Blind Denoising Algorithms within Field-Cycling Medical Imaging

Project Plan

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Introduction

Medical imaging techniques like Computed Tomography(CT), Magnetic Resonance Imaging (MRI), X-ray, and Ultrasound are essential for healthcare diagnostics but often struggle with noise interference, which can obscure crucial details and risk misdiagnosis [1]. Field Cycling Imaging (FCI), an advanced method derived from Nuclear Magnetic Resonance (NMR), has been adapted for biomedical applications to enhance image contrast and reduce noise by dynamically adjusting the magnetic field during imaging [2].

The University of Aberdeen has pioneered a groundbreaking FCI-MRI technique (formerly FFC-MRI), revolutionizing traditional MRI technology [3],[4]. This innovative approach allows swift magnetic field adjustments within 12.5 milliseconds and achieves field strengths from 50μT to 0.2 T[1]. This advancement enables the production of clinically relevant images in just minutes, marking a significant leap in medical imaging [3],[4] (See Fig.5).

FCI's unique approach involves varying magnetic fields during scanning, tailored to emphasize specific tissue properties, resulting in multiple scans with distinct contrast features for accurate diagnosis [2],[3].

While FCI offers distinct images by varying magnetic fields to highlight different tissue types, it can introduce noise - a common imaging issue. Recently, techniques such as single-shot and zero-shot denoising have been developed. They could be applied in medical settings, such as FCI scans, to reduce noise affordably and quickly[5],[6]. However, these methods should not alter the tissue contrasts, which could compromise image quality and diagnosis accuracy. Balancing noise reduction and contrast preservation is vital to the success of FCI in medical imaging.

Related Work

Diffusion-weighted imaging (DWI), closely related to FCI-MRI, measures the motion of water molecules within a brain voxel[2] for insights into tissue properties [7],[8]. Meanwhile,

[1]The Tesla (T) is the SI unit of magnetic flux density.
[2]A 3D pixel, is a 3D cube located on a three-dimensional grid.

FCI varies magnetic field strengths to explore tissue composition [3]. Traditional denoising techniques such as Non-local Means and Block-matching and 3D filtering(BM3D) [9],[10], along with Denoising Convolutional Neural Networks, have been used in MRI for their denoising abilities [11]. However, in practical scenarios, these traditional methods often fall short in efficiency. The demand for fast medical diagnostics in recent years has led to the implementation of J-Invariant techniques[3], such as Path2Self and Neighbour2Neighbour in DWI [12],[13]. Even without clean data, these approaches yield results. Blind denoising methods are founded on several key image properties and noise characteristics assumptions. These include images' smooth variation, self-similarity(every pixel is similar, if from the same image, inspired by the traditional BM3D method), and the potential to model them through generative approaches. Techniques also rely on the assumption of Gaussian distributed noise, the sparsity of images in certain transforms, and their inherent compressibility [5].

Goals

We propose to create and evaluate an effective blind denoising algorithm for FCI scans, notable for its low data requirement compared to traditional, data-heavy methods. This cost-effective and practical approach is ideal for medical settings where extensive data collection is challenging. We will choose the best architecture for creating our model to evaluate different blind denoising algorithms.

The main objectives include (1) employing a zero-shot learning approach to denoise simulated brain scans, using artificial data for testing(See Figures 1-3), and (2) extending this method to denoise phantom medical data, replicating human tissues within a brain.

A vital aspect of the project is comparing and selecting the best blind denoising algorithm for the FCI device, using the Signal-to-Noise ratio (SNR) as a significant metric for image quality.

The chosen algorithm will prioritize preserving tissue contrast during denoising, ensuring diagnostic clarity and accuracy (See Fig.4).

Methodology

The methodology of the project is structured as follows:

- **Comprehensive Literature Review:** Initiate with an in-depth study of existing technologies and denoising techniques, focusing on blind denoising, J-invariant methods, and the best architecture for building the models.

- **Simulation and Testing:** Utilize MATLAB to generate a range of simulated images, each infused with varying degrees of Gaussian noise. The images must be in the format HxWxBxE (height, width, field strength, evolution time) and 90x90 scale to replicate what the scanner produces.

