Evaluating the Impact of Noisy Blades on PROPELLER MRI Reconstruction Quality

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***Abstract*—In clinical MRI, the management of image noise remains a challenge, particularly in Periodically Rotated Overlapping ParallEL Lines with Enhanced Reconstruction (PROPELLER) MRI, where the effects of Gaussian noise on image quality have not been extensively explored. To address this gap, this study investigates the impact of Gaussian noise on the quality of PROPELLER MRI images, a technique pivotal for reducing motion artifacts. Systematic introduction of Gaussian noise into the k-space data of PROPELLER blades, varying in number and intensity, allowed for the simulation of realistic clinical scenarios. The study quantified the effects on image quality using peak signal-to-noise ratio (PSNR) and visual inspections. Results demonstrated a significant decline in image quality as the number and intensity of noisy blades increased. Furthermore, it was observed that removing noisy blades from the reconstruction process could partially ameliorate image quality. These findings emphasize the need for enhanced noise management in PROPELLER MRI and suggest directions for algorithmic improvements to optimize clinical MRI imaging.**

***Index Terms*—PROPELLER MRI, Noise Reduction, Image Reconstruction, Magnetic Resonance Imaging**

I. Introduction

Periodically Rotated Overlapping ParallEL Lines with Enhanced Reconstruction (PROPELLER) MRI [1] represents a significant advancement in clinical imaging, particularly due to its robustness against motion artifacts. Since its inception, PROPELLER MRI has been widely implemented in various clinical settings, leveraging its unique acquisition technique of collecting data in rotating blade-like segments [2, 5, 6, 11-16]. These segments, or blades, consist of parallel phase-encoded lines acquired through either fast spin echo or gradient echo sequences [10]. The technique's inherent ability to correct for patient motion and flow artifacts has rendered it indispensable in scenarios where patient movement is unavoidable or unpredictable [3].

One of the key aspects of PROPELLER MRI is its method of handling motion-corrupted blades. Conventionally, these blades are identified and excluded prior to the blade combination phase, a process crucial for enhancing the resulting image quality. This exclusion is based on the premise that motion-corrupted blades detrimentally affect the overall image clarity and integrity. However, while this approach effectively addresses motion artifacts, it brings forth another aspect that has been less explored in the literature: the impact of inherently noisy blades on the resultant image quality.

In standard clinical practice and existing research, the focus has predominantly been on motion artifacts [9], with less attention given to the influence of noise within individual blades. Noise in MRI can arise from various sources, including patient-induced electrical activity, scanner-related electronic noise, and environmental factors [4]. In the context of PROPELLER MRI, the presence of noise within blades may introduce unique artifacts or degrade image quality, an aspect that has not been thoroughly investigated.

This study aims to fill this gap by systematically evaluating the effects of noisy blades on PROPELLER MRI image quality. We introduce controlled Gaussian noise into individual blades during the image reconstruction process and observe the resultant changes in image quality. This approach allows for a quantitative and qualitative assessment of how noise levels within blades influence the final MRI output. We hypothesize that noisy blades, much like motion-corrupted ones, have a detrimental impact on image quality, potentially leading to the introduction of artifacts or a reduction in the overall signal-to-noise ratio (SNR).

The implications of this research are manifold. Understanding the impact of noisy blades could lead to improved PROPELLER MRI protocols, where noise correction strategies could be implemented alongside motion correction. This might involve the development of new algorithms for noise detection and blade exclusion or adjustment, thereby enhancing the overall image quality. Additionally, insights from this study could inform clinical practices, guiding radiologists in optimizing PROPELLER MRI settings for specific clinical scenarios, particularly those where noise is a significant concern.

In summary, this study aims to provide a comprehensive evaluation of the noisy blade effects in PROPELLER MRI, thus contributing to the optimization of this imaging technique for enhanced clinical outcomes.

