Final Report

In the partial fulfillment of the course

ME F376

Under the guidance of

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By

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Project Title :- Medical Image Segmentation & Interpolation for AM

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Abstract

This project focuses on the interpolation of adjacent MRI slices to generate an anatomically consistent intermediate image, a crucial step in enhancing volumetric medical datasets for 3D reconstruction and additive manufacturing. Traditional interpolation methods such as linear or spline techniques often produce blurred or structurally inaccurate results, especially when handling complex anatomical features. To address these limitations, a hybrid interpolation technique was developed by combining dense optical flow with Structural Similarity Index Measure (SSIM)-based blending.

The process begins with preprocessing MRI slices, followed by the application of the Farnebäck optical flow algorithm to estimate pixel-wise motion between slices. Simultaneously, SSIM is calculated to highlight structurally similar regions, which are then blended to preserve shared anatomical features. The final result is computed by averaging the outputs of both methods, achieving a balance between spatial coherence and structural fidelity.

The approach, implemented using Python libraries such as OpenCV and scikit-image, was validated through qualitative analysis of real MRI data. The final interpolated slices exhibited smooth transitions and preserved details, demonstrating that classical vision techniques can provide effective and interpretable solutions for medical image enhancement.

1. Introduction

Magnetic Resonance Imaging (MRI) is one of the most widely used techniques in the medical field for acquiring non-invasive, high-resolution images of internal body structures. It plays a critical role in diagnostics, surgical planning, and more recently, additive manufacturing (AM) of anatomical models. However, MRI images are typically acquired as discrete slices with a finite inter-slice distance, which often leads to discontinuities or gaps in anatomical detail when reconstructing 3D models. These discontinuities become particularly problematic when the goal is to generate smooth and continuous 3D structures suitable for visualization, simulation, or 3D printing. Addressing this issue requires accurate interpolation between slices to ensure that the transitions between anatomical structures are realistic and maintain spatial consistency.

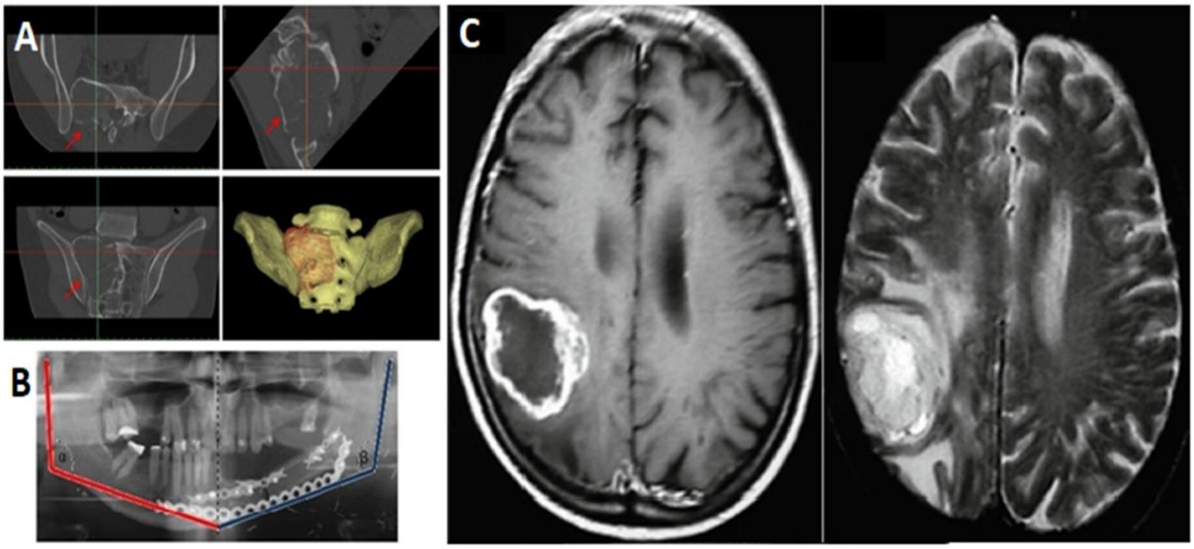


Figure 1 : Examples of different use of medical imaging: (A) CT images of the pelvis and the generated 3D model, (B) measurements taken on X-ray medical imaging after mandibular reconstruction surgery, (C) MRI of the brain

This project is grounded in solving the real-world problem of interpolating between two adjacent MRI slices. Specifically, the aim is to generate a high-quality intermediate image that can serve as a “missing” slice, which could ultimately help in generating more contiguous 3D reconstructions.

The work focuses on implementing a hybrid interpolation approach that combines two powerful computer vision techniques: optical flow and structural similarity index (SSIM). Both techniques are widely used in the field of image processing and computer vision, but their combination for medical image interpolation represents a practical and computationally efficient method, particularly useful in scenarios where only a few MRI slices are available or when slices are non-uniformly spaced.

