DISGAN: Wavelet-informed Discriminator Guides GAN to MRI Super-resolution with Noise Cleaning

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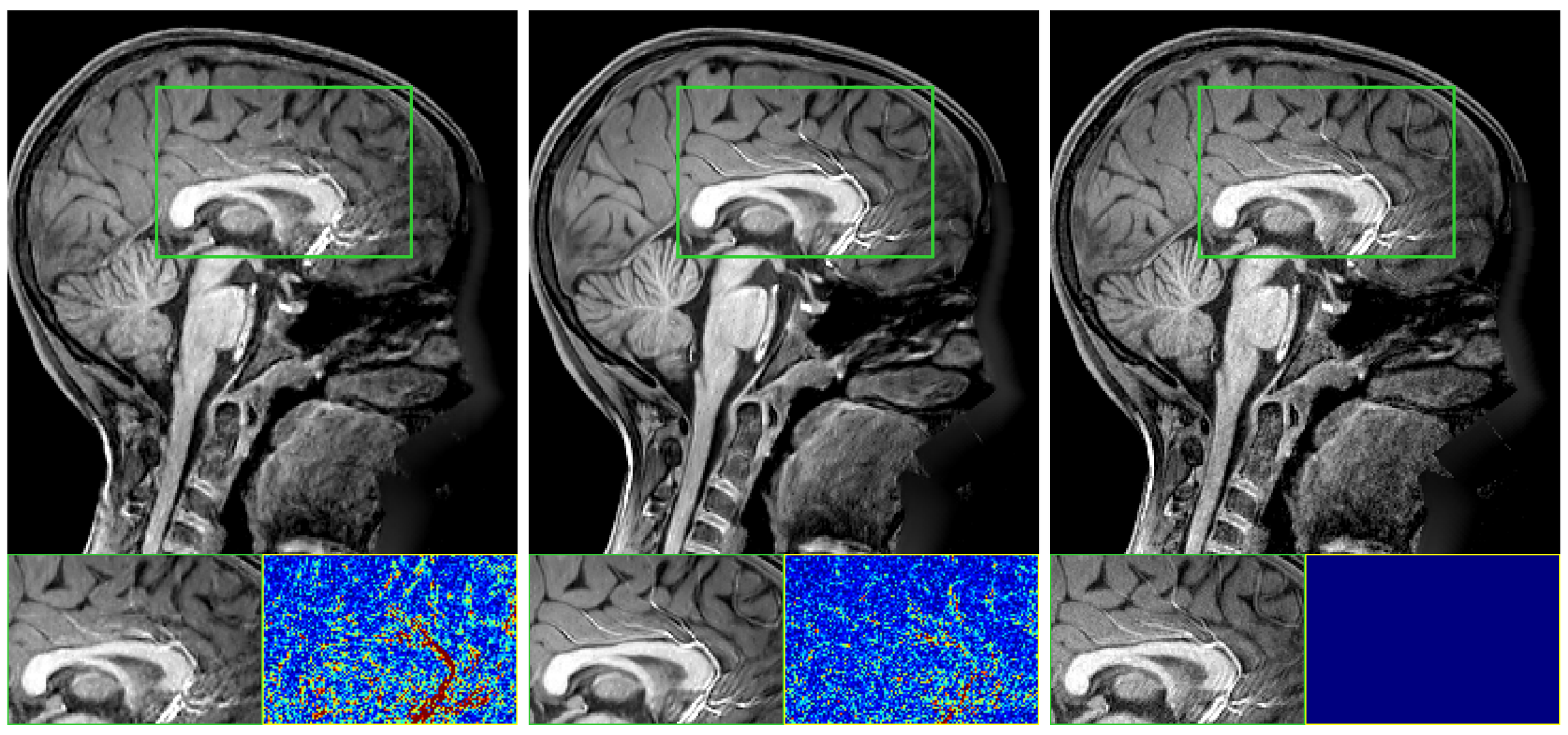
Abstract

- We propose a novel super resolution (SR) model for MRI images, which better recovers fine details and produces coherent brain structures;
- The proposed model (DISGAN) incorporates SR and noise removal in one step, without explicit training on denoising tasks;
- The generated SR images have very low spatial and frequency residual compared with other state-of-the-art methods;
- The DISGAN model can be generalised to clean real-world noisy data;

Super resolution result



(a) DCSRN (b) DISGAN (ours) (c) GT

Figure 1. SR results on 1.2 mm resolution data. The DISGAN model generates more realistic and clean image. Absolute residual error is shown in the heatmap at bottom row.

