# 第五章 结论与展望

## 5.1 结论

深度学习技术的出现大大提升了MRI重建速度与效果。目前，深度学习算法所重建的4倍欠采样的MRI图像已经能够被放射科医生认可[[52](#_ENREF_52" \o "Muckley, 2021 #91)]，但对于更高加速比的重建仍存在混叠伪影，高倍欠采样图像重建的研究依然极具挑战。为了实现更高的加速比和更好的重构质量，可以借助先验知识，除了网络结构本身的深度先验[DIP的参考文献]，还可以从大规模训练数据中获取先验。但由不同扫描仪获取的数据训练得到的模型，在实际应用中很难在特定的目标扫描仪上取得良好的泛化性能。因此，本文针对特定扫描仪的有限数据进行建模，在有限的数据规模下考虑如何充分结合MRI数据本身的特点利用数据先验信息，包括多尺度数据、多模态数据以及*k*空间数据，对欠采样MRI数据进行辅助重建。为了充分利用这些先验信息，本文主要做了两方面的研究工作：（1）提出了一种新的网络训练方法：基于细分的多尺度序贯训练方法；(2) 提出了一种新的网络结构：一种基于同层稠密连接的深度级联网络。

本文所提出的基于细分的多尺度序贯训练方法，主要用于解决如何充分利用自身模态的多尺度信息进行 MRI重建这一问题。首先，该方法对训练过程中所使用的欠采样数据的加速比进行了精细的划分（例如将8倍欠采样的*k*空间数据划分为100份），这种细分的加速比会产生大量的多尺度欠采样数据，本文采用一种渐进的训练方式：先使用低倍欠采样数据训练网络，再逐步使用较高倍欠采样数据训练网络，直至能够较好地完成目标加速比下欠采样数据的重建。这种由易而难的训练方式，既解决了多尺度数据规模过大的问题，又能够更加充分地利用相邻尺度间的相关性。其次，为了能够有效使用细分的多尺度MRI数据进行训练，本文提出了一种迭代补偿方案：由于即便只是学习少量缺失数据的重建，网络的优化仍需要进行很多次迭代，若每一个加速比下的训练都达到最优重建后再进行下一步，整个训练过程将冗长且复杂。为了解决这个问题，本文使用迭代补偿的训练方法，即：针对每个加速比（除了目标加速比）的训练数据，只进行少量迭代（例如，对目标加速比细分得到100个加速比，每个加速比下仅训练2个周期），而针对目标加速比的训练数据，进行充分的迭代和优化。这种训练方式中，尽管针对每个非目标加速比的训练是不充分的，但针对后续加速比的训练会对前次加速比训练所得到的网络模型进行迭代补偿，从而使得网络最终能够得到充分的训练。最后，由于*k*空间中重要的低频数据集中分布在中心区域，本文在构建多尺度欠采样数据时，进一步使用了一种逐渐减小的*k*空间数据的分割方式，使得大量的训练周期能够集中于学习低频数据，从而获得更好的重建性能。

本文第二部分的研究工作提出了一种基于同层稠密连接的深度级联网络。首先，比较了两种网络结构：深度级联网络和以UNet为代表的编解码网络，指出了深度级联网络更有利于进行MRI辅助重建。很多已有的研究工作都是基于UNet的，UNet的“编码-解码”结构能够提取高维特征并减少输入图像中的噪声，但由于编解码结构在网络前向传播过程中会不断改变数据的维度，无法在网络层中直接使用参考模态图像以及已采样的*k*空间数据，因此很难充分发挥参考模态的辅助作用和保证数据的一致性，而深度级联网络则能够解决了这些问题。其次，提出了同层稠密连接，强化深度级联网络的各子网间的信息流动。深度级联网络的主要不足在于：各子网间的重建结构阻碍了子网间的信息流动，针对这一问题，本文在各子网间引入了同层稠密连接，与主流的稠密连接网络不同，本文所提出的稠密连接仅用于各子网的同一层级的网络层间的稠密连接。由于深度级联网络中各子网的结构完全相同，各子网间很容易学习到类似的冗余特征，同层稠密连接通过强化各子网间的信息流动，减少了高层子网重复学习低层子网已经学习到的特征，迫使高层子网学习更有利于重建的信息。最后，为了有效地利用参考模态的频域数据进行辅助重建，本文在每个子网的末端加入了*k*空间集成学习模块，通过集成学习可以充分融合了多个子网的重建结果，从而构成了一种隐式的多监督训练，消除了单个子网重建结果的片面性。与UNet、DenseUNet、RefineGAN和D5C5等现有方法相比，所提出的模型取得了最优的重建性能，尤其是对高加速比的欠采样图像的重建效果更佳，对细节部位的恢复更清晰。

