Denoising of 3D magnetic resonance images using a residual encoder–decoder Wasserstein generative adversarial network

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01 Introduction - Background

MRI Noise

The quality of MR images can be easily affected by noise during image acquisition

Noise : Negative influences on the reliability of subsequent analytic tasks such as registration, segmentation and detection.

(a) Brain MR Image without noise

(b) Brain MR Image with noise

Previous Noise Reduction Methods

<Filtering Based>

The filtering-based methods are the most direct and denoise the MR images in the spatial domain.
Perona-Malik (PM) - Anisotropic Diffusion Method

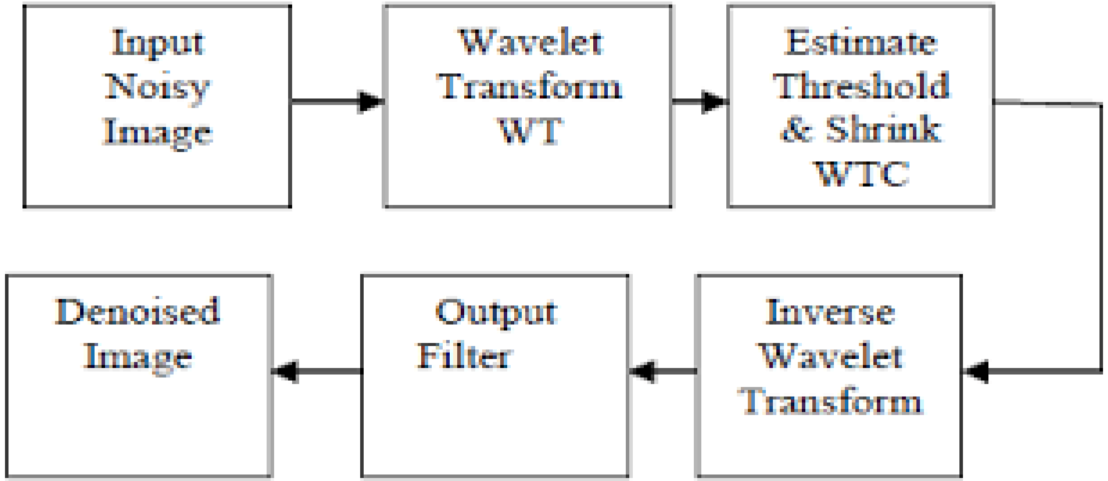
$$\frac{\partial I}{\partial t} = c(x, y, t)\Delta I + \nabla c \cdot \nabla I$$

<Statistical Based>

Etimate the parameters of Rician noise in noisy MR images. After that, the results are used to yield a statistically optimal denoised image

<Transform Based>

Reducing noise in a spatial domain but is also widely researched, and some typical methods include wavelet and discrete cosine transform (DCT)-based methods

