Large Multimodal Model for Simulating Big Training Data in Deep PROPELLER MRI

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***Abstract*—This paper presents a novel approach for generating synthetic PROPELLER MRI blades using the GPT-4 large multimodal model (LMM). The approach addresses the challenge of data scarcity in PROPELLER MRI. Our method simplifies the process of data synthesis. It makes the process accessible to researchers without extensive knowledge of complex MRI algorithms. The approach involves transforming Cartesian MRI data into PROPELLER blades. We utilize a Chain-of-Thought (CoT) prompting technique to guide the model in understanding the specific requirements of PROPELLER MRI. We compare this method with traditional algorithmic approaches. The comparison demonstrates that the GPT-4 based method can produce synthetic MRI data of comparable quality but with greater efficiency and ease of use. Crucially, this study shows that LMMs have the potential to generate synthetic data without requiring extensive computational resources. This capability could greatly assist researchers in training deep learning models more easily.**

***Index Terms*—Magnetic Resonance Imaging, Large Multimodal Models, PROPELLER MRI, GPT-4, Chain-of-thought**

I. Introduction

Magnetic Resonance Imaging (MRI) plays an integral role in medical diagnostics, providing detailed internal images crucial for patient care. However, a significant challenge in the field of MRI is the scarcity of available data. Access to diverse and high-quality MRI datasets is limited, which poses a substantial obstacle for research and algorithm development. This scarcity is particularly acute in the case of PROPELLER (Periodically Rotated Overlapping ParallEL Lines with Enhanced Reconstruction) [10] MRI data, a specialized technique offering advantages in reducing motion artifacts. Unlike other MRI data, PROPELLER MRI datasets are not readily available on open-source platforms, making them a rare resource in medical imaging research.

Deep learning (DL) models have proven to be a crucial tool in accelerating MRI data acquisition. These models, however, require large volumes of training data to achieve effective generalization and avoid underfitting. To address this need, data augmentation has emerged as a practical approach, artificially expanding the training dataset through techniques like image rotation, scaling, and flipping. Although beneficial, data augmentation alone cannot fully resolve the data limitations associated with specialized MRI techniques, such as PROPELLER MRI.

For Cartesian MRI, there exist substantial public databases, providing a robust platform for machine learning and deep learning researchers to focus on Cartesian MRI reconstruction. Additionally, data augmentation techniques have been effectively employed to increase the training data size for deep learning-based Cartesian MRI reconstruction research. However, a stark contrast exists for PROPELLER MRI. Unlike Cartesian MRI, there are no significant public databases available for machine learning or deep learning research in the PROPELLER MRI domain. The unique challenge with PROPELLER MRI lies in its complex motion patterns and the difficulty in augmenting PROPELLER blades, which exhibit various types of rotation and translation across different patients. Therefore, generating synthetic PROPELLER data demands substantial computational resources and a deep understanding of complex algorithms, which may not be readily accessible to all researchers.

To address these challenges, our paper proposes an innovative data augmentation technique utilizing a Large Multimodal Model (LMM), specifically GPT-4 [1], along with a Chain-of-Thought (CoT) [3] approach. The CoT approach, known for its sequential reasoning that mimics human cognitive processes, is applied to GPT-4's multimodal functionalities [4, 20-25]. This combination is aimed at simulating training data specifically fitted for deep learning-based PROPELLER MRI reconstruction. GPT-4, with its advanced capabilities in data processing, is particularly well-suited for this task. The model's ability to handle complex data synthesis tasks facilitates the generation of synthetic PROPELELR blades data. This approach illustrates the feasibility of simulating large-scale training datasets without necessitating in-depth knowledge of complex algorithms typically required for synthetic data generation. By simplifying the data creation process, it promises to conserve both time and resources in clinical settings.