II. Methods

A. PROPELLER MRI Technique Overview

Periodically Rotated Overlapping ParallEL Lines with Enhanced Reconstruction (PROPELLER) MRI [1] is an advanced imaging technique that significantly mitigates motion artifacts

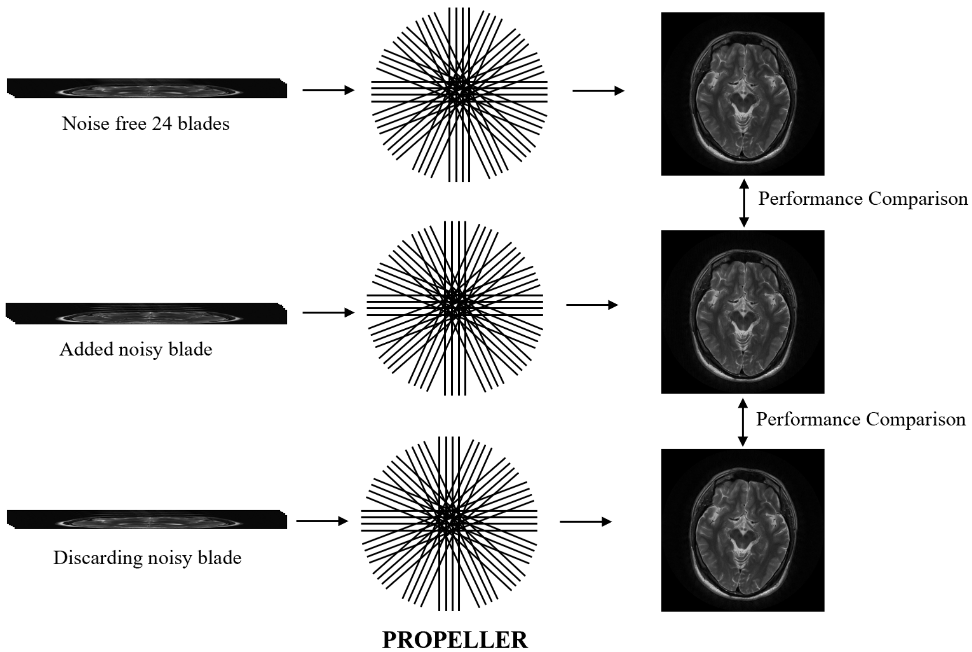

Fig. 1. Workflow Illustrating the Impact of Gaussian Noise on PROPELLER MRI Image Reconstruction

through a unique data acquisition strategy. The fundamental principle of PROPELLER MRI involves acquiring data in a non-conventional manner, where k-space is filled with rotating, rectangular blade-like segments, each comprising parallel phase-encoded lines.

The data acquisition for each blade can be mathematically described as follows: Let $B_i(\theta)$ represent the i-th blade acquired at an angle θ to the initial position. The blades are rotated incrementally to cover the entire k-space. The angle θ typically varies between 10° and 20°, depending on the specific protocol and scanner parameters.

For a blade B_i, the k-space data can be represented as:

$$B_i(\theta) = \{k(x', y') \mid x' = x\cos(\theta) + y\sin(\theta), \quad y' = -x\sin(\theta) + y\cos(\theta)\} \tag{1}$$

where $k(x', y')$ denotes the k-space data at coordinates (x', y'), transformed by the rotation angle θ. This transformation effectively captures data along different orientations, aiding in comprehensive k-space coverage.

Each blade's central region is oversampled, providing a higher signal-to-noise ratio (SNR) at the k-space center. This oversampling is crucial for enabling effective motion correction and for ensuring data consistency across successive blades. The oversampling factor, typically denoted as O, is a critical parameter that influences the quality of the reconstructed image.

The blade combination and image reconstruction process in PROPELLER MRI involves aggregating the data from all acquired blades. This combination takes into account the rotation and position of each blade within k-space. An essential aspect of this process is phase correction and in-plane motion adjustments, which are crucial for compensating for any patient movement during the scan.