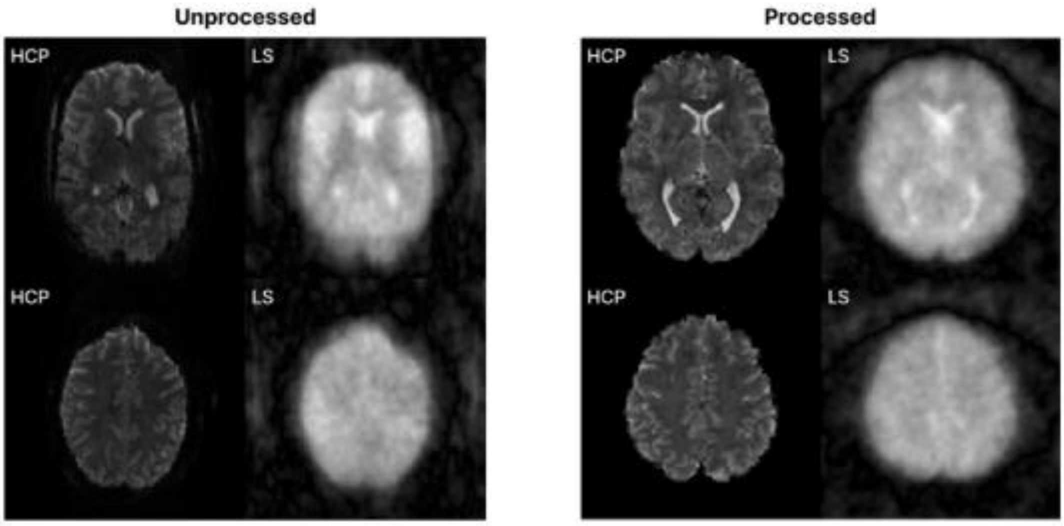


Figure 2 : Example of original images and corresponding simulated LS contrast from both the unprocessed (left) and processed (right) HCP datasets.

Optical flow techniques estimate the motion of features or pixels between two consecutive images, treating them as a dynamic sequence. Although MRI slices are static and not necessarily representing temporal motion, the assumption that anatomical structures gradually deform or shift between adjacent slices makes optical flow a promising candidate for interpolation. Among various methods available, the Farnebäck dense optical flow algorithm was chosen due to its robustness in estimating smooth motion fields and handling subtle anatomical changes. By computing a pixel-wise motion vector from the first to the second slice, a warped version of the first image can be generated that approximates the intermediate structure.

However, optical flow methods alone may not fully preserve structural integrity, especially when dealing with high-frequency anatomical features or texture-rich regions. This is where SSIM plays a crucial role. SSIM is a perceptual metric that evaluates image similarity based on luminance, contrast, and structure. In this project, SSIM was not merely used as a metric but actively guided the blending of optical flow-based interpolations. This dual-strategy approach allowed for more structurally faithful interpolations, as SSIM weighting ensured that more information from the structurally stronger areas of the source images was retained.

