020.
[24] "Super-resolution reconstruction of MR image with a novel residual learning network algorithm", Physics in Medicine & Biology, 2018.
[29] "Deep admm-net for compressive sensing MRI", in IPMI, 2016.

3.2 Accelerated Multi-Modal MR Imaging with Transformers

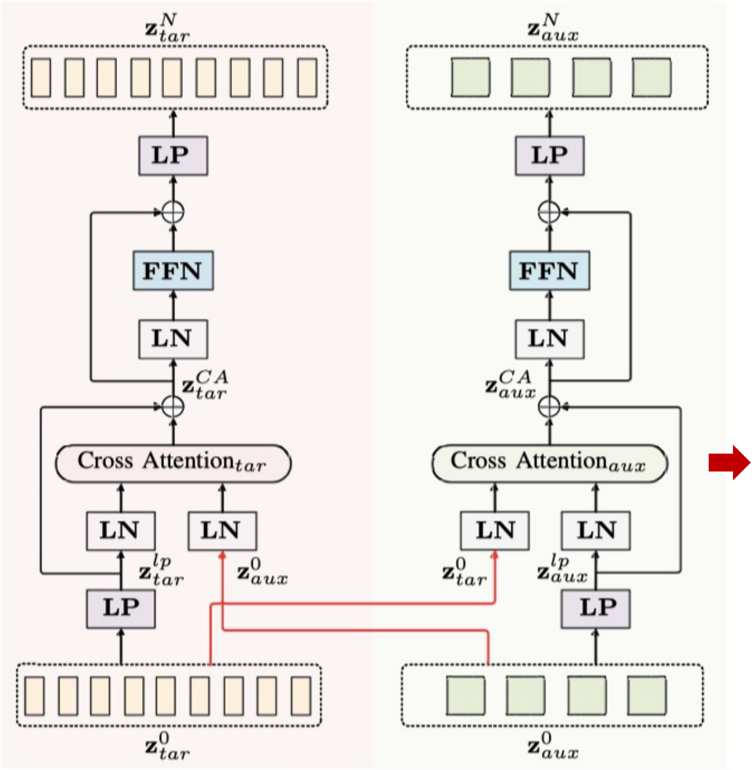


图示为基于transformer的多模态MRI成像，图像块被处理成一系列线性嵌入序列。总体架构由三个组件组成。两个Head提取不同尺度的特征；一个多模态transformer来聚合不同的模态，其中模块以当前分支的特征作为查询，与另一个分支交换信息；两个Tail用于将特征映射到恢复图像中。

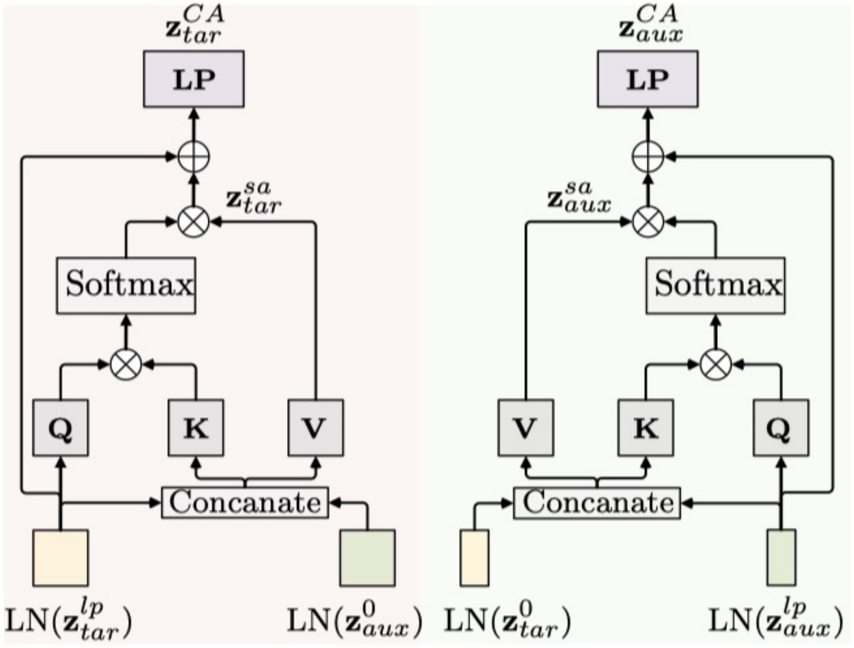
3.2 Accelerated Multi-Modal MR Imaging with Transformers