## 5.2 展望

本文第三章所提出的自模态补偿序贯训练方法也可与多模态辅助重建方法相结合，使得MRI的数据特性能够被更充分的运用，这需要进一步设计合理的网络结构与训练方式。

目前的MRI辅助重建工作的研究工作主要集中在网络结构与数据运用两方面，对损失函数的相关研究较少。目前的损失函数依然以L2损失为主[[38](#_ENREF_38" \o "Lyu, 2020 #50),[39](#_ENREF_39" \o "Xiang, 2018 #66),[49](#_ENREF_49" \o "Zhou, 2020 #58),[60](#_ENREF_60" \o "Xiang, 2019 #1949)]，还有一些基于GAN的交叉熵损失[[33](#_ENREF_33" \o "Dar, 2020 #70),[38](#_ENREF_38" \o "Lyu, 2020 #50)]【文献33和38可没有用交叉熵，band removing中才用到了，RefineGAN是用了GAN损失的】，以及Lyu等人[[38](#_ENREF_38" \o "Lyu, 2020 #50)]所采用的感知损失与纹理匹配损失。然而，以上损失并非针对MRI辅助问题设计的，以MRI辅助问题为目标设计更加有效的损失函数也是一个非常有意义的研究方向。

文中实验所使用的数据集均为MSSEG-2016，MSSEG-2016只提供了MRI图像的模值数据，而没有提供原始的*k*空间数据。由模值数据构建的*k*空间数据【参考文献，Xiang等】，与实际采集的*k*空间数据有较大的差异。为了验证所提出方法的通用性，应进一步使用真实的*k*空间数据，如fastMRI，进行进一步实验，并进一步探讨数据预处理的合理性等问题。本文实验采用的*k*空间采样方法均为一维的笛卡尔采样，接下来可尝试径向采样、螺旋采样等非笛卡尔采样方法，并讨论采样方法与网络性能的相关性，设计更为合理的采样方法。

最近，结合传统算法和深度学习的模型[[18](#_ENREF_18" \o "Sriram, 2020 #49)]取得了不错的成果[[97](#_ENREF_97" \o "Pal, 2021 #99)]，传统算法对模型设计也有一定指导意义，未来可以进一步了解该方面的研究工作，并与深度学习方法相结合，提出更适合MRI重建的网络模型。

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# 致 谢

2019年3月24日，研究生复试。那天清晨，从寝室下楼推开宿舍的玻璃门，凉凉的风和微暖的阳光都迎面扑来，樱花开得正好，阳光透过花瓣的那一刻我记了整整三年。这一天开始即是我的研究生生涯一个波折的开端，而这以后一个个困难与挑战才接踵而至，能走到今日，我心怀感激也常抱歉意。

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我的研究生导师李小薪副教授不仅在学业和研究工作中给了我很多指导，从他的身上我学习到了很多处事的道理。他对人生目标的不懈追求、对几乎一切事情认真严谨的态度、不断反思不断改进不断尝试新方法的坚持，都是让我敬佩不已的优秀品质。希望李老师在接下来的日子里身体健康、工作顺利，在学术界大放异彩。同门的师兄和师弟师妹们，也给了我的研究工作很多的帮助，和他们一起工作的日子是开心且难忘的。在这里感谢楼鑫杰、刘银伟、张晟源和张远成师兄们，陈志杰、王珏成、邢添壹师弟们，以及聪明可爱的方怡小师妹，希望大家学业有成、前程似锦。

想起之前阿姨给我推荐工作，并跟我说，“小雨，我最欣赏的就是你的勇气”，是啊，一路走来是勇气让我不断地挑战自我迎难而上，在接下来人生的新阶段，也要勇敢前进。

2022年3月18日，大雨过后的阴天，花落。

# 作者简介

## 1 作者简历

2019年9月——2022年6月，浙江工业大学大学计算机科学与技术学院软件工程专业学习，攻读专业型学硕士学位。

## 2 参与的科研项目

[1] 2019-10至2020-12: 基于生物特征的人脸识别算法研究, 中国科学院上海微系统与信息技术研究所纵向课题.

## 3 发明专利

[1] 李小薪,郑希雨,王珏成. 一种基于多个扫描仪数据的MRI重建网络的训练方法. 专利号: 202210124817.4

# 学位论文数据集

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