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Paper1511

Noise Level Adaptive Diffusion Model for Robust Reconstruction of Accelerated MRI

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Introduction

▪**MRI Acceleration and Reconstruction**: MRI scans are accelerated by using multiple coils for k-space data acquisition, and reconstruction is enhanced by incorporating sparsity and total variation, with deep learning models further improving the process. [1]

▪**Challenges in Diffusion-Based MRI Reconstruction**: Diffusion models improve MRI reconstruction by integrating k-space data consistency[2], but noise from hardware and thermal fluctuations can disrupt their performance, especially in low-field MRI[3], fMRI, and DWI[4].

▪**Nila-DC**: The proposed Noise Level Adaptive Data Consistency (Nila-DC) operation addresses noise interference, ensuring robust k-space data guidance and improving diffusion model performance in MRI.

Methodology

(a)The proposed data consistency (Nila-DC) operation. The computed gradient $(A^H A x_t - A^H y)$ can be noisy due to MRI noise in y (c.f. Eqs.7 and 8) , and is therefore adjusted by a attenuation function (lambda).

$$\nabla \log(y|x_t) = -(A^H A x_t - A^H y)/\sigma_y^2 \quad Eq.7$$

$$A^H y = A^H A \bar{x} + A^H \sigma_y \quad Eq.10$$

(b)The attenuation function λ_t rescale the DC gradient. t is the index of the reverse step.

$$\lambda_t = \begin{cases} 1, A^H\sigma_y < 1 - \sqrt{\bar{a}_{t-1}} \\ kt + b, \sqrt{\bar{a}_{t-1}} A^H \sigma_y > 1 - \sqrt{\bar{a}_{t-1}} \end{cases}$$

(c)The image reconstruction process, where Gaussian noise initialized x_t undergoes multi-step reverse diffusion process with the guidance from Nila-DC.