B. Dataset Details and Experimental Setup

The dataset for this study comprises fully sampled k-space PROPELLER blades, obtained from a volunteer using a Philips Ingenia 3T scanner, which features a 13-channel head phased-array coil [5]. The data was acquired employing a T2-weighted Turbo Spin Echo (TSE) PROPELLER sequence, characterized by a repetition time (TR) and echo time (TE) of 4000/109 ms respectively, an echo train length (ETL) of 30, a matrix dimension of 436×436, slice thickness set at 4 mm, encompassing 24 slices, and a field of view (FOV) measuring 25×25 cm. In compliance with the guidelines of the institutional review board, informed consent was obtained from all participating volunteers for the in vivo experiments.

The proposed method was executed on a system equipped with a Windows 10 operating system, NVIDIA Quadro P2200 GPU, Intel Core i7 processor, and 64 GB of RAM. The noise injection process was carried out using MATLAB, version R2023a, and PROPELLER reconstruction was conducted via GPILAB [8].

C. Gaussian Noise Injection Process

Gaussian noise was artificially introduced into the imaging data to simulate the presence of noisy blades in PROPELLER MRI. This noise is characterized by a Gaussian distribution, typically denoted as $\mathcal{N}(0, \sigma^2)$, where σ represents the standard deviation of the noise. The choice of Gaussian noise is due to its prevalence in MRI as a model for random noise arising from thermal fluctuations and scanner electronics [7].

The mathematical representation of the noise injection for a single blade is as follows: Let B_i be the original k-space data of the i-th blade. The noise-injected blade $\tilde{B}_i$ is given by:

$$\tilde{B}_i = B_i + \mathcal{N}(0, \sigma^2) \tag{2}$$

where $\mathcal{N}(0, \sigma^2)$ is the Gaussian noise added to the blade. This process involves extracting the k-space data B_i for a selected blade and then augmenting it with the calculated Gaussian noise. The variance σ^2 of the noise was tailored to reflect realistic noise levels encountered in clinical MRI settings.

D. Quantifying the Impact of Noise on Image Quality

This experiment was designed to assess the impact of varying levels of Gaussian noise on image quality in PROPELLER MRI. Our focus was to analyze both the individual and cumulative effects of noisy blades on the reconstructed images. Each brain slice in our study comprised 24 PROPELLER blades, with each blade having a dimension of 30×436 and encompassing 13 coils. Each blade's coils are amalgamated through the square-root of their squared sums, formulated as:

$$s[n] = \sqrt{\sum_{k=1}^{13} |x_k[n]|^2} \tag{3}$$

where $x_k[n]$ signifies the signal from the k-th coil in the n-th blade.

To evaluate the effects of noise, we introduced Gaussian noise selectively into one or more blades. The noise-corrupted blade(s) were then processed through the standard PROPELLER MRI reconstruction pipeline. This allowed us to contrast the image quality between the original, noise-free blades and the noise-injected ones. Subsequently, we discarded the noisy blade(s) from the reconstruction process. This step was crucial in determining the extent to which the exclusion of noisy blades could improve image quality.

Figure 1 outlines the entire workflow of this study. It illustrates the comparative analysis of PROPELLER MRI reconstruction under three scenarios: without any noisy blades (using all 24 blades), with the inclusion of noisy blades, and following the exclusion of these noisy blades. This workflow facilitates a comprehensive understanding of how Gaussian noise, both in single and multiple blades, influences the overall image quality in PROPELLER MRI.

E. PROPELLER Network Setup

The PROPELLER reconstruction process was implemented in GPILAB by building a network. The network structure is shown in Figure 2. It outlines the workflow used in this study. The network uses several key modules, including FFTW for Fourier transforms, SDC for density compensation, and the Grid module for data gridding. The `PROPELLOR_Crds` and `PROPELLOR_ShiftCorrect` modules perform the PROPELLER reconstruction and correct any motion that exists in the blades.