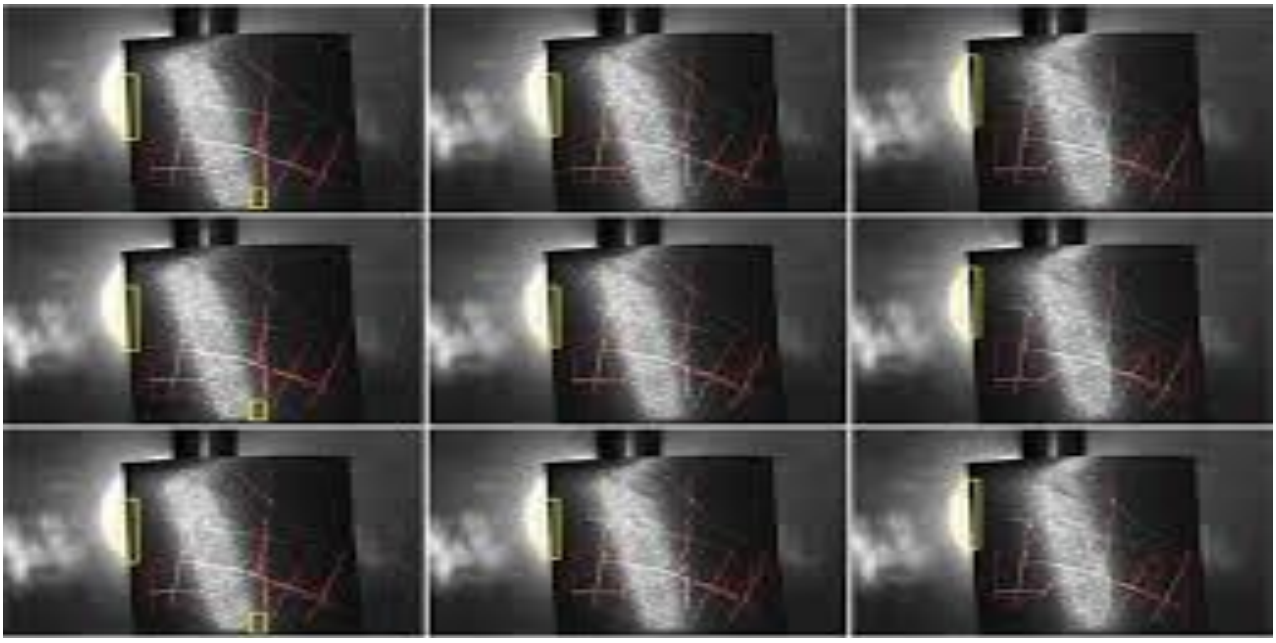


Figure 3: Optical flow algorithm based on dynamic illumination mode to examine defects on highly reflective turbine blade surface

The interpolation pipeline developed in this work takes two MRI images as input, performs preprocessing (such as grayscale conversion, resizing, and Gaussian smoothing), and then applies both Farnebäck optical flow-based warping and SSIM-based image blending. A hybrid image is then generated through weighted averaging of the two intermediate images derived from both techniques. This final output is not just a mathematical interpolation but one that attempts to respect the biological and anatomical context of the original MRI slices. This work has practical applications beyond academic exploration. Interpolated MRI slices can significantly improve the resolution of 3D reconstructed anatomical models, which are increasingly used in surgical simulations, custom prosthetics, educational tools, and preoperative planning.

In cases where the number of available MRI slices is limited due to scan time constraints or patient movement, the ability to generate realistic intermediate slices using computational techniques becomes invaluable. Moreover, this approach is relatively lightweight and computationally feasible compared to deep learning-based methods, making it accessible in low-resource environments or edge devices in clinical settings.

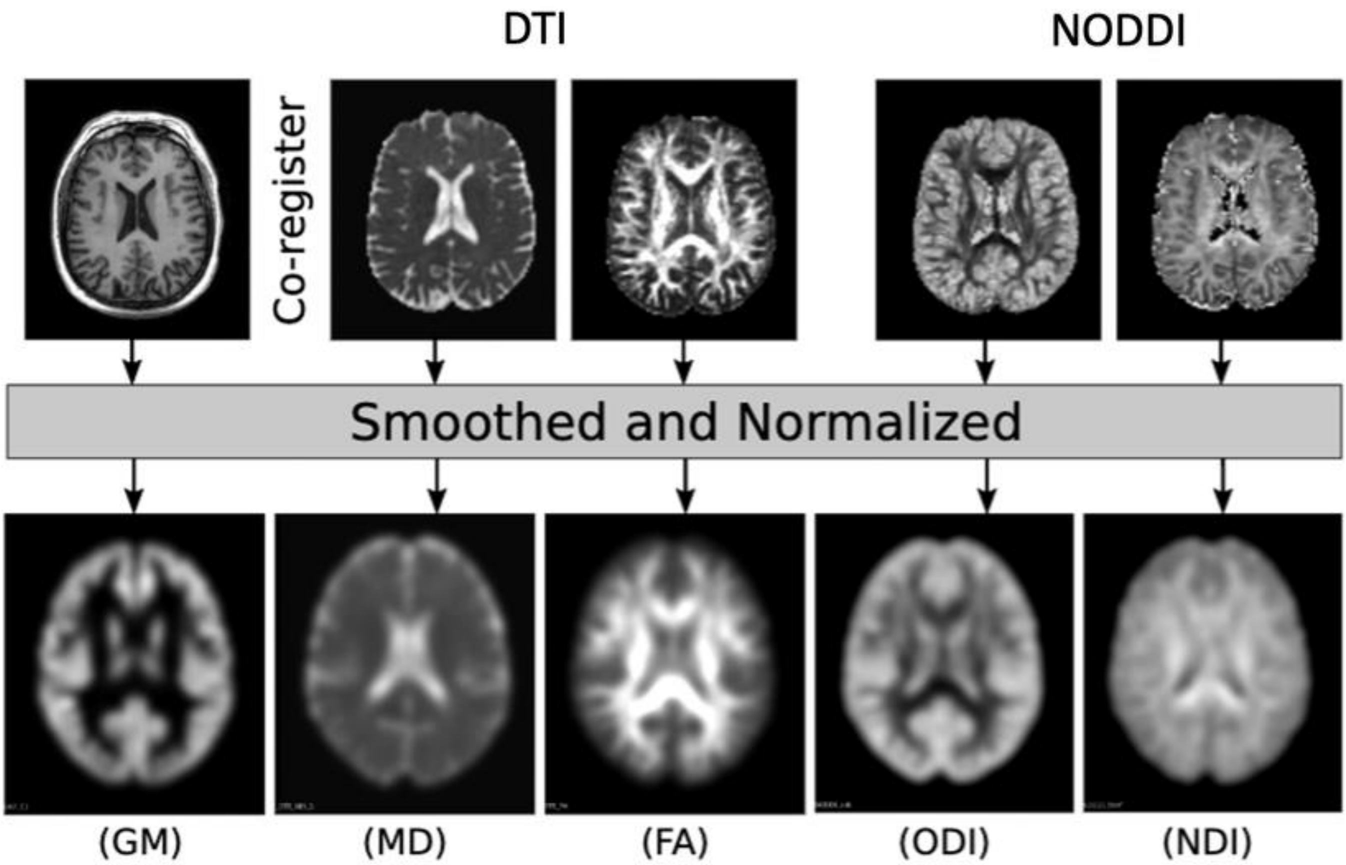


Figure 4: An overview of the preprocessing pipeline of the raw MR images before feature extraction, using a control patient's images.