SR + denoising on simulated noisy data

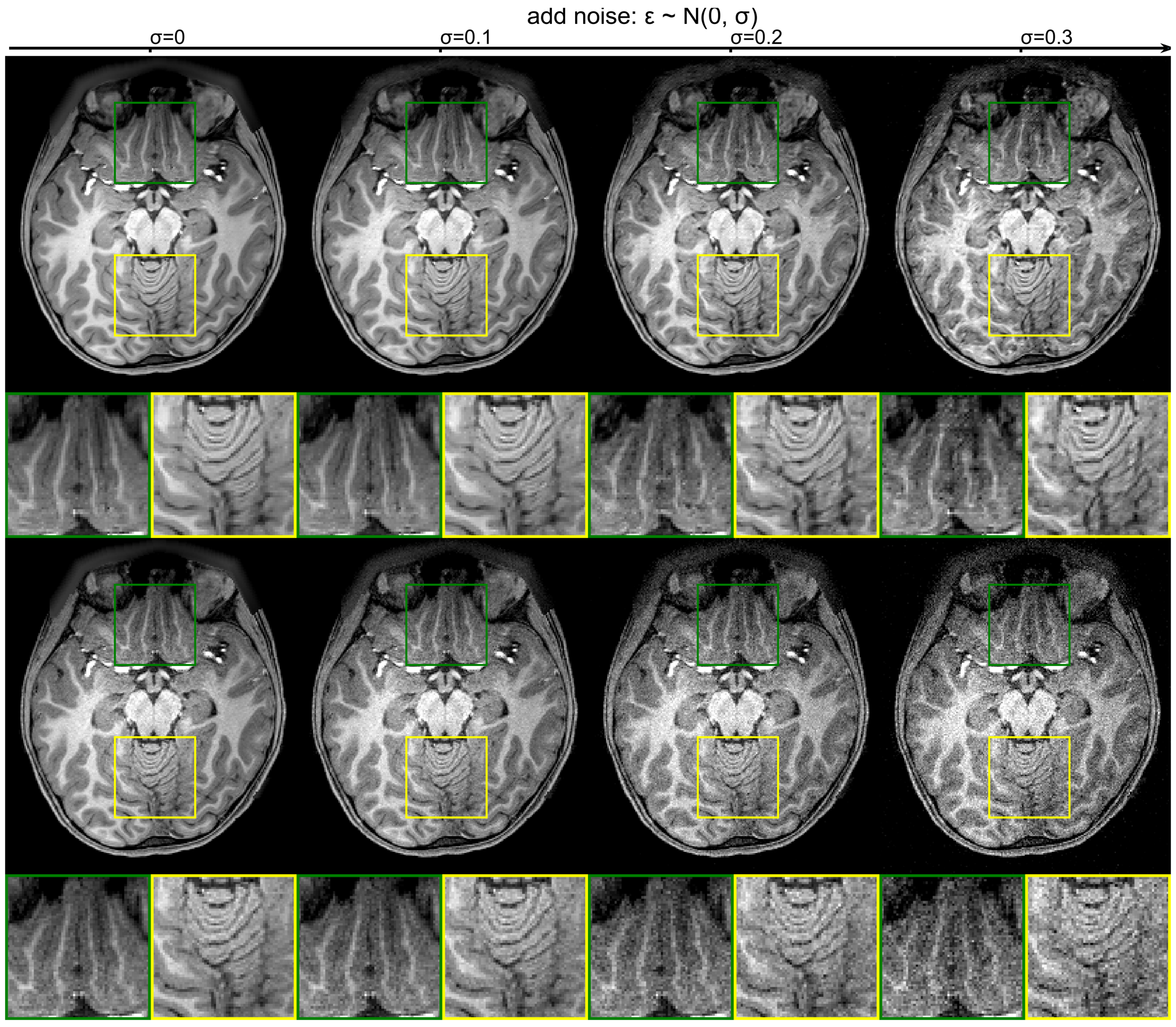