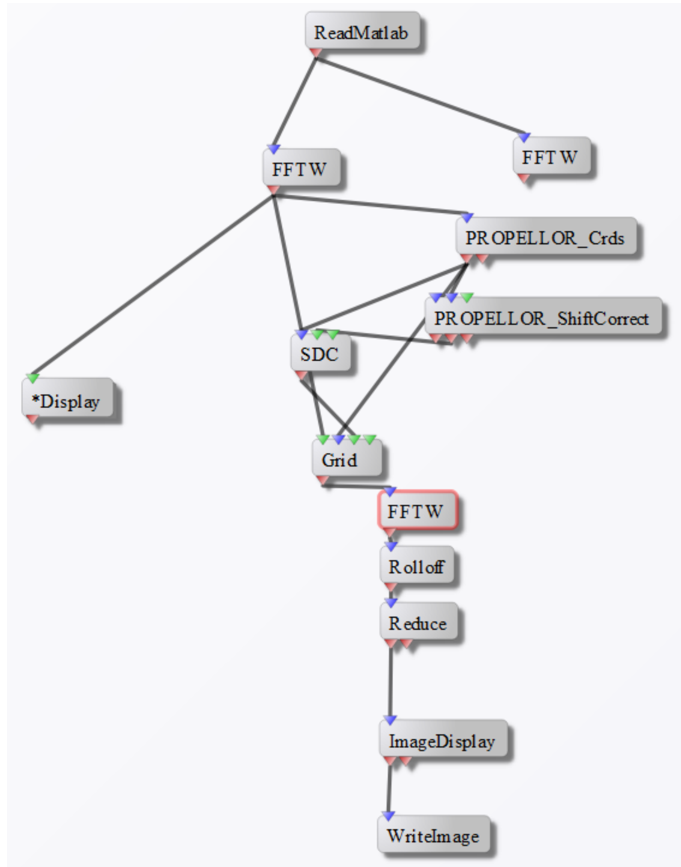

Fig. 2. PROPELLER network setup showing the sequential processing steps involved in the PROPELLER reconstruction pipeline.

III. Results

This section presents the findings from our comprehensive analysis of the impact of Gaussian noise on PROPELLER MRI image quality. Through a series of experiments, we systematically introduced varying levels of noise into the PROPELLER blades and assessed the resultant changes in image clarity. The following descriptions correspond to a set of figures that visually and quantitatively illustrate these effects. The results are crucial in understanding the relationship between noise levels and image degradation in PROPELLER MRI, providing key insights into how noise influences diagnostic imaging quality.

Figure 3 displays four brain images to demonstrate the impact of varying numbers of noisy blades on image quality. A region of interest has been extracted from each brain slice to more clearly illustrate the effect. The first image is the ground truth (full brain slice with 24 PROPELLER blades and no noise). The second image, with one noisy blade out of 24, shows a slight degradation in image quality, with a PSNR of 40.0768 dB. The third image, with two noisy blades, exhibits

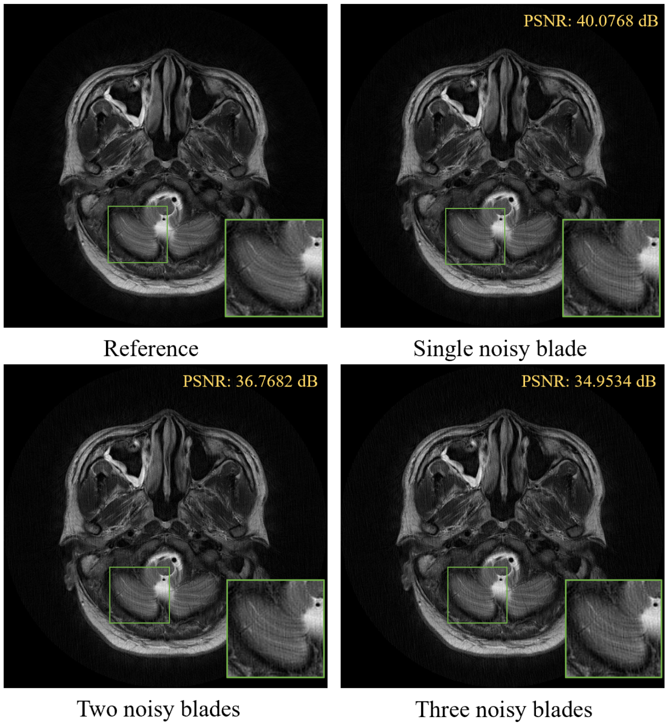

Fig. 3. Sequential Impact of Noisy Blades on Brain MRI Quality. The images, from top to bottom, depict the progressive decline in image quality: (1) ground truth with 24 PROPELLER blades; (2) one noisy blade; (3) two noisy blades; (4) three noisy blades, showcasing the escalating degradation with additional noisy blades.