II. Related Work

A. PROPELLER MRI

The PROPELLER (Periodically Rotated Overlapping ParallEL Lines with Enhanced Reconstruction) [10] MRI technique represents a significant advancement in magnetic resonance imaging, specifically designed to mitigate motion artifacts. This method is characterized by its unique data acquisition

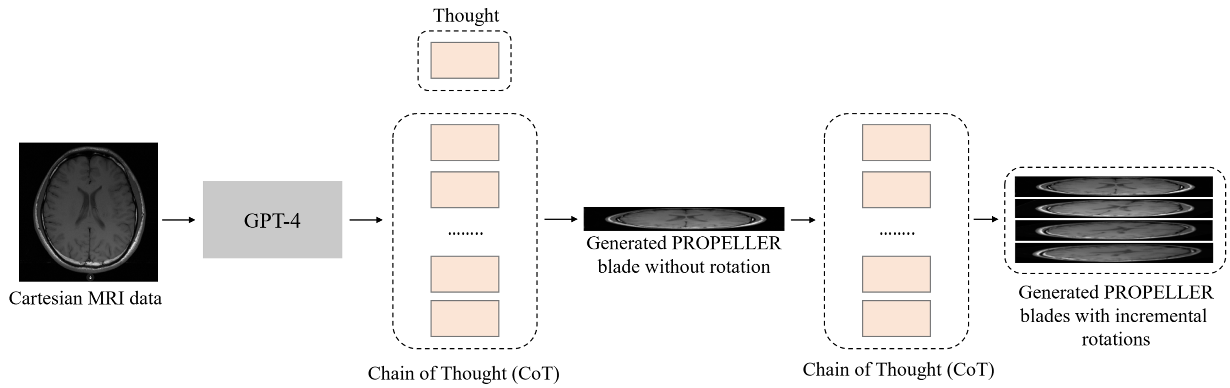

Fig. 1. Architecture demonstrating the generation of synthetic PROPELLER blades using GPT-4.

geometry, where radially oriented blades rotate around the k-space center. Each blade scans a narrow rectangular region in k-space, and their periodic rotation ensures comprehensive k-space coverage.

Mathematically, the rotation of PROPELLER blades is depicted by the rotation matrix $R(\theta) = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}$, where R represents the rotation matrix and θ the angle of rotation. This matrix formulation is critical in capturing the rotational dynamics of the blades within k-space.

Recently, deep learning approaches have been employed to further improve PROPELLER MRI reconstruction [7, 9, 15]. Deep learning models, known for their ability to extract intricate patterns from large datasets, offer potential advancements in image quality and processing speed [11]. Recent deep learning (DL) based approaches in PROPELLER MRI have aimed to address the issue of data scarcity in this domain. One such approach implemented an untrained neural network for PROPELLER MRI reconstruction, which eliminates the need for training data [9]. Another study proposed a method for data augmentation in deep PROPELLER MRI [7]. This method introduced a novel process for generating synthetic PROPELLER blades, augmenting these with real PROPELLER blades for reconstruction using a DL framework.

B. Large Multimodal Model Based Data Augmentation

The Large Language Model (LLM) signifies a major advancement in the field of artificial intelligence [12]. Following progress in text processing, these models have evolved to become capable of performing a variety of tasks, including image and data processing. This evolution is exemplified by the introduction of Large Multimodal Models (LMMs) like GPT-4. The architecture of GPT-4 enables it to process and synthesize information across multiple modalities [14]. Recent advancements in LMMs have shown promising applications in the medical imaging sector [5, 12, 13, 16-19, 25].

Our inspiration to employ GPT-4 in generating synthetic PROPELLER MRI data stems from the study by Anders et al. [6]. The study showed that synthetic data generated by GPT-4 could effectively supplement training datasets, enhancing model performance. The innovative use of GPT-4 in this paper, particularly in generating diverse and informative synthetic examples through careful prompt crafting, provided a crucial insight into its applicability in other domains. Drawing from this research, we recognized the potential of GPT-4 in overcoming the limitations posed by the scarcity of training data in PROPELLER MRI. This led to the novel approach presented in our work.

C. Traditional Approach for Synthetic PROPELLER Blade Generation

The traditional approach for generating synthetic PROPELLER blades from Cartesian MRI data involves several key steps as described by Saju et al. [7]. Initially, an original MRI brain image of dimensions 256×256 is used, and the number of phase-encoding lines is reduced to match the requirements of PROPELLER blades. Complex-valued sensitivity maps are generated for different coils, simulating the sensitivity of each coil element. Each of the 24 PROPELLER blades is generated by rotating the original image at specific angles using an affine transformation matrix $T(\theta)$. The rotated images are then transformed to k-space using the Fourier transform $\mathcal{F}$. The k-space data is subsequently reduced to align with the PROPELLER blade requirements, and the reduced k-space data $K'_b(u', v)$ is transformed back to the spatial domain via the inverse Fourier transform $\mathcal{F}^{-1}$ to obtain the blade images $B_b(x', y')$. The final blade images are combined with the sensitivity maps to generate multi-coil blade images $B_{b,k}(x', y') = B_b(x', y') \times S_{i,j,k}$. This entire process can be summarized by the following key transformations:

$$I_r = T(\theta) \times I$$

$$K_b(u, v) = \mathcal{F}\{I_r(x, y)\}$$

$$B_b(x', y') = \mathcal{F}^{-1}\{K'_b(u', v)\}$$

$$B_{b,k}(x', y') = B_b(x', y') \times S_{i,j,k}$$

Finally, a total of 24 synthetic blades are integrated into the PROPELLER reconstruction pipeline. This traditional approach, while robust, requires significant computational resources and a detailed understanding of MR physics. Our proposed method using GPT-4 simplifies this process by generating high-quality synthetic PROPELLER blades without extensive computational demands or specialized expertise.

D. Chain-of-Thought (CoT)

Chain-of-Thought (CoT) is an advanced prompting technique designed to enhance the reasoning capabilities of large language models (LLMs) [3], [4], [20], [21]. It guides the model through a sequential reasoning process that mirrors human cognitive patterns. CoT breaks down complex problems into smaller, manageable sub-tasks, allowing the model to address each step methodically.

The CoT approach begins with an initial prompt that sets the context and outlines the problem. Subsequent prompts build on this foundation, introducing intermediate steps and decisions that guide the model towards the solution. This iterative process ensures that the model maintains context and produces coherent and logical outputs.

The strength of CoT lies in its ability to decompose tasks into logical sequences. Each prompt serves as a step in the chain, directing the model's focus and ensuring that it considers all necessary aspects of the problem. This structured approach enhances the model's performance on tasks requiring multi-step reasoning and logical deduction.

In CoT, the model processes each step independently but within the context of the overall task. This helps in maintaining the coherence of the final output. CoT is particularly effective for tasks involving complex data transformations and intricate decision-making processes.

Additionally, CoT minimizes the computational resources required for problem-solving. By breaking down the task into simpler steps, the model can process and generate outputs more efficiently. This makes CoT a valuable technique for improving the reasoning capabilities of LLMs in various applications.

III. Proposed Method

A. Dataset and Implementation Details

An axial brain image dataset was utilized in this study. The data was acquired on a GE 3T scanner, using an 8-channel head coil. This data was saved in the MATLAB data format. This particular dataset was obtained through a 2D spin echo sequence. Key parameters of this imaging sequence include a repetition time (TR) of 700 milliseconds and an echo time (TE) of 11 milliseconds. The matrix size for the image was set at 256×256, and the field of view (FOV) was established at 220 square millimeters.

In the study, GPT-4, a Large Multimodal Model by OpenAI, was utilized for synthesizing data. Concurrently, MATLAB was employed for conducting comparative analyses. This approach provided a balanced framework for assessing the generated synthetic data against the traditional methodology.

B. Generation of PROPELLER Blades Utilizing GPT-4

The process begins with the provision of MRI data to the GPT-4 model. The data employed is Cartesian MRI data, characterized by its square format. To facilitate the generation of PROPELLER blades, GPT-4 is engaged using a Chain-of-Thought (CoT) approach. CoT prompts are designed to guide the model towards an understanding of PROPELLER MRI's unique blade format. Specifically, GPT-4 is queried about the nature and geometric characteristics of PROPELLER MRI blades. This step is crucial in aligning the model's synthetic data generation capabilities with the specific requirements of PROPELLER MRI.

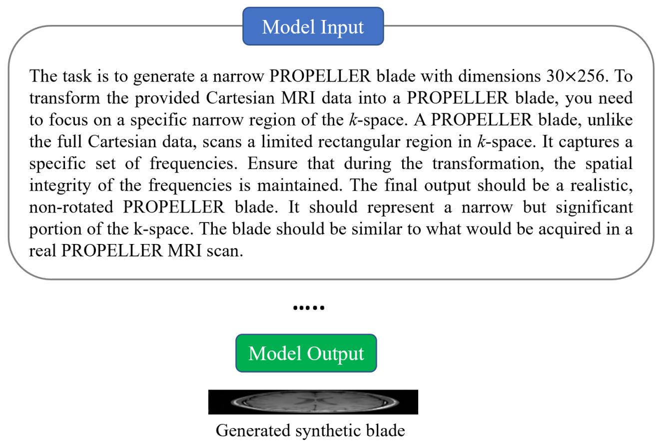

Fig. 2. Prompt for Non-Rotated Blade Generation and Resulting Output. This figure displays a portion of CoT prompting used to guide the AI model in generating a non-rotated 30x256 PROPELLER blade from Cartesian MRI data.