[3] A J-Invariant denoising function predicts each pixel's outcome independently from its original image value, enabling effective noise reduction.

- **Algorithm Benchmarking**: Conduct a comprehensive evaluation of prominent denoising algorithms and choose the best architecture to build the models. This evaluation will encompass MATLAB-simulated images and a medical phantom that accurately simulates human brain tissue.

- **Algorithm Development and Refinement:** Based on the comprehensive evaluation, the most suitable algorithm will be chosen and progressively refined to suit the FCI scanner. The algorithm will be tailored to meet the requirements and challenges identified in FCI scans.

- **Performance Metrics Implementation:** Implement a suite of performance metrics, ensuring a comprehensive and objective assessment of all denoising methods tested. These metrics will include, but not be limited to, accuracy, efficiency, and the ability to preserve image integrity.

- **Quality Assurance:** Vigilantly address and resolve any contrast issues. This step is crucial to ensure the reliability and effectiveness of our algorithm.

- **Additional features:** Consider creating a versatile tool to showcase the project's capabilities. Explore opportunities to introduce supplementary features.

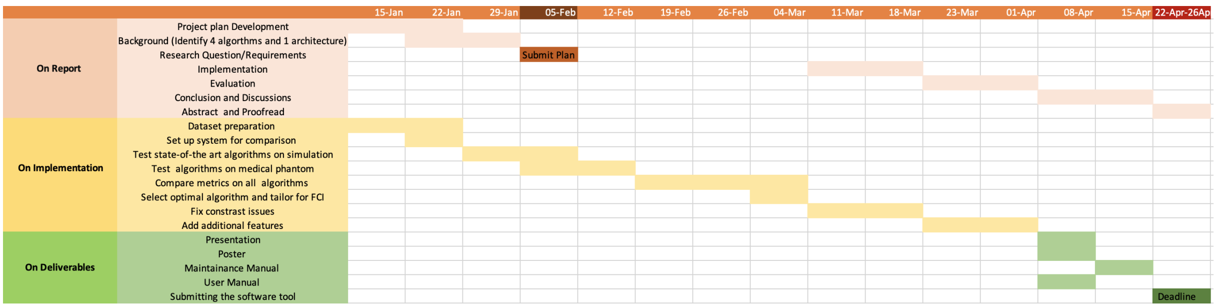
- **Documentation and Enhancement:** Maintain thorough documentation throughout the project, culminating in detailed reports, user manuals, and maintenance guidelines.

Resources Required

- **Hardware:** PC/Laptop, High-Performance Computing (HPC) for dealing with confidential data

- **Software:** Programming Environment(IDE), Python programming language, Github for Virtual Control, MATLAB for validation and testing denoising algorithms, Neptune AI for experiment management and model tracking, PyTorch for developing machine learning models

Timetable



Risk Assessment

Table 1: Project Risk Matrix

Likelihood	**Risk**	**Mitigation**	**Impact**
High (90%)	Blind Denoising Complexity and Overfitting Risk due to Limited Data	Test blind denoising using open-source DWI medical dataset for feasibility and try standard ML denoising methods.	High
Medium (50%)	Project Delays due to Challenges or Mitigating Circumstances	Implement agile project management with incremental stages and code reviews for timely feedback. Focus on building MVP(Minimum viable product).	High
Low (30%)	Ethical considerations	Use High-Performance Computing(HPC) and cloud services for secure, private access and analysis of medical simulation data, ensuring data security and compliance with privacy regulations.	Medium
Low (25%)	Hardware/Software Failure and Secure Access Control	Regularly back up data, secure cloud storage, and enforce access controls.	High
Low (10%)	Project finishes too quickly and deemed as too simple	Add additional project features.	Medium