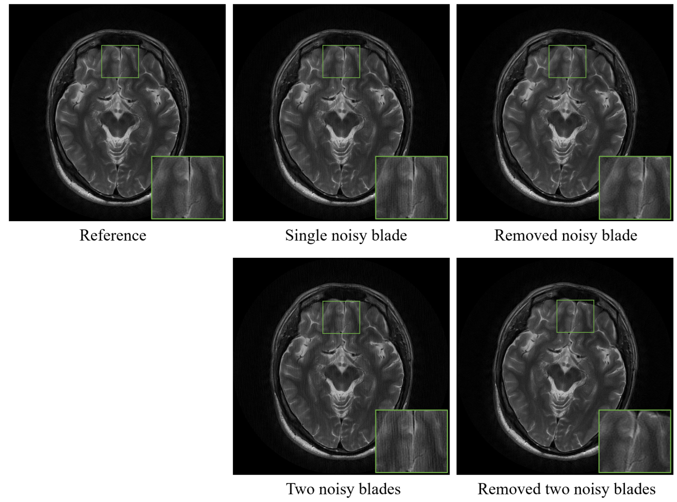

Fig. 4. Effectiveness of Excluding Noisy Blades in Brain MRI Quality Enhancement. The first row displays three images: ground truth, one with a single noisy blade, and one post removal of the noisy blade. The second row shows two images: one with two noisy blades and one reconstructed after their removal. This comparison emphasizes the improvement in image quality achieved by excluding noisy blades.

more pronounced artifacts, resulting in a further reduced PSNR of 36.7682 dB. The fourth image, with three noisy blades, demonstrates significant quality degradation, with a PSNR of 34.9534 dB.

Figure 4 presents a comparative analysis of image quality with and without the inclusion of noisy blades, focusing on a region of interest (ROI) for clearer demonstration. The first row shows three brain images: the ground truth, one with a single noisy blade, and one reconstructed after removing the noisy blade. After the exclusion of the noisy blade the third brain image is reconstructed with 23 PROPELLER blades. The second row contains two images: one with two noisy blades and one reconstructed after removing these two blades similar like the first row. This comparison, by highlighting a specific region of interest in each image, underscores the effectiveness of excluding noisy blades in enhancing image quality.

In Figure 5, we examine the impact of Gaussian noise with varying Signal-to-Noise Ratio (SNR) levels on image quality in PROPELLER MRI. The experiment involves the injection of Gaussian noise in a single blade out of the 24 blades at different SNR levels, specifically 5 dB, 10 dB, and 20 dB. Consistent with standard MRI principles, the image with the lowest SNR of 5 dB shows the most noise and poorest quality, while the image with the highest SNR of 20 dB displays the least noise and best quality. This is quantitatively supported by the Peak Signal-to-Noise Ratio (PSNR) values. The 5 dB SNR image has a PSNR of 40.0768 dB, indicating high noise; the 10 dB SNR image has a moderately better PSNR of 44.7599 dB; and the 20 dB SNR image shows the best quality with a PSNR of 52.7550 dB. This demonstrates the typical trend in MRI where lower SNR results in higher noise and lower PSNR, and vice versa.

In the evaluation of the computational performance, the execution time and memory usage for PROPELLER reconstruction with different number of blades were measured. The data included 24 blades, removing single noisy blade (23 blades), and removing double noisy blades (22 blades) scenarios. The results are summarized in Table I. The observations indicate that removing blades reduces execution time and memory usage of PROPELLER reconstruction.

The results indicate a clear trend of decreasing image quality with the introduction of noisy blades and increasing noise levels. Quantitatively, this trend is evident in the decreasing PSNR values. The study also demonstrates the potential benefit of removing noisy blades from the reconstruction process, as indicated by the partial restoration of image quality and PSNR values.