Multi-modal transformer



Cross transformer encoder



Cross attention module

3.2 Accelerated Multi-Modal MR Imaging with Transformers

TABLE I: Average (with standard deviation) **reconstruction** results, in terms of SSIM, PSNR and NMSE, under different undersampling patterns. The best and second-best results are marked in red and blue, respectively.

fastMRI	Equispaced		
Method	SSIM↑	PSNR↑	NMSE↓
Zero-filling	0.442±0.10	24.5±1.37	0.057±0.05
UNet	0.565±0.06	28.2±1.15	0.046±0.02
TransMRI	0.607±0.05	28.4±0.81	0.038±0.01
MDUNet	0.600±0.05	28.6±1.00	0.040±0.01
rsGAN	0.608±0.04	28.9±1.03	0.033±0.02
MTrans	0.638±0.03	29.3±0.89	0.030±0.01

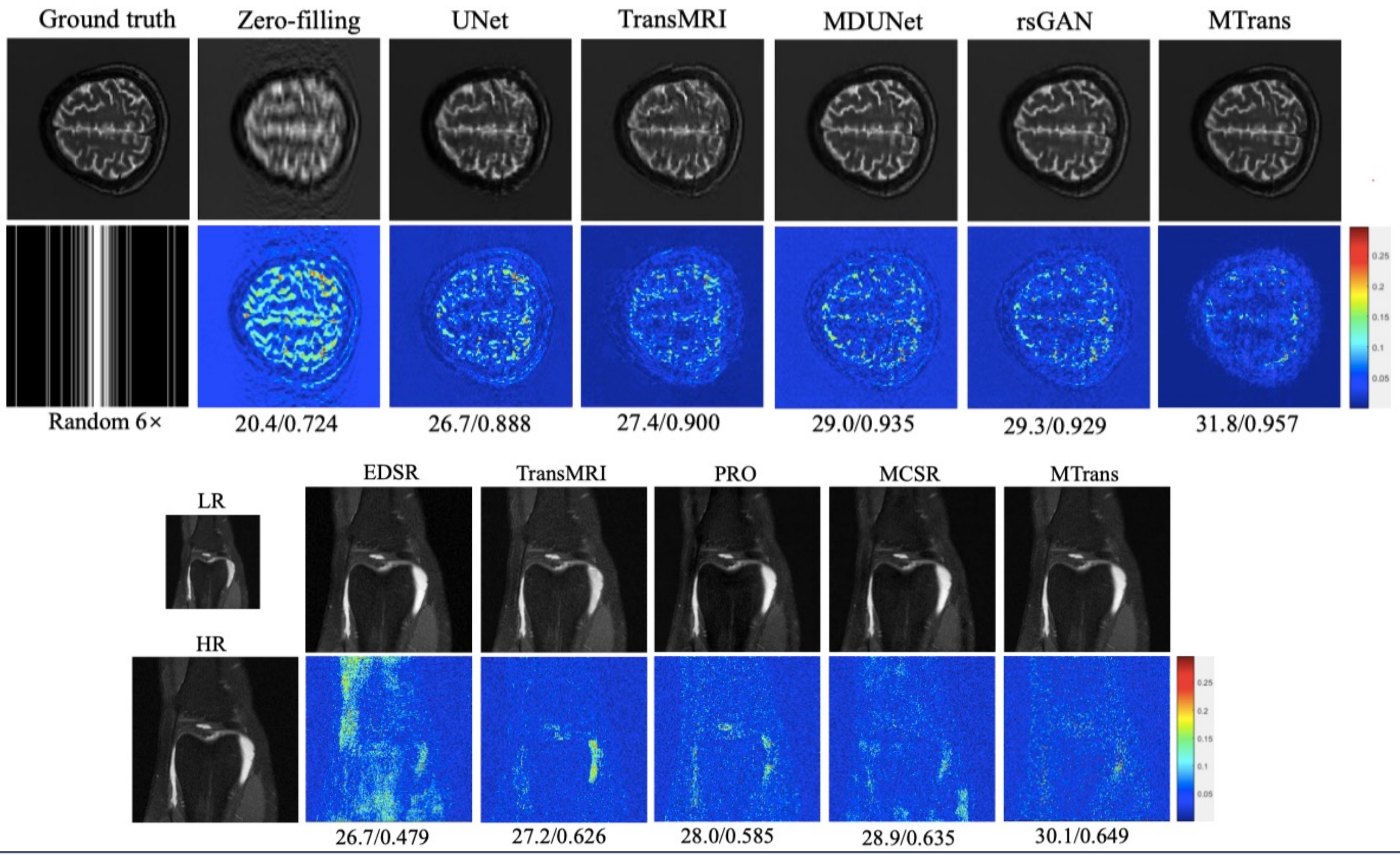
uiMRI	Random		
Method	SSIM↑	PSNR↑	NMSE↓
Zero-filling	0.700±0.09	27.0±1.70	0.067±0.010
UNet	0.849±0.05	28.9±1.57	0.044±0.006
TransMRI	0.861±0.02	28.9±1.31	0.044±0.005
MDUNet	0.900±0.03	30.0±1.53	0.034±0.006
rsGAN	0.908±0.03	30.7±1.46	0.028±0.005
MTrans	0.931±0.02	31.7±1.33	0.024±0.004