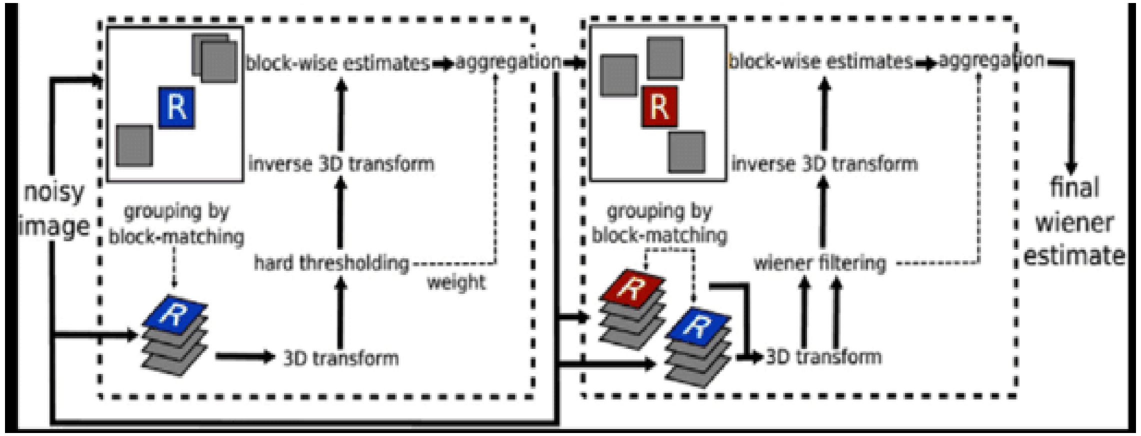


Wavelet Transform

Previous Noise Reduction Methods

<Non Local Mean (NLM)>

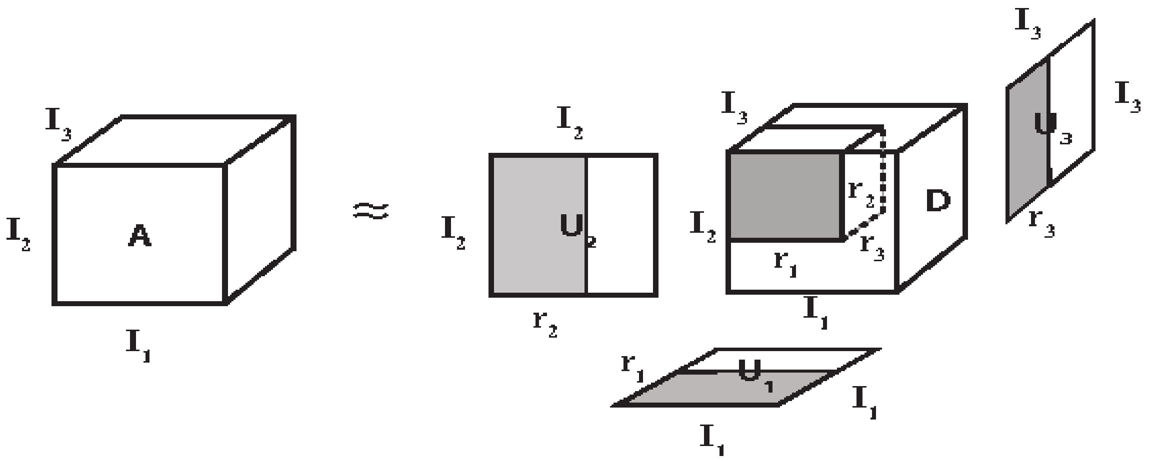
Method based on the self-similarity and sparsity of images. estimates the current pixel by weighted aver-aging its similar patches in a search window.
Ex) NLM, ONLM, BM3D Filter, BM4D Filter



BM3D Filter

<ML/DL Based>

HOSVD (higher-order singular value decomposition)
Multilayer perception
autoencoders and convolutional neural network (CNN)



HOSVD

01 Introduction - Contribution

- The proposed model is based on the **WGAN framework,** which has demonstrated a powerful ability to learn the data distribution in a low dimensional manifold

- The ideas of residual networks and autoencoders are utilized to main tain the structural details and edges, which are clinically important

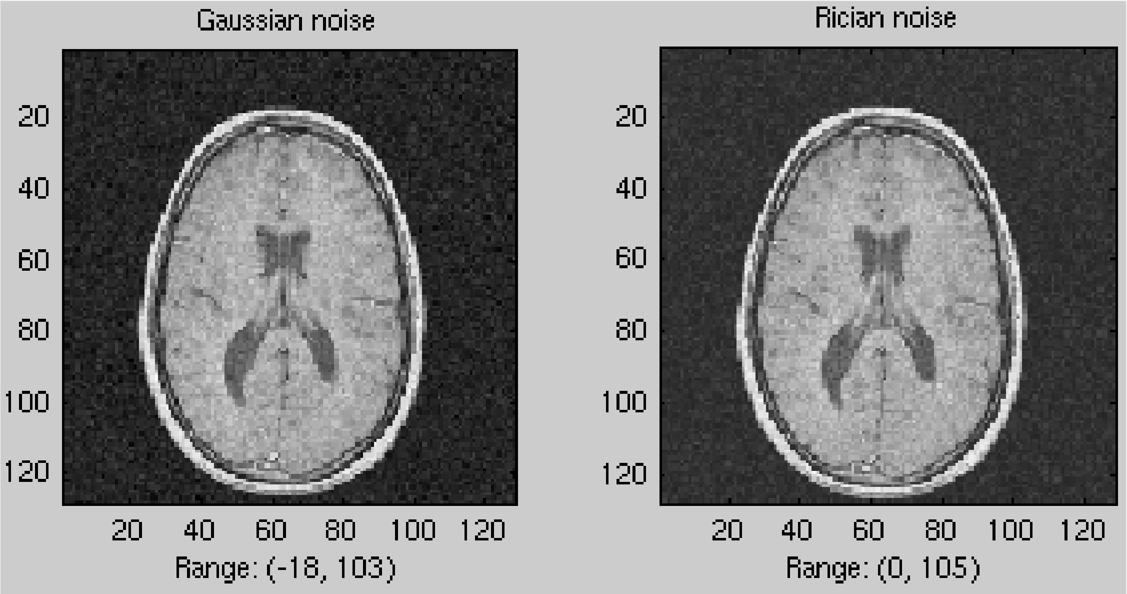
- With a proper training procedure, our method yields results that are competitive with several state-of-the-art methods