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Appendix

Figure 1: Clean Image

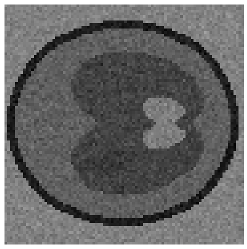

Figure 2: Noisy Grayscale Image

Figure 3: Two Simulated Images with a 90x90 Ratio

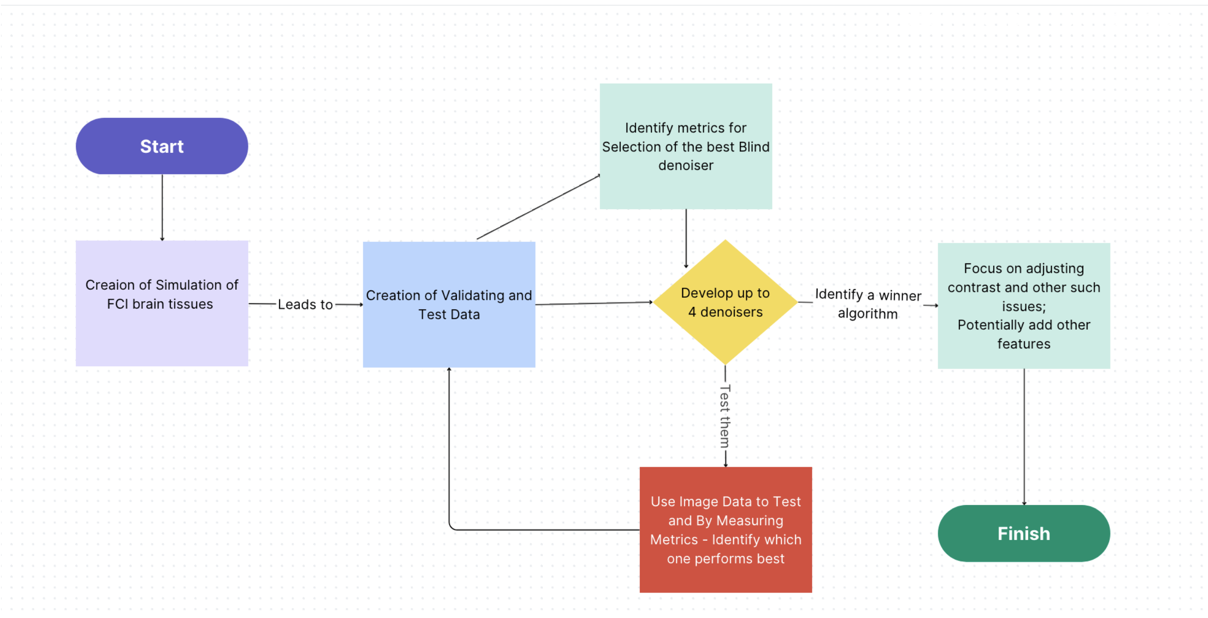

Figure 4: Flowchart illustrating the development process of denoising algorithms for FCI.

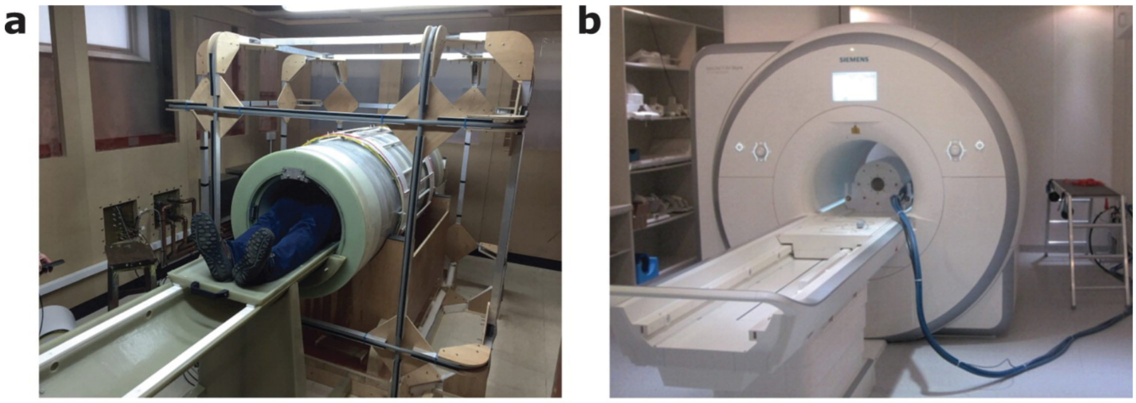

Figure 5: (1)FCI vs (2)Commerical MRI