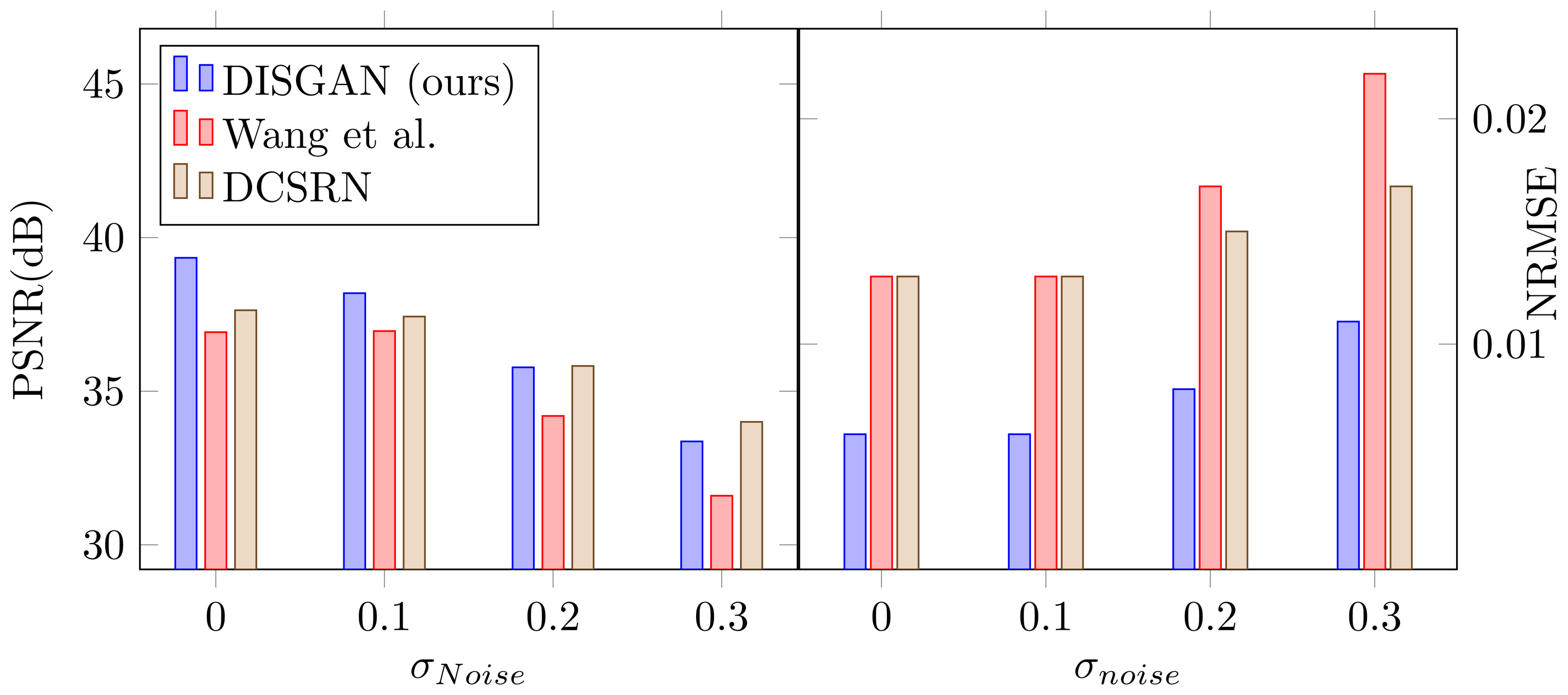