- Our method is highly computationally fast and compatible for parallel implementation on graphic processing units (GPUs)

Methods and Experiments : Noise reduction model

- **The Rician distribution,** which is much more complex than traditional additive noise, such as Gaussian and impulse noise

< Rician Noise >



$x = \sigma(y)$

$$\underset{f}{arg\,min} \left\| \hat{y} - y \right\|_2^2$$

x = Noisy MR Image
y = Free Noise MR Image
σ = noise contamination

02 Methods and Experiments

Loss Function

- Pn = Noisy image distribution , Pr = Noise-free image distribution, Pg = Distribution generated by generator, y~Pr = Real Distribution, x~pn = Generated Distribution
- λ = Penalty Coefficient, Px^ is a distribution that uniformly samples along straight lines between pairs of points sampled from the real data distri bution Pr and the generator distribution Pg

<WGAN Loss>

Vanilla GAN

$$\min_G \max_D L(D, G) = \mathrm{E}_{y\sim P_r}[\log D(y)] + \mathrm{E}_{x\sim P_n}[\log(1 - D(G(x)))]$$

RED-WGAN (Discriminator)

$$L_{WGAN}(D) = -\mathrm{E}_{y\sim P_r}[D(y)] + \mathrm{E}_{x\sim P_n}[D(G(x))] + \boxed{\lambda \mathrm{E}_{\hat{x}\sim P_{\hat{x}}}\left[\left(\left\|\nabla_{\hat{x}} D(\hat{x})\right\|_2 - 1\right)^2\right]}$$

Gradient Penalty

RED-WGAN (Generator)