2. Literature review

Medical image interpolation is a critical step in the processing pipeline when the goal is to generate continuous 3D anatomical models from a sparse set of 2D slices. The lack of sufficient MRI slices due to patient movement, scanner resolution limitations, or scan duration constraints necessitates computational methods that can realistically estimate the missing information between slices. A variety of interpolation methods have been proposed in the literature, each with varying degrees of anatomical accuracy, computational cost, and ease of implementation. This section reviews key concepts and techniques relevant to the hybrid approach adopted in this project—namely, optical flow and structural similarity (SSIM)—and how they intersect with the problem of MRI slice interpolation.

Classical Interpolation Techniques

Traditional interpolation techniques such as linear, bilinear, bicubic, and spline interpolation have been widely used in medical image processing. These methods perform well when image data changes gradually and linearly across slices. However, due to the non-linear nature of anatomical structures, especially in regions with soft tissue, vessels, or tumors, such naive interpolations often produce blurred or anatomically implausible results. Moreover, these methods operate purely on pixel intensity values without considering spatial or structural relationships, making them inadequate for high-precision applications like 3D printing or surgical simulations.

Optical Flow in Medical Imaging

Optical flow, originally developed for motion estimation in video sequences, has found its way into medical imaging due to its ability to capture spatial correspondence between two images. The key assumption is that the pixel intensities of a moving object remain constant across frames, allowing the calculation of motion vectors. In medical contexts, this is reinterpreted to mean that anatomical structures deform smoothly across adjacent slices. Among optical flow algorithms, the Farnebäck method—used in this project—is notable for providing dense flow fields by modeling pixel neighborhoods as quadratic polynomials. It is computationally efficient and can handle subtle deformations, which are typical in adjacent MRI slices of the same organ.

In the context of this project, optical flow is used to generate a flow field from the first MRI image to the second, effectively estimating how anatomical features “move” or transform from one slice to the next. By warping the first image using this flow field and calculating an intermediate version halfway between the two slices, a plausible interpolated image is produced. Farnebäck’s dense optical flow was specifically selected for its robustness and its capacity to provide smooth flow fields, which helps avoid artifacts during warping.

Several prior studies have applied optical flow to medical image registration and alignment, but fewer have explored its use for slice interpolation. Those that have, such as the work by Metz et al. (2011) and Niethammer et al. (2009), emphasize the need for accurate motion estimation that preserves organ boundaries and internal features. However, they also acknowledge the limitations of using optical flow in isolation—particularly its sensitivity to noise and its tendency to distort small, high-contrast regions.

