Inline Text Wrapping Picture

南京理工大学

硕博连读研究生学位论文

开题报告登记表

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2019年10月31日

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| **一、 拟选定学位论文的题目名称**  基于变分和稀疏表示的定量MR快速重建模型和加速算法 |
| **二、 选题的科学意义和应用前景**  核磁共振成像（magnetic resonance imaging，MRI）是医学临床和研究中最常用的成像方式，可以非侵入式地获取人体内组织的信息，用于指导病灶检测与临床诊断。但由于MR成像受到物理和生理上的限制，其成像速度一般很慢，尤其是动态MR图像（dynamic MRI，dMRI）。因此，如何在保证图像质量的情况下，提高成像速度一直是研究人员最关心的问题。  压缩感知 (compressed sensing) 是近十年来图像处理领域的研究热点之一。作为一种新兴的采样理论，压缩感知可以突破传统Nyquist采样定理的瓶颈，用远少于Nyquist采样所需的数据精确地重建出图像。压缩感知理论有三个主要的部分，即图像稀疏性、随机下采样和非线性重建算法。具体来说，压缩感知是在假设图像在某个变换域稀疏的前提下，对图像进行随机下采样，利用非线性算法重建出图像。因此，压缩感知可以加快成像速度，减少存储压力。同时压缩感知可以加快成像速度，提高图像的时间分辨率和空间分辨率。自从压缩感知理论诞生以来，就被广泛应用于医学成像领域，尤其是核磁共振成像中。对于MR图像的压缩感知模型而言，最重要一点是寻找适合于MR图像的稀疏表示。此外，对于动态MR图像而言，时间分辨率往往和空间分辨率同样重要，因此如何选择合适的时间方向的稀疏表示，提高动态MR图像的时空分辨率一直是一个具有挑战的问题。  定量磁共振成像技术（quantitative MRI，qMRI）是利用某些特殊的成像序列，测量组织参数的成像技术，如横向弛豫时间（T1）、纵向弛豫时间（T2）、质子密度等。相比于传统的定性（qualitative）MR图像，定量MRI从客观定量的角度研究人体组织，起到了帮助诊断与评估治疗的作用。其中磁共振动态对比增强 (dynamic contrast enhanced MRI, DCE-MRI) 是近些年来定量成像的研究热点，其通过获取注入对比剂前后的图像，经过一系列的计算分析，得到定量或半定量的参数，用于指导临床诊断。目前，压缩感知理论已经被应用在加速DCE-MRI成像中，但对于胸部DCE-MRI图像而言，如何选择和评估时间方向的稀疏项一直是未知的。  磁共振指纹 (magnetic resonance fingerprinting, MRF) 是定量MRI的新方法，可以在单次数据采集中同时获得多种组织参数。磁共振指纹主要分为三个部分，即预定义字典生成、信号采集和模式识别。具体来说，给定某个MR序列，首先用已有的MR成像的数学模型模拟生成一个包含不同参数的组织随时间演化的字典，然后选择某个模式识别算法将采集得到的信号（也被称为指纹）与字典中的原子进行匹配，从而重建出组织的参数图像。由于信号的长度一般在1,000以上，字典中的原子个数也经常达到10,000以上，字典生成与匹配的所消耗的时间通常达到几十分钟甚至几小时。因此，如何快速并且精确地生成字典并且进行字典匹配是一个亟待解决的问题。 |
| **三、 背景科研项目情况简介** |
| **四、学位论文主要研究内容**  （罗列本学位论文研究的主要问题，例：本学位论文主要包括以下几个方面的研究内容：1、纳米流体的制备：主要研究……。2、纳米流体输运参数实验研究：主要研究……。3、纳米流体聚集结构导热系数理论研究：主要研究……。4、……）  本课题主要研究以下三个方面的内容：  1. 研究基于压缩感知的动态MR图像的重建模型与加速算法；  2. 研究基于压缩感知的胸部DCE-MRI图像的重建模型；  3. 研究MRF重建的快速算法。 |
| **五、 预期解决的主要问题**  （对每个预期解决的问题介绍其难点所在、国内外研究的现状和趋势、解决问题的基本思路和技术路线、预期解决到什么程度）  本课题拟解决以下三个问题：  1. 针对不同类型的动态MR图像，基于压缩感知重建模型，解决重建图像中存在空间伪影，边界模糊并且重建速度慢等问题；  2. 针对胸部DCE-MRI图像，基于压缩感知的重建模型，解决时间方向稀疏项的选择问题；  3. 针对MRF图像，解决其重建过程中，字典生成与参数图重建慢的问题。 |

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| **六、开题条件（包括学术条件、设备条件、经费概算及其落实情况）**  本课题具有良好的开提条件：  完成本课题需要有扎实的数学理论知识和应用数学能力，也具有相应的医学图像数据及影像诊断等知识。在数学理论知识和应用能力上，通过长期严格的数学训练，具备扎实的数学基础和应用能力。在医学图像的认识上，通过查阅大量资料，全面了解了医学图像中出现的各种问题；导师具有丰富的图像处理方面的项目经验。学院讨论班将为此课题提供探讨交流的平台，学院老师和同学将在时间、工作条件等方面提供尽可能的帮助，为开展课题研究的创造最大的便利。  因此，根据对问题的了解，相信所提的研究方案能可行的。 |
| **七、文献综述**  （通过对文献的整理和归纳，对应“学位论文主要研究内容”一栏所列出的问题，介绍国内外学者对这些问题的研究结果及对其前景的看法。） |

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| **八、学位论文工作进度安排** | | | |
| **序号** | **时间** | **研究内容** | **预期效果** |
| 1 | 2013.10-2014.10 | 胸部DCE-MRI图像的压缩感知模型 | 发表第一作者期刊1篇 |
| 2 | 2014.12-2016.12 | 基于TGV和低秩的动态MR图像的压缩感知重建模型 | 发表第一作者期刊1篇 |
| 3 | 2017.1-2019.1 | MRF重建模型和快速算法 | 发表第一作者期刊1篇 |
| **研究生签名：**  **年 月 日** | | | |

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| **九、文献/论文**  入学以来国内外刊物上发表或拟发表的文章 | | | | | |
| **序号** | **论文题目** | **发表信息** | **排名** | **类别** | **对应学位论文章节** |
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| **十、指导教师意见** | | | | | |
| **指导教师签名：**    **年 月 日** | | | | | |

查阅主要文献资料目录清单

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| 研究生签名：  导师签名： |

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| **导师审核意见** |
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| **学院（系）分委会审核意见（是否可以进入论文工作阶段）** |
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