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SUPER-RESOLUTION OF 3D MRI CORRUPTED BY HEAVY NOISE WITH THE MEDIAN FILTER TRANSFORM

CIS-01: MEDICAL IMAGING: IMAGE FORMATION, RECONSTRUCTION, RESTORATION

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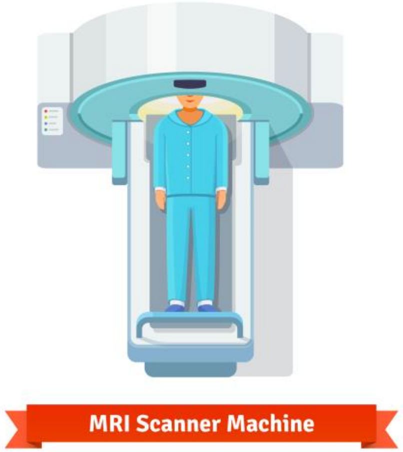
OUTLINES

1. Medical imaging problems: resolution and noise
2. The 3D Median Filter Transform
3. Methods
4. Results
5. Conclusions

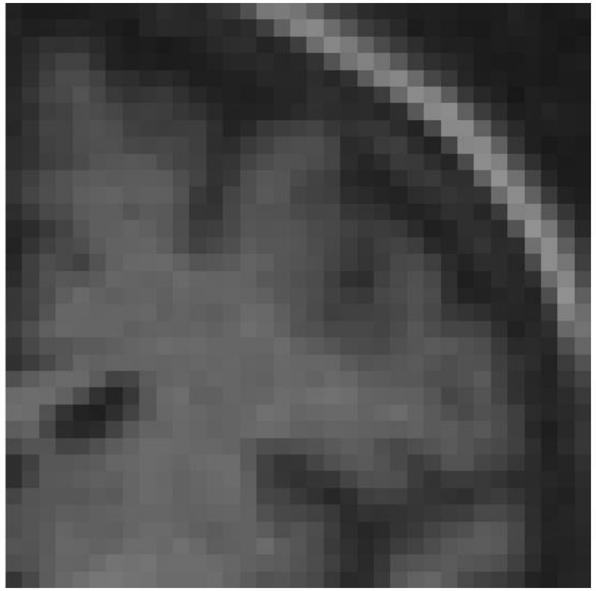
MEDICAL IMAGING

- High-quality acquisition technologies: CT, MRI, PET…
- Limitations of Magnetic Resonance:
  - Hardware
  - Signal-to-Noise ratio, blurring
  - Limited acquisition time or movements of the patient
- The goal is to increase the resolution and remove noise of medical images simultaneously



INTRODUCTION: IMAGE SUPER-RESOLUTION

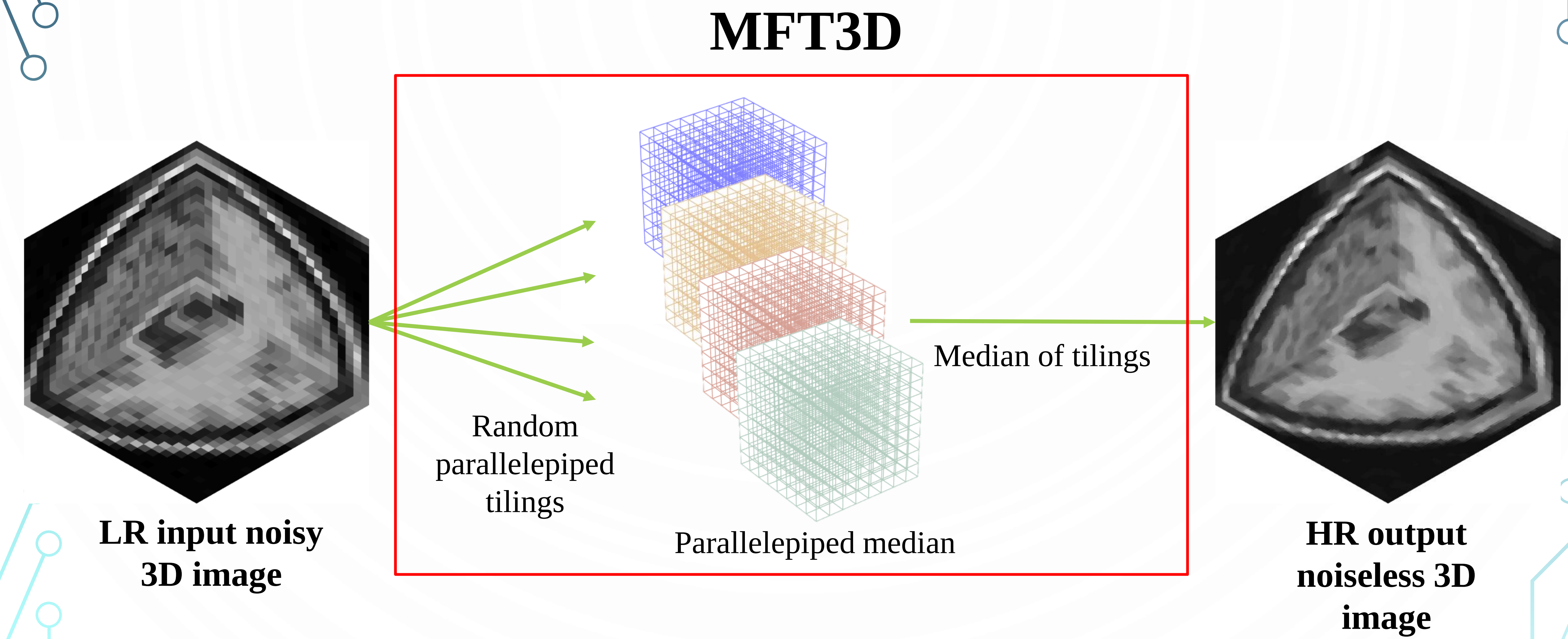
- Technique reconstructs a higher-resolution (HR) image or sequence from the observed low-resolution (LR) images
- Challenging:
  - High-frequency content typically cannot be recovered from the LR image
  - LR image can yield several possible HR images
- Several approaches: traditional interpolation, Frequency domain algorithms, example-based or self-similarity methods…
- They usually assume there is little noise in the images