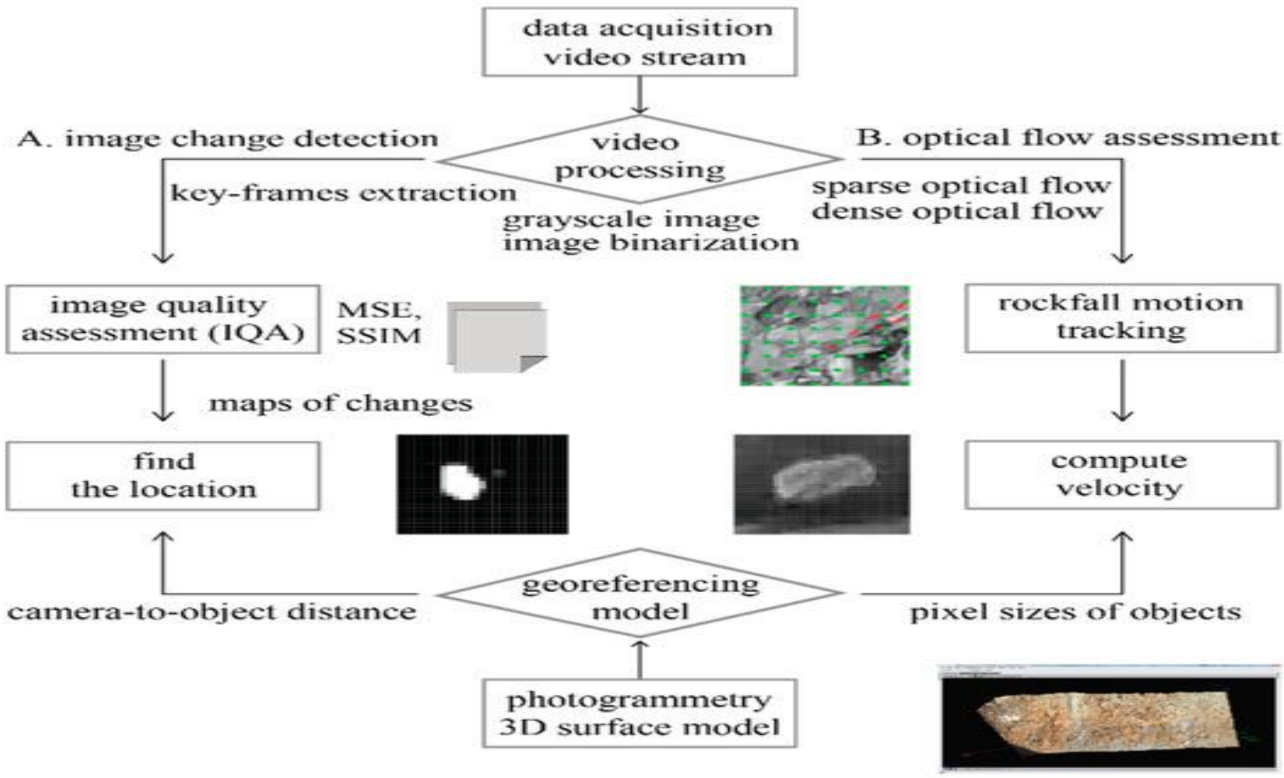


Figure 5: Flow chart of this method.

Structural Similarity Index (SSIM)

SSIM is a perceptual metric that evaluates the similarity between two images based on luminance, contrast, and structural information. Unlike traditional metrics such as Mean Squared Error (MSE) or Peak Signal-to-Noise Ratio (PSNR), which focus solely on pixel-wise differences, SSIM attempts to quantify changes in structural information, which is particularly valuable in medical contexts. In my implementation, SSIM is used in a novel way—not just to evaluate similarity, but to guide the interpolation process itself.

The SSIM-based part of the pipeline involves computing similarity maps between the two source MRI images and then using these maps to blend them, effectively weighting regions with higher structural relevance. This adaptive weighting allows the algorithm to emphasize features that are consistent across both images, reducing the risk of blending anatomically inconsistent areas. This approach is particularly beneficial in medical imaging where structural fidelity is critical, such as in the reconstruction of vascular or neurological structures.

