

Patch-Based Diffusion Inverse Solver for T2-Weighted Prostate Imaging Reconstruction

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Impact

Patch-based diffusion inverse solver (PaDIS) improves T2-weighted prostate MRI image quality and artifacts suppression at both 3T and 0.55T. This can potentially enable higher-quality, faster prostate MRI in routine clinical workflows, and accelerate low-field prostate MRI adoption.

Synopsis

Motivation: Prostate MRI must balance scan time, SNR, and artifact suppression, especially at low field. Diffusion priors improve reconstruction, but whole-image diffusion models need large datasets, long training, and high-memory GPUs.

Goals: Achieve high-quality, accelerated prostate T2-weighted MRI at 3T and 0.55T using a diffusion prior without whole-image training.

Approach: We adapt PaDIS, a patch-based diffusion inverse solver to learn a diffusion prior from spatially encoded 3T prostate image patches and enforces k-space consistency during reconstruction. We use it for both 3T and 0.55T clinical T2-weighted image reconstruction.

Results: PaDIS improves image quality over GRAPPA and $\ell 1$ -wavelet and performs comparably to whole-image diffusion models.

Introduction

Prostate MRI benefits from fast, high-quality T2-weighted imaging, but acceleration is limited by SNR loss and undersampling artifacts, especially at 0.55T. Long scans and noisy images can introduce motion artifacts and reduce diagnostic confidence.

Diffusion models¹⁻⁴ learn powerful image priors and have been adapted for accelerated MRI reconstruction^{5,6}, but whole-image diffusion requires large curated datasets, long training, and high GPU memory. The Patch-based Diffusion Inverse Solver (PaDIS⁷) addresses these limits by training on small spatially encoded patches and assembling local patch scores into a global prior at inference. This enables strong priors from limited data and lower memory, which has been shown for brain MRI⁶.

In this work, we extend PaDIS to prostate T2-weighted imaging and evaluate accelerated reconstruction at 3T and 0.55T. We compare PaDIS with GRAPPA⁸, $\ell 1$ -wavelet⁹, and whole-image diffusion⁴, including blinded 0.55T reader scoring on artifact level, SNR, sharpness, and overall quality.

Methods

PaDIS has two stages ([Figure 1](#)): (1) learning an image prior from prostate data using patches only, and (2) performing data-consistent reconstruction with the learned prior.

Stage 1 – Patch prior. From complex images (real/imaginary channels), we extract random patches and concatenate normalized positional coordinates. A U-Net denoiser (D_θ) is trained by denoising score matching: given a noisy patch and its noise level, the network predicts the clean patch, yielding a patch score

$$\mathbf{s}_{i,j,r}(\mathbf{x}_{i,j,r}) \approx \nabla_{\mathbf{x}_{i,j,r}} \log p(\mathbf{x}_{i,j,r}).$$

Whole-image scores are then formed by summing scores from tiled patches

$$\nabla_{\mathbf{x}} \log p(\mathbf{x}) = \sum_{i,j=1}^M \left(\mathbf{s}_{i,j,B}(\mathbf{x}_{i,j,B}) + \sum_{r=1}^{(k+1)^2} \mathbf{s}_{i,j,r}(\mathbf{x}_{i,j,r}) \right),$$

where i, j denotes the patch index in the X and Y dimensions and $\mathbf{s}_{i,j,B}$ denotes scores for patches at zero-padded borders.

Stage 2 – Reconstruction. Given undersampled data $\mathbf{y}$, we alternate between enforcing data consistency $\|\mathbf{y} - \mathbf{Ax}\|_2^2$ with multi-coil forward model $\mathbf{A}$ and applying the PaDIS prior. Starting from complex noise, the current image was zero-padded and divided into randomly shifted patch tilings. The U-Net denoiser was applied to each position-encoded patch to produce denoised predictions and patch scores, which are then combined to form a whole-image prior gradient. We then update the current image estimate by stepping along this prior gradient while also enforcing multi-coil k-space data consistency. This update is repeated across iterations until convergence, with random shifts preventing persistent patch seams.

Data and comparisons. PaDIS and the whole-image diffusion baseline were trained on 6,000 fastMRI 3T prostate¹⁰ slices, and tested at 3T and 0.55T. We compare against GRAPPA⁸, $\ell 1$ -wavelet⁹, and whole-image diffusion⁴, with blinded radiologist assessments on 0.55T images.

In vivo experiments. The fastMRI prostate data were acquired at 3T. Additional in-house scans included one healthy subject at 3T (Siemens Vida), and two healthy subjects and five patients with suspected prostate cancer at 0.55T (Siemens FreeMax). Axial T2-weighted turbo-spin-echo (TSE) images was

acquired with following parameters: FOV=180x180mm², resolution=0.56x0.56mm², slice thickness 3mm, 6x-retrospectively undersampled (fastMRI); FOV=200x200mm², resolution=0.52x0.52mm², slice thickness 3mm, 3x-prospective undersampled (3T healthy subject); FOV=220x220mm², resolution=0.85x0.85mm², slice thickness 3mm, 4x-prospectively undersampled (0.55T health subjects and patients).