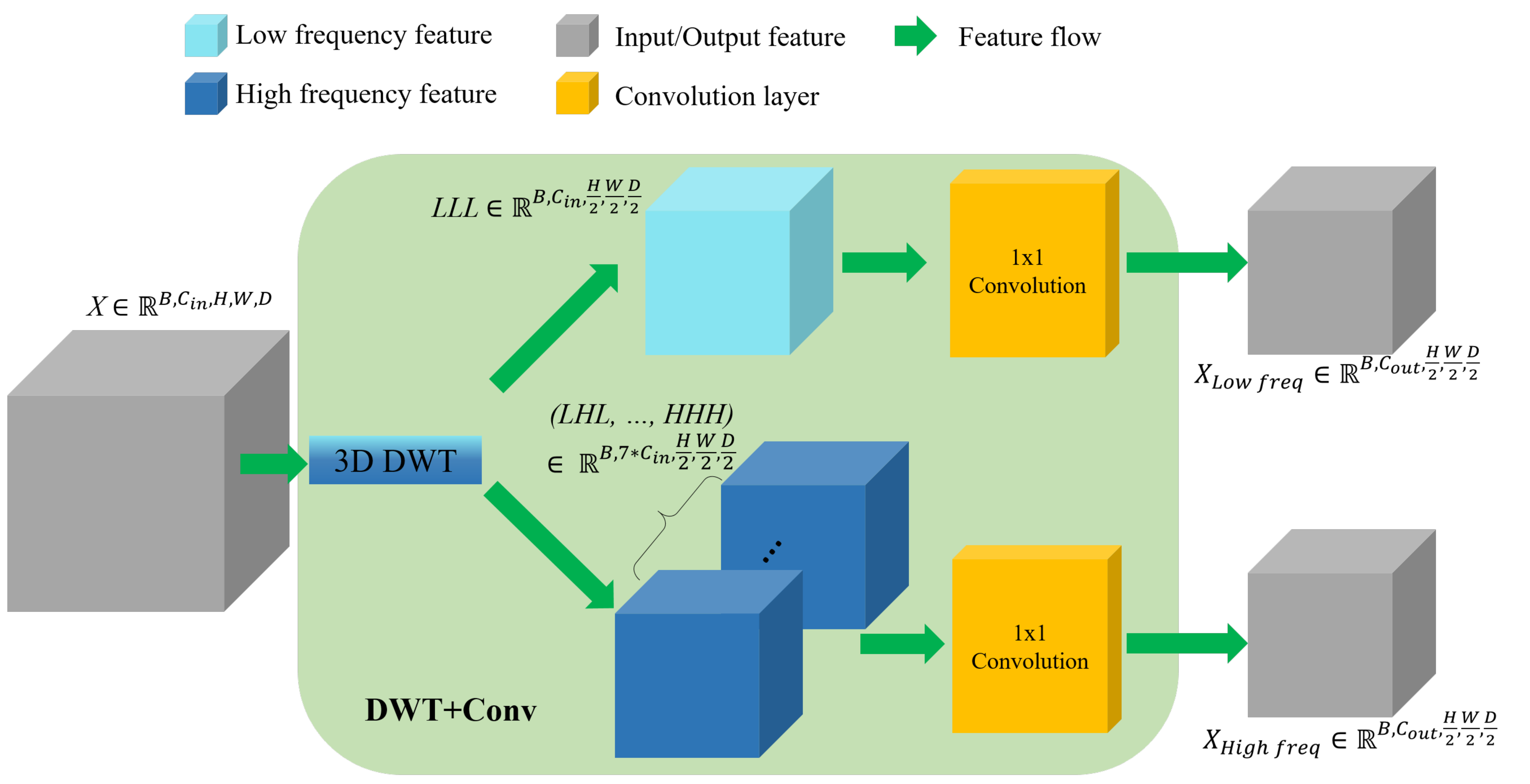
Figure 2. SR results on simulated noisy data, with different noise levels. Top row shows cleaned images, bottom row shows GT.



