Cross-Modality Synthesis（CMS）

论文名	链接	任务	方法	下游任务	数据集	数据描述	时间	发表
Cross-Modality Synthesis from CT to PET using FCN and GAN	https://arxiv.org/abs/1802.07846	PET_to_CT	FCN、CGAN	应用于病灶检测软件减少误报	自建数据，60例配对的PET、CT	肝脏数据，并非所有数据都包含病变	2018	Engineering Applications of Artificial Intelligence
MRI Cross-Modality Image-to-Image Translation	https://www.nature.com/articles/s41598-020-60520-6	跨模态图像迁移（就是将CGAN用于跨膜态图像生成，然后用于下游任务）	CGAN	图像配准、分割	BraTs2015、Iseg2017、MRBrain13、ADNI、RIRE	见后附图片	2020	scientific reports
Simultaneous Super-Resolution and Cross-Modality Synthesis of 3D Medical Images using Weakly-Supervised Joint Convolutional Sparse Coding	[1705.02596] Simultaneous Super-Resolution and Cross-Modality Synthesis of 3D Medical Images using Weakly-Supervised Joint Convolutional Sparse Coding (arxiv.org)	目的：现实中很多任务缺乏高清数据、并且随着设备的变化图像质量会变化；SR、CMS	卷积稀疏编码（不是很了解）	同时超分与跨膜态生成	IXI、NAMIC	IXI(n=587,T1_T2_PD、MRA、DWI); NAMIC(n=20,T1,T2)	2017	CVPR

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Unsupervised cross-modal synthesis of subject-specific scans	https://openaccess.thecvf.com/content_iccv_2015/papers/Vemulapalli_Unsupervised_Cross-Modal_Synthesis_ICCV_2015_paper.pdf	T2生成T1	无监督KNN+耦合稀疏表示（没看）	无	NAMIC	同上	2015	ICCV
Cross-modality Synthesis from MRI to PET Using Adversarial U-Net with Different Normalization	https://ieeexplore.ieee.org/abstract/document/9098219	PET生成T1	GAN+Unet+一种新的归一化方法	无	ADNI	n=680 MRI、PET	2019	ICNIPE
Magnetic Resonance Image Example-Based Contrast Synthesis	https://ieeexplore.ieee.org/abstract/document/6600832	CMS	图像块稀疏重建（很多文章都引了这一篇）	自动分割、多峰配准			2013	TMI
Cross-Modality Neuroimage Synthesis: A Survey	https://arxiv.org/abs/2202.06997	综述					2023	ACM Computing Surveys

(1)*BraTs2015*: The BraTs2015 dataset[60] contains multi-contrast MR images from 220 subjects with high-grade glioma, including T1, T2, T2-Flair images and corresponding labels of tumors. We randomly select 176 subjects for training and the rest for testing. 1924 training images are trained for 600 epochs with batch size 1. 451 images are used for testing.

(2)*Iseg2017*: The Iseg2017 dataset[61] contains multi-contrast MR images from 23 infants, including T1, T2 images and corresponding labels of Grey Matter (gm) and White Matter (wm). We randomly select 18 subjects for training and remaining 5 subjects for testing. 661 training images are trained for 800 epochs with batch size 1. 163 images from the 5 subjects are used for testing.

(3)*MRBrain13*: The MRBrain13 dataset[62] contains multi-contrast MR images from 20 subjects, including T1 and T2-Flair images. We randomly choose 16 subjects for training and the remaining 4 for testing. 704 training images are trained for 1200 epochs with batch size 1. 176 images are used for testing.

(4)*ADNI*: The ADNI dataset[30] contains T2 and PD images (proton density images, tissues with a higher concentration or density of protons produce the strongest signals and appear the brightest on the image) from 50 subjects. 40 subjects are randomly selected for training and the remaining 10 for testing. 1795 training images are trained for 400 epochs with batch size 1. 455 images are used for testing.

(5)*RIRE*: The RIRE dataset[63] includes T1 and T2 images collected from 19 subjects. We randomly choose 16 subjects as for training and the rest for testing. 477 training images are trained for 800 epochs with batch size 1. 156 images are used for testing.

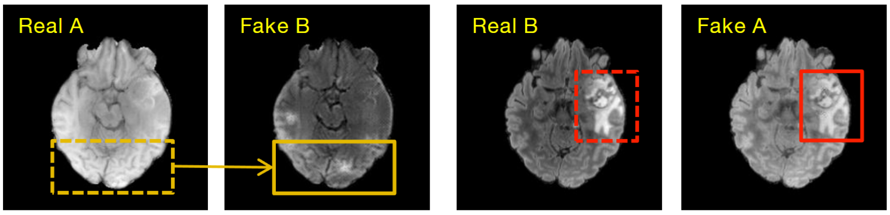

Fig. 3. A failed case in multi-modality brain image synthesis. In addition to generating low-resolution images, another problem is that the disease-related regions cannot be synthesized well. For example, when the target modality (Fake B) is generated from the input real modality (Real A), there exist failed regions (box) that are learned from the original ones (dashed box).