Results

Figure 2a shows 6x-undersampled fastMRI prostate T2-weighted reconstructions; **Figure 2b** summarizes metrics. PaDIS matches whole-image diffusion performance while yielding sharper prostate detail in the zoom, trains ~3x faster and uses ~2x less GPU memory. Quantitatively, PaDIS averages 32.66 dB PSNR and 0.915 SSIM, outperforming ℓ_1 -wavelet (31.41 dB, 0.879) and GRAPPA (30.05 dB, 0.869).

Figure 3 shows images from in-house scans at 3T. GRAPPA and ℓ_1 -wavelet exhibit residual aliasing anteriorly near the pubic symphysis, and GRAPPA appears noisier overall; PaDIS suppresses both artifacts and noise.

Figure 4 shows images from two healthy subjects at 0.55T. PaDIS improves SNR over other methods, whereas GRAPPA shows fold-over in the femoral heads.

Figure 5 shows five 0.55T patient cases. Across all patients, PaDIS improves SNR while keeping aliasing low. Two board-certified radiologists scored artifact level, SNR, overall diagnostic quality, and blurriness in a blinded read. PaDIS had similar artifact and overall quality scores to ℓ_1 -wavelet (4.4 and 3.6 vs. 4.4 and 3.6) and outperformed GRAPPA (3.3 and 2.4). PaDIS achieved the highest SNR score (3.9 vs. 3.5 for ℓ_1 -wavelet and 3.2 for GRAPPA), but was rated slightly blurrier (3.2) than ℓ_1 -wavelet (3.6) and similar to GRAPPA (3.2).

Discussion and Conclusion

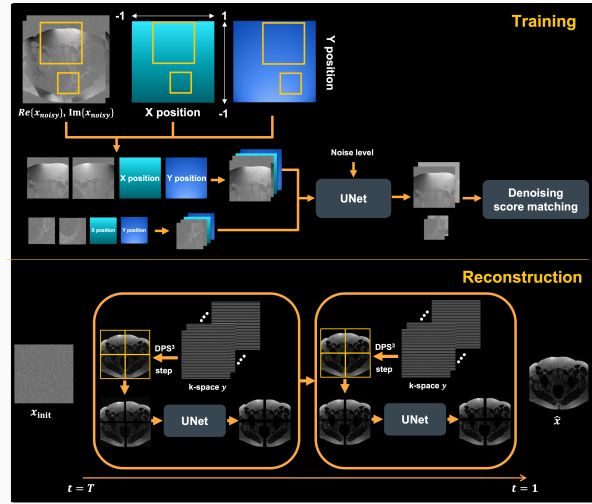
PaDIS introduces a data-driven diffusion prior for accelerated prostate MRI reconstruction that requires only patch-based training, reducing memory requirement and data demands compared to whole-image diffusion models. Across both 3T and 0.55T acquisitions, PaDIS demonstrated improved SNR, reduced aliasing artifacts compared to images reconstructed using GRAPPA and ℓ_1 -wavelet methods, and received similar or higher preference ratings from radiologists. This approach can potentially enable higher-quality, faster prostate MRI in routine clinical workflows, especially for low-field imaging, and is readily extensible to imaging of other anatomical regions.

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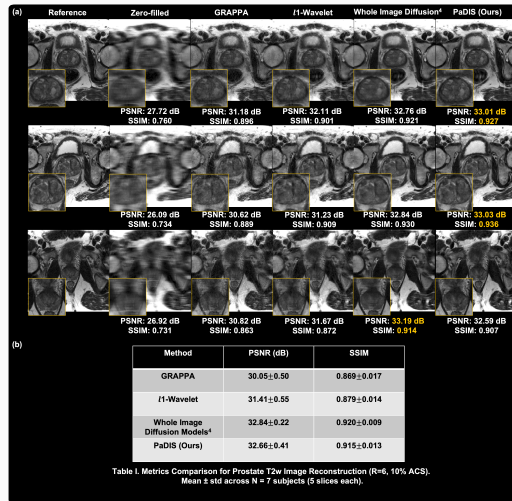
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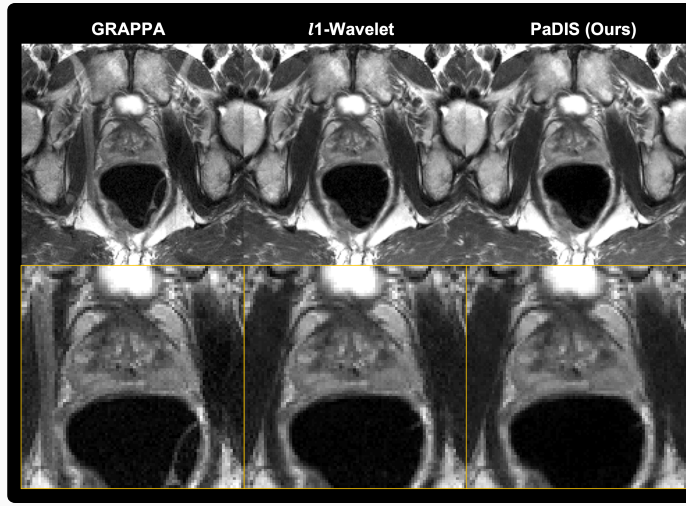
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Figure 1: (a). PaDIS training for prostate MRI. Random patches of the complex image are extracted and stacked with normalized X/Y position arrays as two extra channels, then fed to a UNet for denoising score matching. (b). Reconstruction. Starting from noise at $t = T$, DPS³ data consistency and the patch UNet are applied on random tilings of the zero-padded image to estimate the full-image score.