IV. Discussion and Conclusion

This study systematically investigated the effects of Gaussian noise on image quality in PROPELLER MRI, a technique widely recognized for its efficacy in reducing motion artifacts. Through a series of controlled experiments, we demonstrated how the introduction of noisy blades, varying in number and noise intensity, impacts the overall image clarity and integrity.

Our findings reveal a clear correlation between the presence of noisy blades in PROPELLER MRI and the degradation of image quality, as quantitatively evidenced by the decrease in peak signal-to-noise ratio (PSNR). Specifically, the inclusion

TABLE I
EXECUTION TIME AND MEMORY USAGE FOR PROPELLER RECONSTRUCTION WITH DIFFERENT NUMBER OF BLADES

Scenario	**Execution Time (s)**	**Memory Usage (MB)**
PROPELLER Reconstruction 24 blades (Noise Free)	4.90	173.2
PROPELLER Reconstruction 23 blades (Discarding Single Noisy Blade)	4.85	174.0
PROPELLER Reconstruction 22 blades (Discarding Noisy Blades)	4.47	173.6

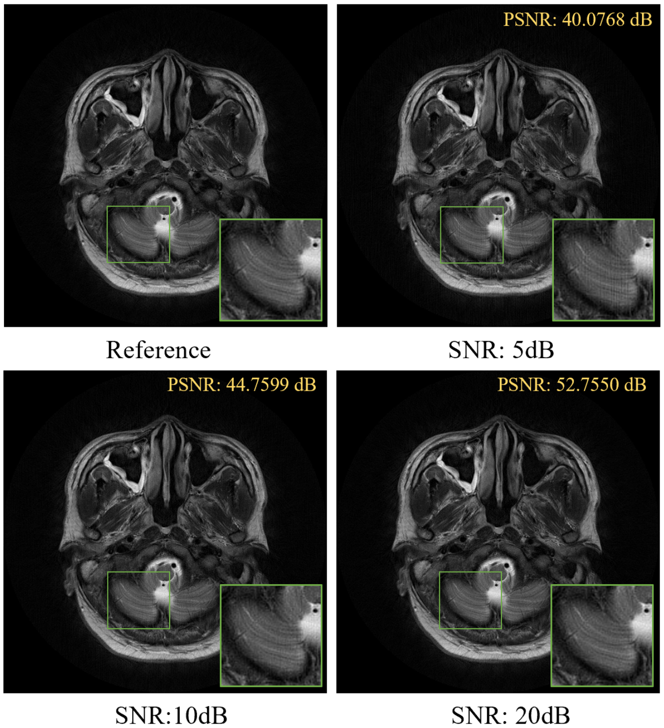

Fig. 5. Influence of Gaussian Noise Levels on PROPELLER MRI Quality. Starting with the ground truth, subsequent images show increasing SNR levels (5 dB, 10 dB, 20 dB).

of one, two, and three noisy blades progressively worsened the image quality, introducing artifacts and reducing the PSNR significantly. Moreover, the study highlighted that different levels of Gaussian noise (5 dB, 10 dB, and 20 dB) injected into a single blade resulted in a noticeable decline in image quality, further underscoring the sensitivity of PROPELLER MRI to noise interference.

Importantly, our results also showed that the removal of noisy blades from the reconstruction process could partially restore image quality, suggesting that identifying and excluding such blades could be a viable strategy for enhancing PROPELLER MRI images in clinical practice. This finding opens avenues for the development of advanced algorithms capable of detecting and compensating for noisy blades, thereby optimizing the utility of PROPELLER MRI in scenarios where noise is a significant concern.

In conclusion, this study provides critical insights into the impact of noise on PROPELLER MRI and lays the groundwork for future research aimed at refining this imaging technique. The implications of our findings are significant for clinical imaging, particularly in optimizing MRI protocols to achieve higher-quality images in challenging scenarios involving patient movement and environmental noise factors. By enhancing our understanding of noise effects in PROPELLER MRI, this research contributes to the ongoing efforts to improve diagnostic accuracy and patient outcomes in the field of medical imaging.

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