Following the establishment of an understanding of PROPELLER MRI blades, GPT-4 is instructed to generate synthetic blades from the provided Cartesian MRI data. The query is framed to leverage GPT-4's advanced data processing capabilities, directing it to transform the square Cartesian data into narrow, radially oriented PROPELLER blades. The model is prompted to consider the essential aspects of PROPELLER MRI, including the blade's dimensions and their arrangement in k-space.

GPT-4 processes the input Cartesian MRI data, applying a series of transformations to create synthetic PROPELLER blades. GPT-4 employs advanced algorithms to ensure that these synthetic blades are representative of real MRI scans, both in terms of their geometric properties and their ability to reduce motion artifacts. The transformation process is anchored in the model's understanding of MR physics and the specific requirements of PROPELLER MRI data acquisition.

C. Generation of Rotated PROPELLER Blades

In PROPELLER MRI, a single slice may comprise various configurations of rotated blades, typically 8, 12, or 24. These rotated blades are crucial for comprehensive k-space coverage. This subsection elaborates on employing GPT-4 to generate a set of 24 rotated blades, simulating a full 360-degree rotation, a common configuration in PROPELLER MRI.

Again, GPT-4 is engaged with Chain-of-Thought (CoT) prompts to facilitate the generation of rotated blades. These prompts guide the model in understanding and implementing rotational transformations to the synthetic PROPELLER blades, focusing on the MRI blade geometry.

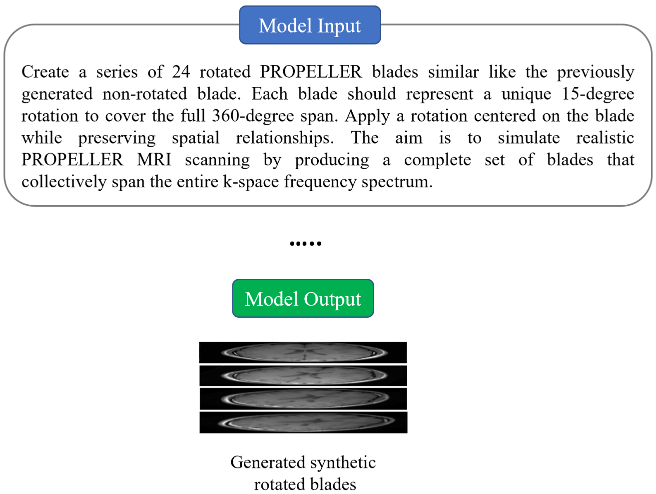

Fig. 3. Prompt for Rotated Blade Generation and Corresponding Outputs. This figure illustrates a part of the CoT prompting for creating rotated PROPELLER blades, with an incremental 15-degree rotation.

The rotation of each PROPELLER blade is mathematically represented by the rotation matrix $R(\theta)$ as described in equation (1) of the related work section. Given that a complete 360-degree rotation is evenly divided among n blades, the rotation angle for each blade is $\theta = \frac{360^\circ}{n}$. For the generation of 24 blades, each blade is rotated by $\theta = \frac{360^\circ}{24} = 15^\circ$.

The application of the rotation matrix by GPT-4 involves recalculating the position of each point in the blade's dataset post-rotation. For a point (x, y) in a blade, its new position (x', y') is determined by:

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = R(\theta) \cdot \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} \tag{1}$$

This computational process yields 24 uniquely rotated blades, each contributing a distinct view of the k-space. The rotated blades are critically evaluated for their geometric accuracy, fidelity to PROPELLER MRI specifications, and the maintenance of image integrity. The entire process of generating rotated PROPELLER blades is demonstrated in Figure 1, which provides a visual representation of the architecture and workflow used in this study.