INTRODUCTION: NOISE REMOVAL

- MR images are mainly corrupted by Rician noise
- There are specific approaches to remove noise: *Non-local means filters, Wavelet subbands mixing, Grouping and collaborative filtering*
- How to combine them with SR?
  - Denoising before applying SR
  - Iterative procedure (denoising and SR)
  - Using external data (an additional HR image)
- These methodologies may remove details and fine textures, which will be magnified in the SR step

THE MODEL


MFT3D
Random parallelepiped tilings
Median of tilings
Parallelepiped median
LR input noisy 3D image
HR output noiseless 3D image

MFT3D DEFINITION

LR coordinates	LR-HR association	HR coordinates
$\boldsymbol{x} = (x_1, x_2, x_3) \in \mathbb{Z}^3 \leftrightarrow$	$\alpha\boldsymbol{x} = (\alpha x_1, \alpha x_2, \alpha x_3) \in \mathbb{R}^3, \alpha \in \mathbb{R}$	$\leftrightarrow \boldsymbol{y} = (y_1, y_2, y_3) \in \mathbb{Z}^3$

- We consider the LR voxel values which belong to the parallelepiped where the HR voxel $\boldsymbol{y}$ belongs:

$$\zeta(\boldsymbol{y}, \boldsymbol{A}, \boldsymbol{b}) = \{f(\boldsymbol{x}) \mid \mathrm{round}(\boldsymbol{A}\alpha\boldsymbol{x} + \boldsymbol{b}) = \mathrm{round}(\boldsymbol{A}\boldsymbol{y} + \boldsymbol{b})\}$$

- Matrix $\boldsymbol{A}_{3\times3}$ and vector $\boldsymbol{b}_{3\times1}$ defines de tiling space (bins)
- The **MFT3D** is defined as:

$$\hat{f}(\boldsymbol{y}) = \Theta(\{\psi(\boldsymbol{y}, \boldsymbol{A}_1, \boldsymbol{b}_1), \dots, \psi(\boldsymbol{y}, \boldsymbol{A}_H, \boldsymbol{b}_H)\})$$

$$\forall i \in \{1, \dots, H\},\ \psi(\boldsymbol{y}, \boldsymbol{A}_i, \boldsymbol{b}_i) = \Theta\big(\zeta(\boldsymbol{y}, \boldsymbol{A}_i, \boldsymbol{b}_i)\big)$$

MFT3D FUNDAMENTALS

- Θ represents a median operation by using sample quantiles based on mid-distribution functions
  - For discrete distributions, they behave better than the classical sample quantiles, which have no asymptotic normality properties
- Demonstrated properties:
  - The MFT3D converges to the median of the distribution of the parallelepiped medians $\psi(\boldsymbol{y}, \boldsymbol{A}, \boldsymbol{b})$
  - The MFT3D defines regions so that inside a region it always converges to the same value as $H \to \infty$
  - The MFT3D converges in distribution when the mid-sample median is employed