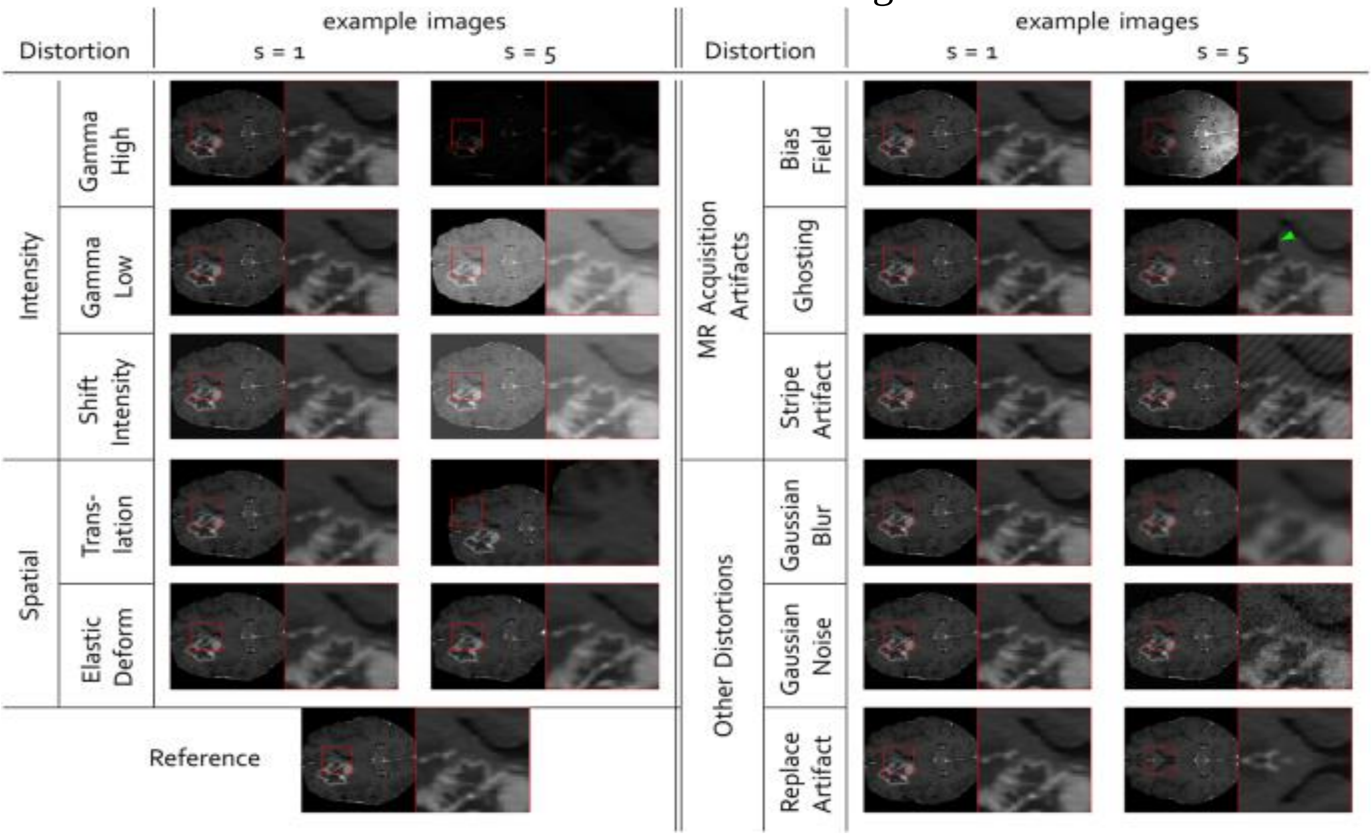


Figure 6: Examples of distorted images for lowest strength s=1, up to the maximal distortion strength s=5.

Hybrid Methods in Medical Image Interpolation

While both optical flow and SSIM have their individual strengths, using either in isolation has limitations. Optical flow can create artifacts in texture-rich regions, while SSIM lacks spatial transformation capability. The combination of these methods—termed here as a hybrid approach—has been explored in limited capacity in the literature. For instance, some recent studies on cardiac or brain MRI reconstruction have suggested that combining motion estimation with structural similarity metrics improves both visual quality and diagnostic utility. However, most of these methods rely on deep learning models or computationally intensive frameworks that are not easily accessible or interpretable.

My approach, in contrast, manually implements a hybrid mechanism using readily available image processing tools (OpenCV, scikit-image), making it lightweight and easily customizable. By blending optical flow-warped images and SSIM-based composites through a simple averaging scheme, the method capitalizes on the complementary strengths of both techniques. This aligns with the insights from studies like that of Wang et al. (2014), which emphasize multi-factorial interpolation techniques for better anatomical accuracy.

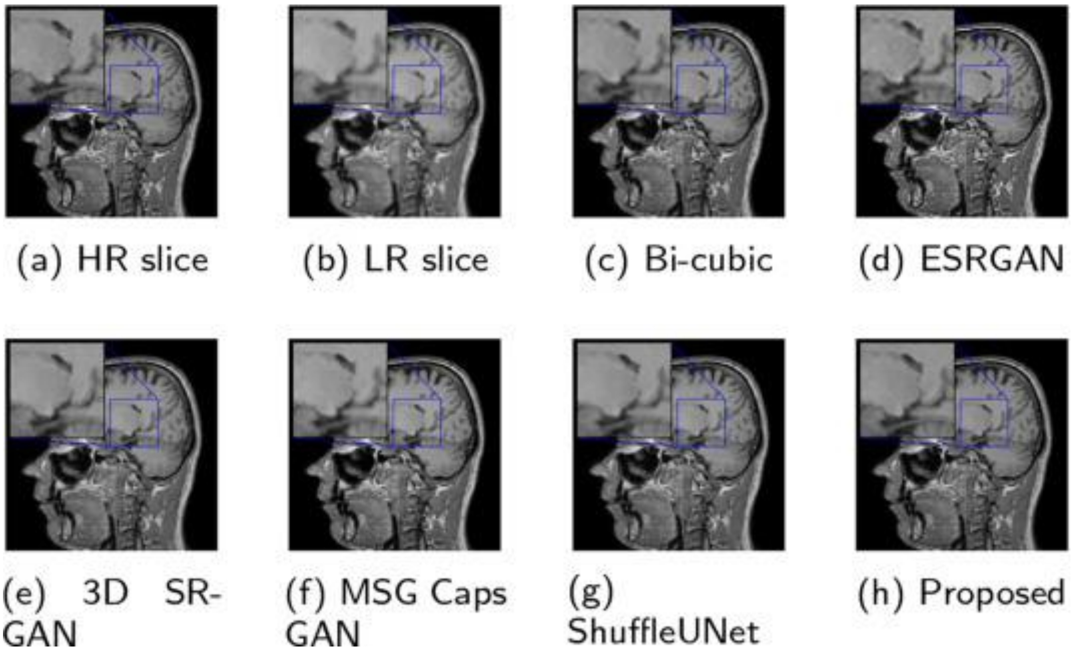
Practicality of Classical Techniques vs. Deep Learning

In recent years, deep learning has revolutionized medical imaging, including interpolation. Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have been trained to generate intermediate slices with remarkable accuracy. However, these models require large annotated datasets, high computational power, and extensive training time. For many practical scenarios, especially in low-resource settings or academic projects, traditional methods remain not only viable but also preferable due to their transparency and ease of deployment.