IV. Results

This section presents the outcomes of our study, focusing on the comparison between the synthetic PROPELLER blade generation using the GPT-4 based method and a traditional algorithmic approach proposed by Saju et al. [7]. This method involves several intricate steps such as Fourier transformations, generation of sensitivity maps, and complex mathematical manipulations for blade rotation and k-space data reduction. This approach, while robust, requires a comprehensive understanding of MR physics, signal processing, and mathematical algorithms, making it less accessible to researchers without a specialized background. In contrast, our GPT-4 based method simplifies the generation of synthetic MRI data.

Figure 4 in the results section visually illustrates the comparative analysis between the traditional method of generating PROPELLER MRI blades, as described by Saju et al. [7], and our novel GPT-4 based approach. The figure is organized into three columns, each highlighting a different aspect of the generated MRI data. First columns presents the original Cartesian MRI data that serves as the reference point for both methods. The image provides a baseline for assessing the quality and accuracy of the synthetic PROPELLER blades generated by the two approaches. In the second column, there are six rotated PROPELLER blades, each generated using the traditional algorithmic method. These blades are arranged to show different rotation angles, with an equal incremental rotation between successive blades. Notably, the first blade in this series is marked with an arrow, drawing attention to the presence of minor artifacts in the blade image. These artifacts exemplify some of the challenges inherent in the traditional synthetic data generation process. The final column showcases six PROPELLER blades generated using our GPT-4 based method. Like the second row, these blades are also displayed at varying rotation angles with the same incremental rotation. A significant observation here is the absence of artifacts in the blades, as indicated by an arrow on the first blade. This row demonstrates the efficacy of the GPT-4 based approach in generating cleaner and more accurate synthetic PROPELLER blades compared to the traditional method.

The layout of Figure 4 effectively facilitates a direct visual comparison between the two methods. It underscores the enhanced quality of the synthetic blades generated by the GPT-4 model, particularly in terms of reducing artifacts, which is a crucial factor in medical imaging. This comparison substantiates the main proposition of the study, highlighting the advantage of using advanced AI models like GPT-4 for generating synthetic MRI data without the need for complex algorithmic knowledge.

V. Conclusion

This study introduced a novel method for generating synthetic PROPELLER MRI blades using GPT-4, addressing the significant challenge of data scarcity in PROPELLER MRI research. Our approach simplifies the process of synthesizing MRI data, eliminating the need for intricate algorithmic understanding. Comparative analysis with traditional algorithmic method, demonstrated that our GPT-4 based approach can produce synthetic MRI data of comparable quality, but with greater efficiency and accessibility. Particularly, the absence of artifacts in the GPT-4 generated blades underscores the method's effectiveness.

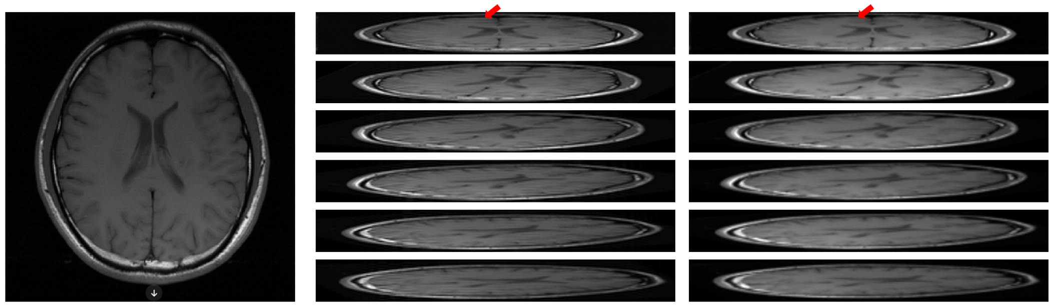

Fig. 4. Comparative Analysis of Synthetic PROPELLER Blades: The first column displays Reference Cartesian MRI Data. The second column illustrates six PROPELLER blades generated using a traditional method. The third column shows six blades generated using the GPT-4 based method.

The findings suggest that utilizing advanced AI models like GPT-4 can significantly benefit MRI research, offering a practical solution to the challenges of data limitation. This approach could potentially accelerate the development of MRI reconstruction algorithms and enhance the overall quality of MRI diagnostics.

In conclusion, using GPT-4 for MRI data creation shows a lot of potential for future studies. It makes a good balance between being technically advanced and easy to use. This method allows more researchers to help improve MRI technology, even if they don't have a deep understanding of complicated MRI data processing.

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