$$L_{WGAN}(G) = -\mathrm{E}_{x\sim P_n}[D(G(x))]$$

<Feature Extractor Loss>

MSE

$$L_{MSE} = \frac{1}{whd}\|G(x) - y\|^2$$

Perceptual Loss

$$L_{Perceptual} = \frac{1}{whd}\|\boxed{\emptyset}(G(x)) - \emptyset(y)\|_F^2$$

Pretrained VGG19 Loss

$$L_{VGG} = \frac{1}{whd}\|\boxed{VGG}(G(x)) - VGG(y)\|_F^2$$

Final RED-WGAN Loss

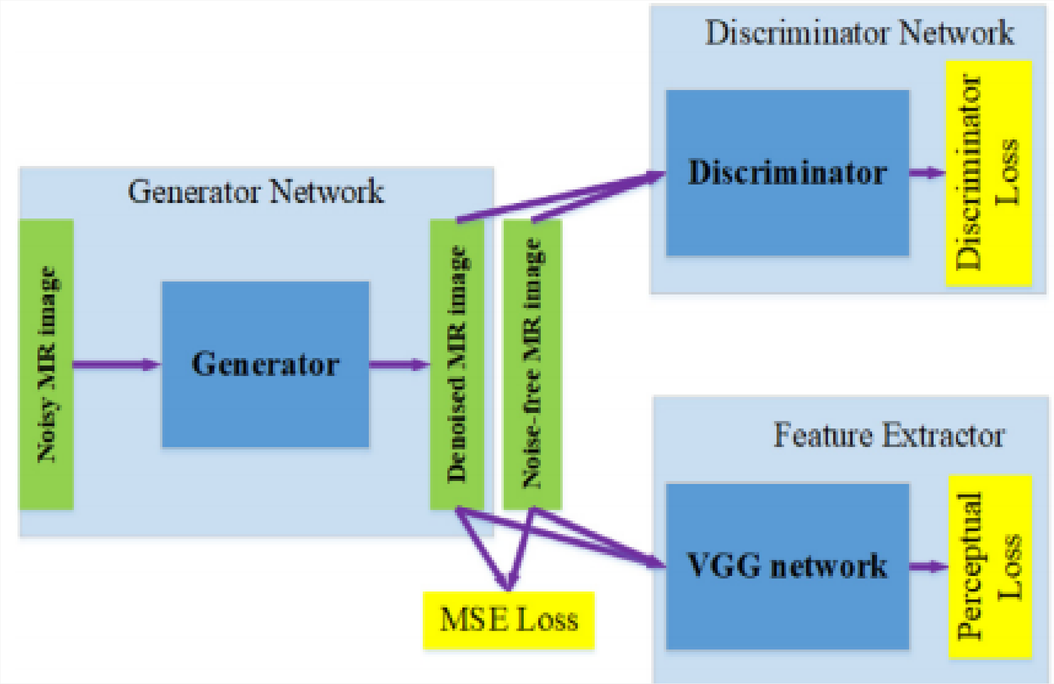
$$L_{RED-WGAN} = \lambda_1 L_{MSE} + \lambda_2 L_{VGG} + \lambda_3 L_{WGAN}(G)$$

02 Methods and Experiments

Proposed Framework

- To accelerate the training procedure and preserve more details, short connections and deconvolution layers are introduced, The convolution and deconvolution layers are symmetrically arranged.

< Proposed Framework >



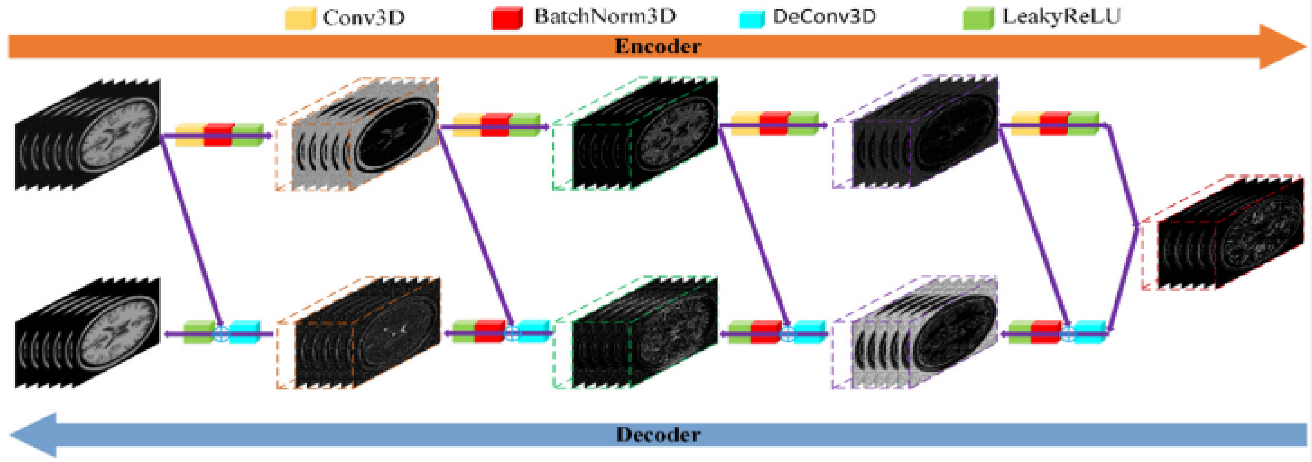


Fig. 2. The architecture of the generator network *G*.