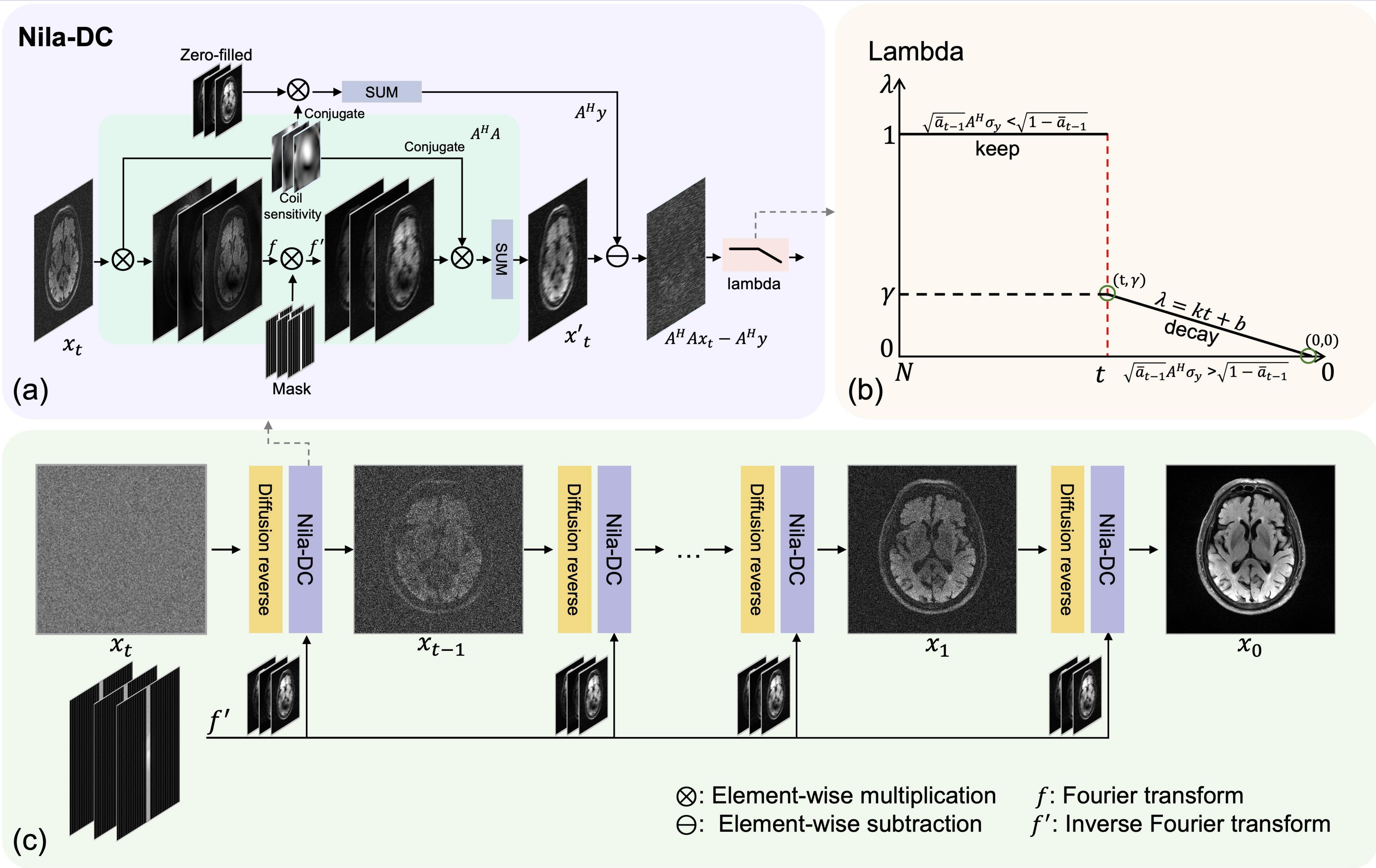

Fig.1 Overview of the proposed method.