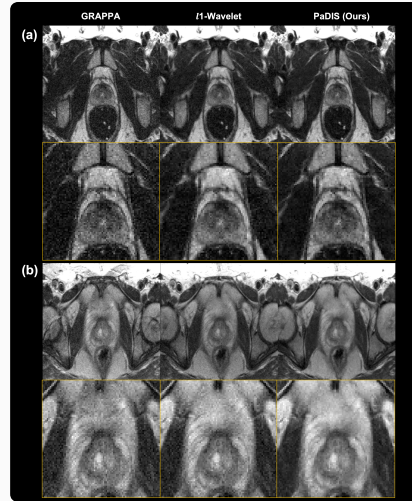
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Figure 2: (a). Prostate T2-weighted images from the fastMRI 3T dataset. k -space was retrospectively undersampled $6\times$ with 10% fully-sampled center. (b). Quantitative comparison (PSNR / SSIM) of GRAPPA, $\ell 1$ -wavelet, whole-image diffusion, and PaDIS, averaged over 7 subjects (5 slices each). PaDIS matches whole-image diffusion performance while yielding sharper prostate detail. Quantitatively, PaDIS averages 32.66 dB PSNR and 0.915 SSIM, outperforming $\ell 1$ -wavelet (31.41 dB, 0.879) and GRAPPA (30.05 dB, 0.869).



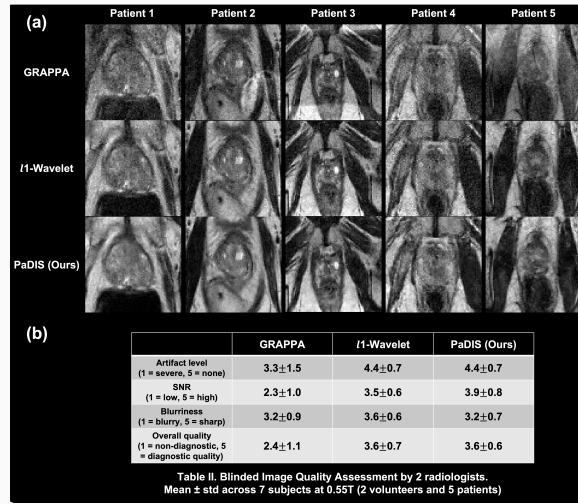
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Figure 3: 3T Healthy Subject Reconstruction comparisons (3x prospectively undersampled without fully-sampled center k -space) on clinical axial T2-weighted acquisition with $FOV=200 \times 200 \text{ mm}^2$, $\text{resolution}=0.52 \times 0.52 \text{ mm}^2$ and 3mm slice thickness. GRAPPA and $\ell 1$ -wavelet exhibit residual aliasing anteriorly near the pubic symphysis, and GRAPPA appears noisier overall; PaDIS suppresses both artifacts and noise.



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Figure 4: 0.55T Healthy Subjects Reconstruction comparisons (3x prospectively undersampled without fully-sampled center k -space) on clinical axial T2-weighted acquisition with $FOV=220 \times 220 \text{ mm}^2$, $\text{resolution}=0.85 \times 0.85 \text{ mm}^2$ and 3mm slice thickness. PaDIS improves SNR over other methods, whereas GRAPPA shows fold-over in the femoral heads.



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Figure 5: (a). 0.55T Patient Reconstruction comparisons (4x prospectively undersampled without fully-sampled center k -space) on clinical axial T2-weighted acquisition with $FOV=220 \times 220 \text{ mm}^2$, resolution= $0.85 \times 0.85 \text{ mm}^2$ and 3mm slice thickness. (f). Blinded radiologist Image quality assessment for volunteers and patients reconstruction in Figure 4 and 5 (a). PaDIS matches $\ell 1$ -wavelet for artifacts/overall, yields highest SNR, and is slightly blurrier than $\ell 1$ -wavelet (similar to GRAPPA).