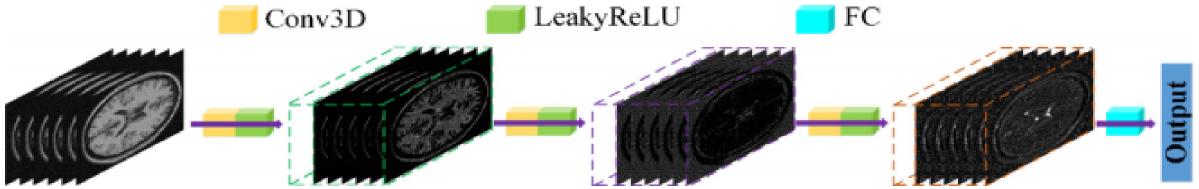
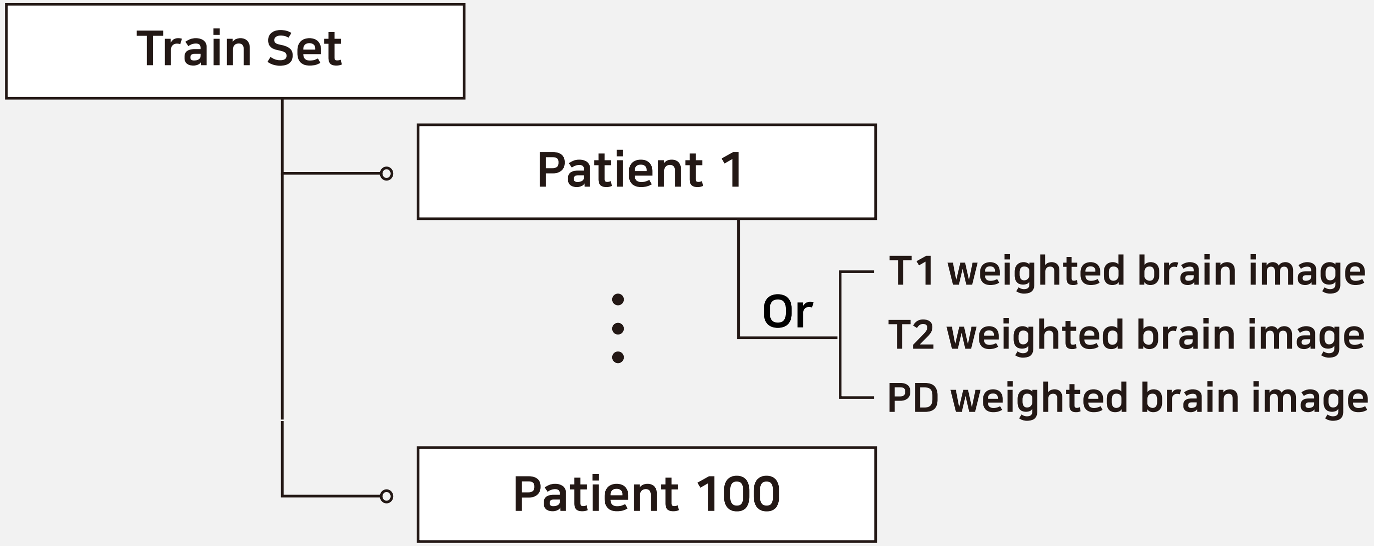


Fig. 3. The structure of the discriminator network *D*.

03 Methods and Experiments

Dataset

- We randomly selected 110 T1-, T2- and PD-weighted brain image volumes from the Hammersmith data-set acquired from a Philips 3T scanner, which is a subset of the IXI dataset
- To solve a great deal of training samples, overlapping voxels were extracted from the samples to train the network.



< Hyperparameters >

Penalty Coefficient -
λ1 = 1, λ2 = 0.1, λ3 = 1e^-3
Optimizer -
Adam (α = 5e−5, β1 = 0.5, β2 = 0.9)

$$L_{RED-WGAN} = \lambda_1 L_{MSE} + \lambda_2 L_{VGG} + \lambda_3 L_{WGAN}(G)$$

03 Methods and Experiments

Results

- PSNR = Peak Signal-to-Noise Ratio, SSIM = Structural Similarity Index Measure, IFC = Information fidelity Criterion
- Different noise levels from 1% to 15% with a step of 2% are illustrated