Qualitative Evaluation

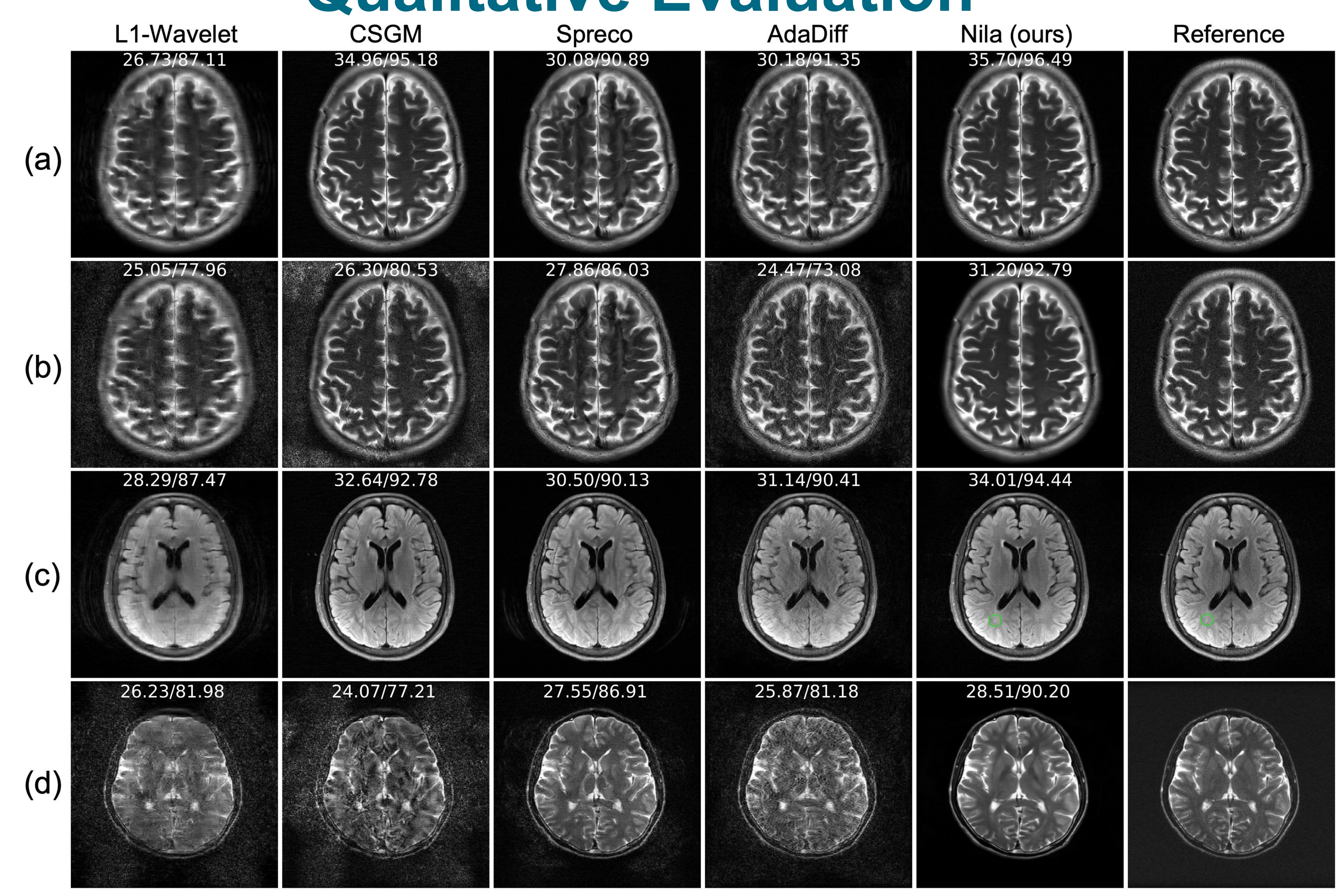

Fig.3 Visual comparison of reconstruction results. (a) 6× acceleration on fastMRI. (b) 6× acceleration on fastMRI with added Gaussian noise. (c) 6× acceleration on the clinical dataset. (d) 4× acceleration on M4Raw.

Quantitative Results

Table 1. Quantitative assessment for the three test datasets at different acceleration factors. No extra noise was added.

Dataset	fastMRI				Clinical				M4Raw			
Acceleration factor	6×		8×		6×		8×		3×		4×	
Metric	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Zero-filled	26.12	82.27	25.41	80.36	27.07	82.40	26.33	80.34	27.15	87.81	25.97	85.43
L1-wavelet	30.04	89.43	27.31	84.55	31.27	89.60	28.35	84.59	28.86	87.50	28.02	86.57
CSGM	35.04	93.53	32.11	90.78	34.67	92.65	31.57	88.94	26.73	84.53	25.63	82.78
Spreco	32.24	90.70	28.65	85.28	32.27	89.84	28.77	84.07	29.77	90.34	28.88	88.68
AdaDiff	33.25	91.79	29.62	86.66	32.84	90.81	29.60	85.65	29.10	88.29	28.10	86.22
Nila (ours)	37.08	95.74	34.82	94.21	36.10	94.34	33.54	91.55	30.23	91.59	29.86	90.06

Table 2. Quantitative assessment under various noise levels at 6x acceleration factor. Note that the sigma values represent the added noise to full sampled data.

Dataset	fastMRI						Clinical					
noisy level	$\sigma = 0.025$		$\sigma = 0.05$		$\sigma = 0.1$		$\sigma = 0.025$		$\sigma = 0.05$		$\sigma = 0.1$	
Metric	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Zero-filled	26.06	81.40	25.90	79.22	25.32	74.08	27.01	81.73	26.84	79.96	26.23	75.31
L1-wavelet	29.07	85.86	26.78	78.15	21.28	64.98	30.15	85.86	27.55	77.51	21.22	63.77
CSGM	31.15	87.64	25.08	76.16	19.47	61.78	31.53	87.16	25.93	75.73	19.64	61.52
Spreco	31.31	89.03	29.62	84.93	25.89	74.23	31.32	88.03	29.58	83.88	26.41	74.10
AdaDiff	29.29	82.93	25.83	73.8	21.99	64.82	29.45	82.74	26.04	73.50	22.12	64.45
Nila (ours)	34.98	93.96	33.56	92.49	31.86	90.38	34.11	91.53	32.80	89.59	31.25	87.15

Reference

[1] Block, K.T., Uecker, M., Frahm, J.: Undersampled radial mri with multiple coils. iterative image reconstruction using a total variation constraint. Magnetic Resonance in Medicine 57(6), 1086–1098 (2007)
[2] Fan, Y., Liao, H., Huang, S., Luo, S., Fu, H., Qi, H.: A survey of emerging applications of diffusion probabilistic models in mri. arXiv preprint arXiv:2311.11383(2023)
[3] Marques, J.P., Simonis, F.F., Webb, A.G.: Low-field mri: An mr physics perspective. Journal of magnetic resonance imaging 49(6), 1528–1542 (2019)
[4] Biswal, B., Zerrin Yetkin, F., Haughton, V.M., Hyde, J.S.: Functional connectivity in the motor cortex of resting human brain using echo-planar mri. Magneticresonance in medicine 34(4), 537–541 (1995)

Conclusion

We identify and address the issue that existing diffusion model-based reconstruction methods are sensitive to the MRI noise level by introducing a noise level adaptive data consistency operation for the reverse diffusion process, which permits robust guidance. The proposed method is comprehensively evaluated to demonstrate outstanding performance under various experimental conditions.