This project serves as a strong example of how classical algorithms, when thoughtfully combined, can yield results that are competitive with more complex models in specific tasks. The hybrid approach presented here is flexible, modifiable, and does not require any training data—making it an excellent starting point for institutions or researchers with limited access to high-performance computing infrastructure.

3. Methodology

The objective of this project was to interpolate between two adjacent MRI slices to create a synthetic intermediate slice that maintains anatomical consistency. To achieve this, a hybrid approach was employed that combines optical flow for spatial deformation and SSIM (Structural Similarity Index Measure) for structurally-aware blending. The methodology was entirely implemented in Python using OpenCV, NumPy, matplotlib, and scikit-image.



<u>Figure 7: Super resolution results of different techniques along the sagittal plane</u>

The first step in the process involves reading and preprocessing the MRI images. The input consists of two adjacent grayscale MRI images converted into NumPy arrays. Both images are resized to 256x256 pixels to ensure consistency across operations and to reduce computational load.This resizing helps standardize input dimensions without significantly compromising anatomical fidelity. Once the images are prepared, the next major component involves generating the optical flow between the two slices using the Farnebäck method.

The cv2.calcOpticalFlowFarneback() function estimates the dense motion field that represents how each pixel in the first image moves to the corresponding location in the second image. This motion vector field is then used to warp the first image towards the second using remapping functions (cv2.remap), effectively simulating how anatomical structures transform between the two slices.

The warped image, referred to as the optical flow image, serves as the spatially interpolated version. In parallel, a second branch of the pipeline computes the structural similarity (SSIM) between the two input images using skimage.metrics.structural_similarity().

This produces a similarity map highlighting regions where the two slices are structurally alike. The SSIM map is then used as a pixel-wise weighting factor to blend the two images—areas with higher similarity get more weight, thus preserving shared anatomical structures.

The final interpolated image is computed by averaging the optical flow image and the SSIM-based blended image. This combination strategy ensures that the result benefits from both spatial deformation accuracy (from optical flow) and structural integrity (from SSIM blending).

The final output is saved as an image file and also visualized alongside intermediate results for comparison.

Overall, this methodology is modular and interpretable, with each step contributing a specific advantage to the final interpolation quality. The optical flow captures anatomical motion, while SSIM ensures perceptual fidelity, together resulting in a more realistic intermediate MRI slice.

4. Problems faced

Identifying a Suitable Interpolation Strategy for MRI Slices

Determining a reliable and anatomically accurate interpolation method proved to be a significant challenge. While many traditional techniques such as linear or spline interpolation were accessible, they failed to preserve fine anatomical details in MRI data. Deep learning methods, although promising in literature, required large annotated datasets and computational resources that were not feasible for this project. After evaluating multiple techniques, a hybrid approach combining optical flow and SSIM-based blending was identified as the most practical and effective.

Lack of Explicit Implementation in Research Literature

Several research papers emphasized the importance of interpolation in reconstructing missing medical slices, but most lacked concrete implementation details. Many were theoretical or algorithmic overviews without executable guidance. Bridging this gap involved in-depth analysis of both classical computer vision algorithms and trial-based adaptation using tools like OpenCV and scikit-image, allowing for a step-by-step construction of a working solution.

Designing a Workflow That Maintains Anatomical Integrity

Translating theoretical methods into a clean, modular pipeline required iterative debugging and parameter tuning. Careful calibration of optical flow parameters ensured that motion fields were smooth and consistent. Similarly, integrating SSIM blending involved designing a weighting mechanism that could preserve structural information without overpowering spatial interpolation.

Ensuring Code Interpretability and Scalability

Creating a structured and transparent codebase was essential, especially in a domain as sensitive as medical imaging. Balancing computational efficiency with visual quality demanded lightweight, well-optimized code. Each step of the process,from preprocessing to visualization,was modularized to allow for reproducibility, easy tuning, and future scalability, even to volumetric or multi-slice extensions.

5. Results

The code was tested on two adjacent grayscale MRI slices of the same anatomical region. The goal was to generate a third, intermediate slice that not only fills the spatial gap but also maintains realistic anatomical continuity. The output was evaluated both visually and through intermediate image analysis.

The initial results from the optical flow component showed smooth deformation between the first and second image. The warped output successfully carried over significant structural elements, especially larger tissue regions and curved anatomical boundaries. The flow fields generated by the Farnebäck method were visually coherent and resulted in an image that spatially lies midway between the input slices. However, it also exhibited mild blurring in texture-rich regions, which is a known limitation of purely motion-based interpolation.