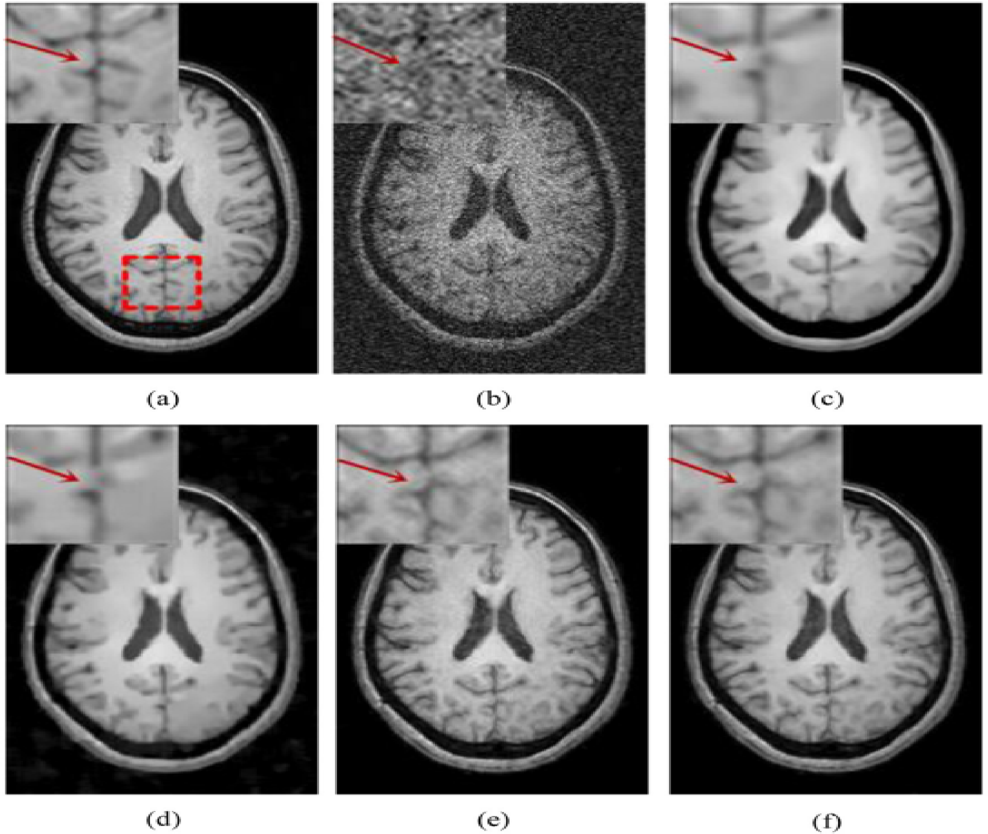
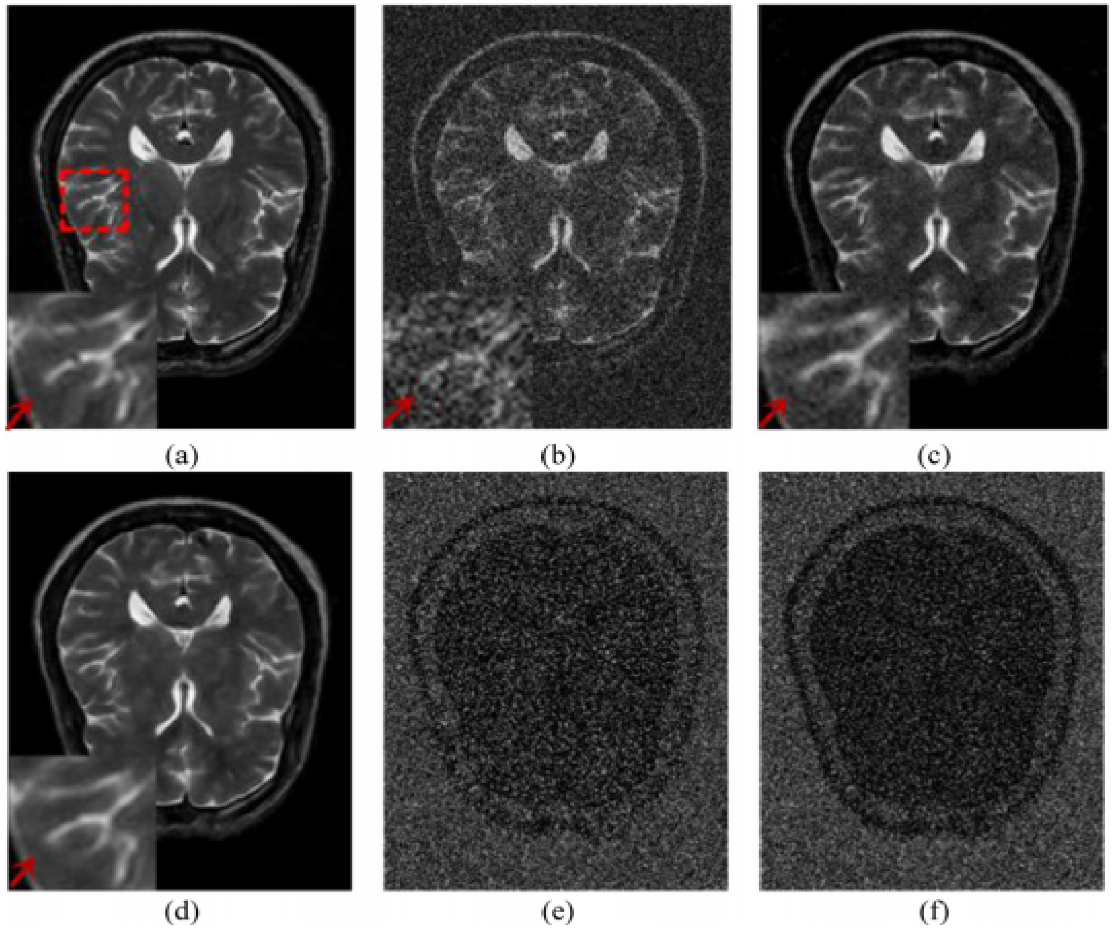