(a) PSNR (b) NRMSE

Figure 3. Quantitative comparison of SR results on simulated noisy data. DISGAN outperforms Wang et al. [1] and DCSRN [2] on both metrics. Note, the PSNR metric shows higher the better, for NRMSE the lower the better.

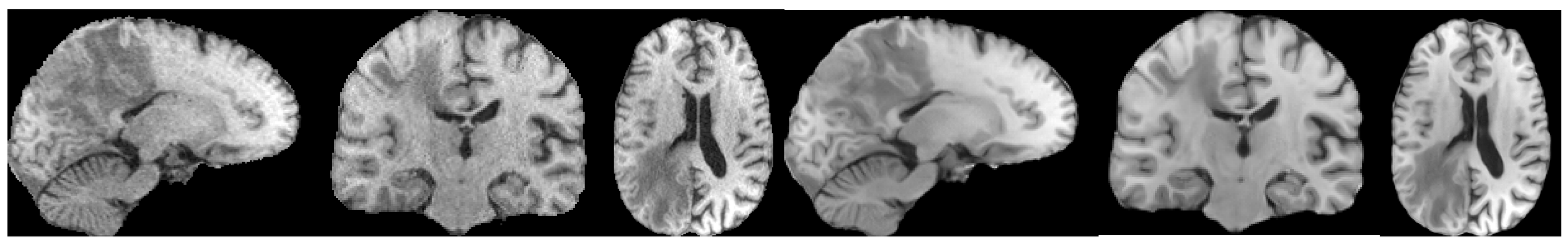
Denoising block: DWT+conv



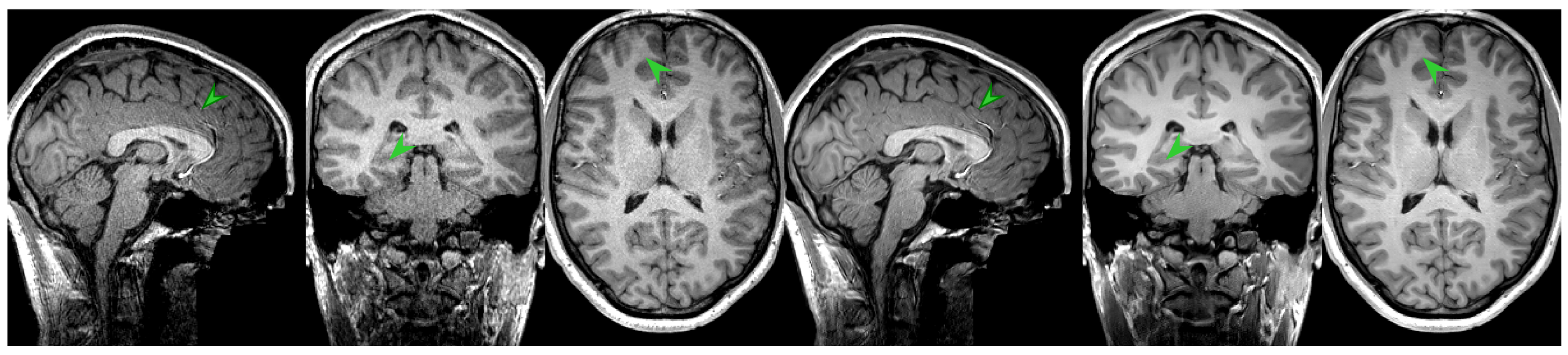
Methods

1. During training, we used T1w structural MRI data from 20 healthy subjects acquired at 3T, downloaded from Human Connectome Project[3].
2. The original data resolution was $0.8mm$ isotropic, then it was linearly downsampled to $1.6mm$ as simulated LR images.
3. The training data was acquired from patching the complete images into $64 \times 64 \times 64$ for HR patches and $32 \times 32 \times 32$ for LR patches, with 75% overlapping.
4. Then the corresponding LR patches were paired with their HR patches to train the GAN model.
5. In the real-world noisy data testing, we used data with brain tumor from BraTS [4] and epilepsy data from OpenNeuro [5].

SR + denoising on real-world noisy data



(a) GT from BraTS (b) DISGAN denoised BraTS



(c) GT from epilepsy data (d) DISGAN denoise epilepsy data

Figure 4. Qualitative results of DISGAN applied to real-world noisy data for noise-cleaning. BraTS data contains more random noise (Fig.4a), while epilepsy data contains more ringing noise (Fig.4c). Both are cleaned by DISGAN leading to enhanced image quality (Fig.4b and d).

Discussion

Our proposed DISGAN model tackles SR and denoising problem at one step, without additional training on denoising tasks. The denoising block is a DWT+conv unit, which is a simple and effective way to remove noise. The SR results are very realistic and clean, with very low residual errors. The DISGAN model can be generalised to real-world noisy data, and the SR results are still very realistic and clean. This is a promising result for future unified generative models for medical image enhancement.

Reference

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