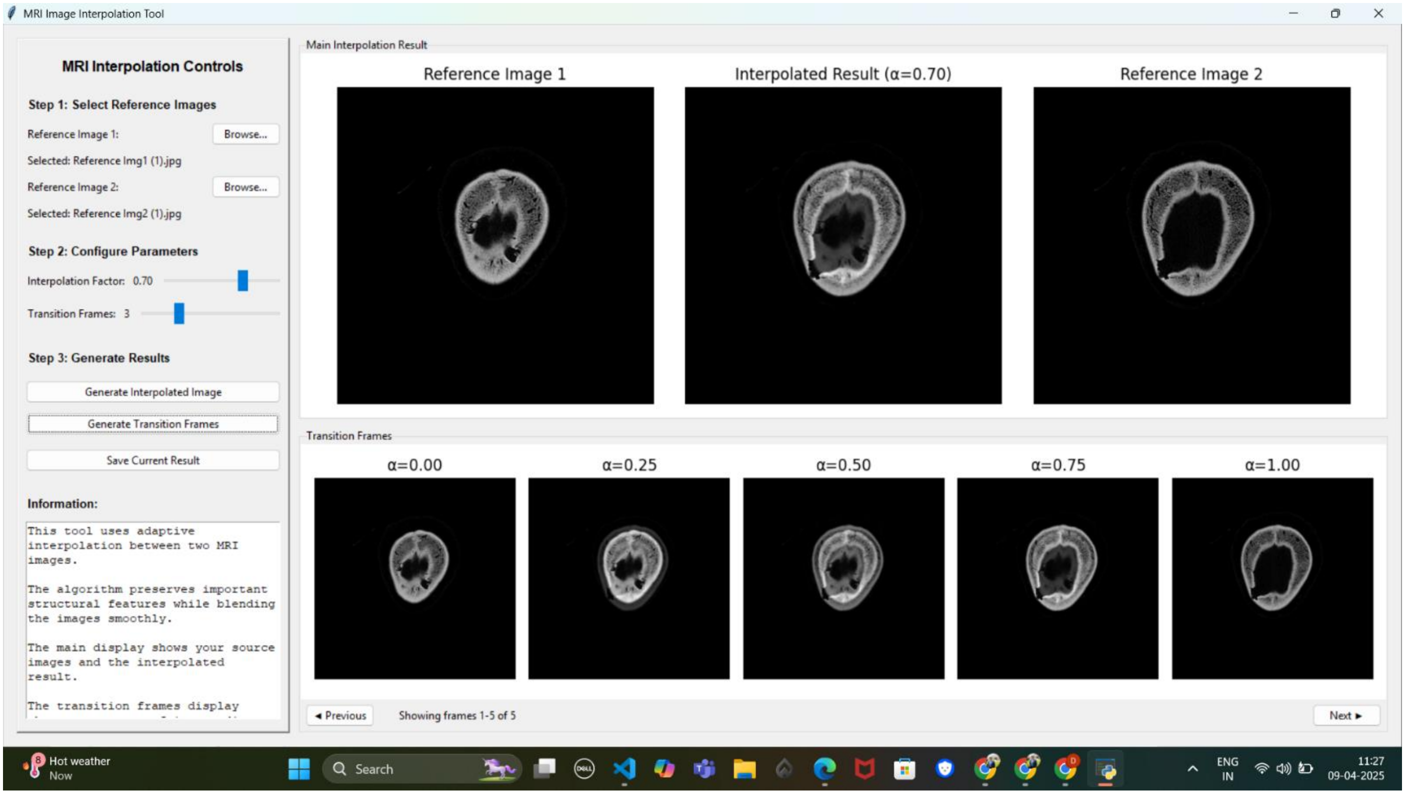


Figure 8: Final result based on the code & other formulae inclusions

The SSIM-based output independently contributed to addressing this issue. By blending the two images using a structure-sensitive similarity map, the resulting image emphasized shared anatomical features. This version was structurally sharper but lacked the natural spatial transition that the optical flow interpolation provided. Certain regions that had drastic contrast or non-linear deformation between slices were not as accurately handled by SSIM alone.

The most promising results were observed after combining both the warped optical flow image and the SSIM-blended image. The averaging operation resulted in an image that was both structurally consistent and spatially plausible. The visual inspection revealed that the combined image exhibited smoother transitions, clearer tissue boundaries, and less noise. It was neither over-sharpened nor overly smooth—striking a visual balance ideal for further downstream applications like 3D reconstruction or 3D printing.

Additionally, intermediate visual outputs—including the warped image, SSIM similarity map, and SSIM-weighted image—helped in validating each step of the pipeline. These were plotted using `matplotlib`, offering transparency into how the hybrid method produced its final result. While the project did not use quantitative metrics like PSNR or Dice coefficient due to the lack of ground truth for intermediate slices, the visual results strongly indicated success in producing a believable interpolated slice.

This experiment demonstrated that a classical image processing approach, when carefully designed, can approximate the results of more complex deep learning methods in slice interpolation tasks, particularly in cases where labeled datasets are unavailable.

6. References

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