Table 1
From top to bottom, the PSNR, SSIM and IFC measures of different methods on T1w images with different noise levels.

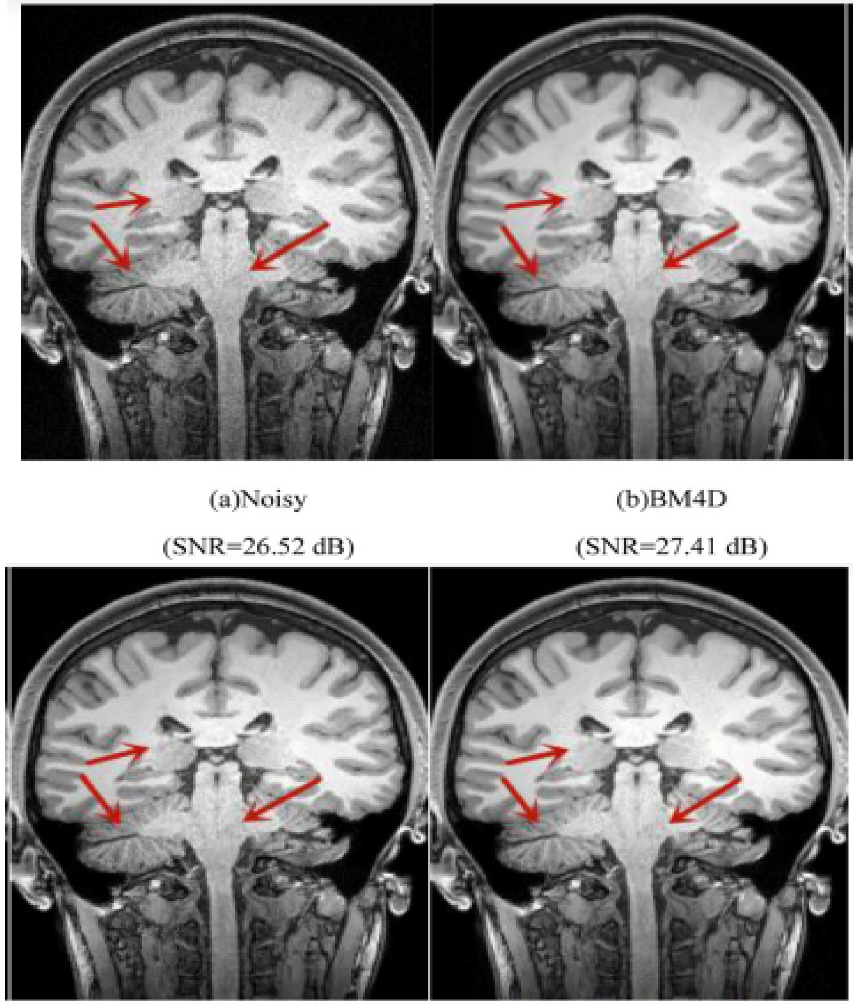
	1%	3%	5%	7%	9%	11%	13%	15%
Noise	39.2092	29.2209	24.6349	21.6248	19.3978	17.6280	16.1530	14.8845
	0.8325	0.6007	0.4964	0.4242	0.3667	0.3186	0.2771	0.2417
	6.9618	3.8510	2.7399	2.1268	1.7276	1.4405	1.2262	1.0577
BM4D	43.7217	37.3037	34.5095	32.6762	31.3338	29.7973	28.1597	25.9018
	0.9832	0.9393	0.9034	0.8926	0.8798	0.8622	0.8417	0.8126
	7.3469	4.6026	3.6226	3.0635	2.6889	2.3640	2.0850	1.8054
PRI-NLM3D	42.5101	36.7709	33.8254	31.3052	29.4420	27.9812	26.8905	26.3974
	0.9601	0.9357	0.8854	0.7830	0.7432	0.6767	0.6816	0.6664
	6.9492	4.4683	3.4591	2.8532	2.4492	2.1196	1.8879	1.6662
CNN3D	**44.7101**	**38.4564**	**35.8638**	**33.6071**	32.7940	31.4896	29.9069	28.6901
	0.9867	**0.9542**	**0.9293**	**0.9091**	0.9005	**0.8927**	0.8659	0.8525
	7.6368	**4.9561**	**4.0391**	3.2551	3.0046	2.6684	2.1961	2.0109
RED-WGAN	44.4336	36.5281	34.4664	33.0387	**33.0367**	**32.1459**	**30.5995**	**29.5566**
	0.9806	0.9205	0.8957	0.8957	**0.9021**	**0.8927**	**0.8779**	**0.8679**
	7.5411	4.5158	3.7543	**3.2673**	**3.0780**	**2.8640**	**2.4169**	**2.1702**