TABLE II: Average (with standard deviation) **super-resolution** results, in terms of SSIM, PSNR and NMSE, under different datasets. The best and second-best results are marked in red and blue, respectively.

fastMRI	4×		
Method	SSIM↑	PSNR↑	NMSE↓
Bicubic	0.400±0.07	16.9±1.70	0.917±0.06
EDSR	0.580±0.04	28.1±1.64	0.045±0.04
TransMRI	0.600±0.03	29.9±1.44	0.048±0.02
PRO	0.700±0.02	30.8±1.60	0.038±0.03
MCSR	0.704±0.03	31.0±1.31	0.033±0.03
MTrans	0.719±0.02	31.9±1.19	0.031±0.02

uiMRI	4×		
Method	SSIM↑	PSNR↑	NMSE↓
Bicubic	0.526±0.05	8.3±1.20	0.900±0.030
EDSR	0.941±0.07	32.3±1.04	0.012±0.004
TransMRI	0.940±0.04	33.5±1.17	0.009±0.005
PRO	0.945±0.07	34.4±0.97	0.007±0.003
MCSR	0.944±0.07	34.8±0.97	0.006±0.003
MTrans	0.959±0.05	36.1±0.99	0.005±0.003

3.2 Accelerated Multi-Modal MR Imaging with Transformers



Agenda

- **Background of Accelerated MRI Reconstruction.**
- **Multi-modal MRI Reconstruction.**
  - “Multi-modal Aggregation Network for MR Image Reconstruction”, *arXiv*, 2021.
  - "Multi-Contrast MRI Super-Resolution via a Multi-Stage Integration Network", *MICCAI*, 2021.
- **Multi-Modal MRI Reconstruction with Transformers.**
  - "Task Transformer Network for Joint MRI Reconstruction and Super-Resolution", *MICCAI*, 2021.
  - "Accelerated Multi-Modal MR Imaging with Transformers", *arXiv*, 2021.
- **Conclusion.**

Conclusion

- Multi-modal images under different settings but with the same anatomical structure can provide complementary information to each other.
- MR image reconstruction could be effectively restored the target modality under the guidance of the auxiliary modality.
- Transformer provides a latent cross-modal attention with target-specific query, which is suitable for multi-modal and multi-task learning.

Reference:

1. **"Task Transformer Network for Joint MRI Reconstruction and Super-Resolution",** Chun-Mei Feng, Yunlu Yan, Huazhu Fu, Li Chen, and Yong Xu, *MICCAI*, 2021.
2. **"Multi-Contrast MRI Super-Resolution via a Multi-Stage Integration Network",** Chun-Mei Feng, Huazhu Fu, Shuhao Yuan, and Yong Xu, *MICCAI*, 2021.
3. **"Accelerated Multi-Modal MR Imaging with Transformers",** Chun-Mei Feng, Yunlu Yan, Geng Chen, Huazhu Fu, Yong Xu, and Ling Shao, *arXiv:2106.14248*, 2021.
4. **"Multi-modal Aggregation Network for MR Image Reconstruction",** Chun-Mei Feng, Huazhu Fu, Tianfei Zhou, Yong Xu, Ling Shao, and David Zhang, *arXiv:2110.08080*, 2021.

Collaborators:


Chun-Mei Feng


Yunlu Yan


Prof. Geng Chen


Prof. Yong Xu


Prof. Ling Shao

Huazhu FU

Web: https://hzfu.github.io

Email: hzfu@ieee.org

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