Results



(a) (b) (c)

(d) (e) (f)



(a)Noisy (SNR=26.52 dB)

(b)BM4D (SNR=27.41 dB)

(c)PRI-NLM3D (SNR=27.00 dB)

(d) RED-WGAN (SNR=28.34 dB)

Results

Table 4
Quantitative results associated with different methods for Fig. 4 (T1w), 5(T2w) and 6(PDw).

Method	T1w			T2w			PDw			Average execution time
	PSNR	SSIM	IFC	PSNR	SSIM	IFC	PSNR	SSIM	IFC	
Noise	14.7437	0.2603	1.0887	14.6613	0.1797	0.9352	14.2264	0.2164	1.0564	
BM4D	27.0763	0.8354	2.1528	22.9486	0.7173	1.5034	25.7049	0.7776	1.7739	5.73
PRI-NLM3D	28.2652	0.7901	2.0454	26.0788	0.5612	1.2938	26.3631	0.6897	1.4646	4.16
CNN3D	29.1561	0.8742	2.2831	29.8515	0.8254	1.9280	28.3651	0.7893	2.1017	0.17
RED-WGAN	**30.0584**	**0.8892**	**2.4639**	**29.9575**	**0.8351**	**1.9467**1.868	**31.1590**	**0.8624**	**2.6937**	**0.16**

Table 6
Quantitative results associated with different method outputs in Figs. 11 (T1w), 12 (T2w) and 13 (PDw).

Method	T1w			T2w			PDw		
	PSNR	SSIM	IFC	PSNR	SSIM	IFC	PSNR	SSIM	IFC
Noise	15.0129	0.2698	1.2038	15.0275	0.2108	1.0588	14.6892	0.1966	1.0953
WGAN-MSE	28.9253	0.8280	2.1799	26.7390	0.7212	1.8081	31.7060	**0.8449**	2.2641
RED-WGAN	**29.8372**	**0.8743**	**2.2834**	**29.3393**	**0.8156**	**1.9494**	**32.2121**	0.8309	**2.4691**

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Conclusion

- Wasser stein generative adversarial network to remove the Rician noise in MR images while effectively preserving the structural details
- The innovative generator structure and mixed weighted loss function. im-provement of our method is the adaptation of the mixed loss function
- RED-WGAN effectively avoids oversmoothing effects while preserving more details, validate the robustness and generalization
- RED-WGAN model achieved a performance better than the traditional meth-ods in both visual effects and quantitative results.