METHODS

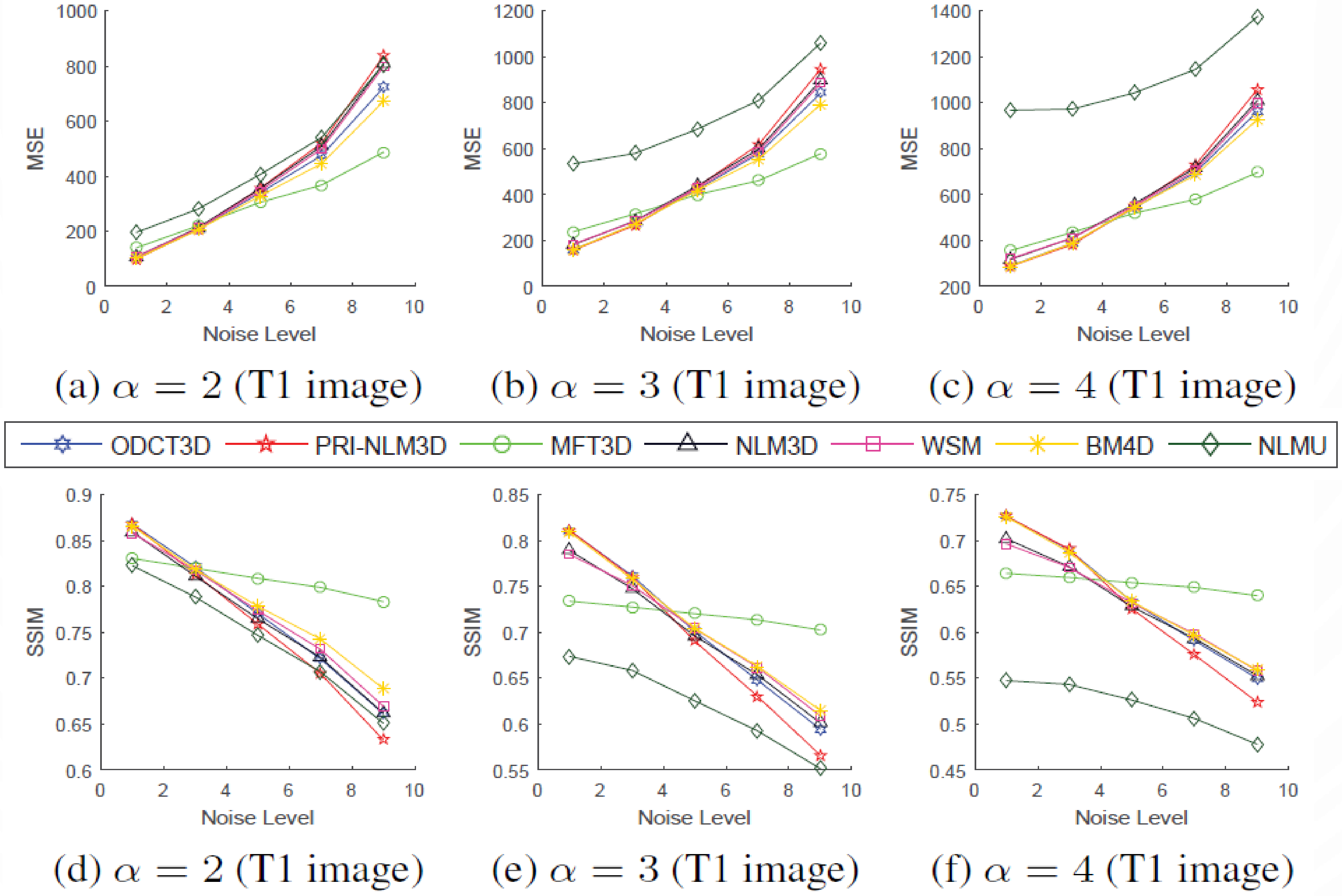
- **Dataset:** BrainWeb (T1, T2, PD) and CIMES (T2)
- **Competitors:**
  - *3D Denoising method + spline interpolation*: NLM3D (non-local means), WSM (wavelets), ODCT3D (cosine transform), PRI-NLM3D, BD4M (local correlation)
  - *3D upsampling method effective against noise:* NLMU (non-local means upsampling):
- **LR images generation:** 3D Gaussian filter + cubic spline interpolation
- **Evaluation:** MSE (lower is better) and SSIM (higher is better)
- **Parameters:** $\alpha \in \{2,2.5,3,3.5,4\},\ H = 150$

PARAMETER SELECTION

- We define $BinSize$ as the length of the sides (the same) of the parallelepiped which defines the bin, measured in pixels in the LR image

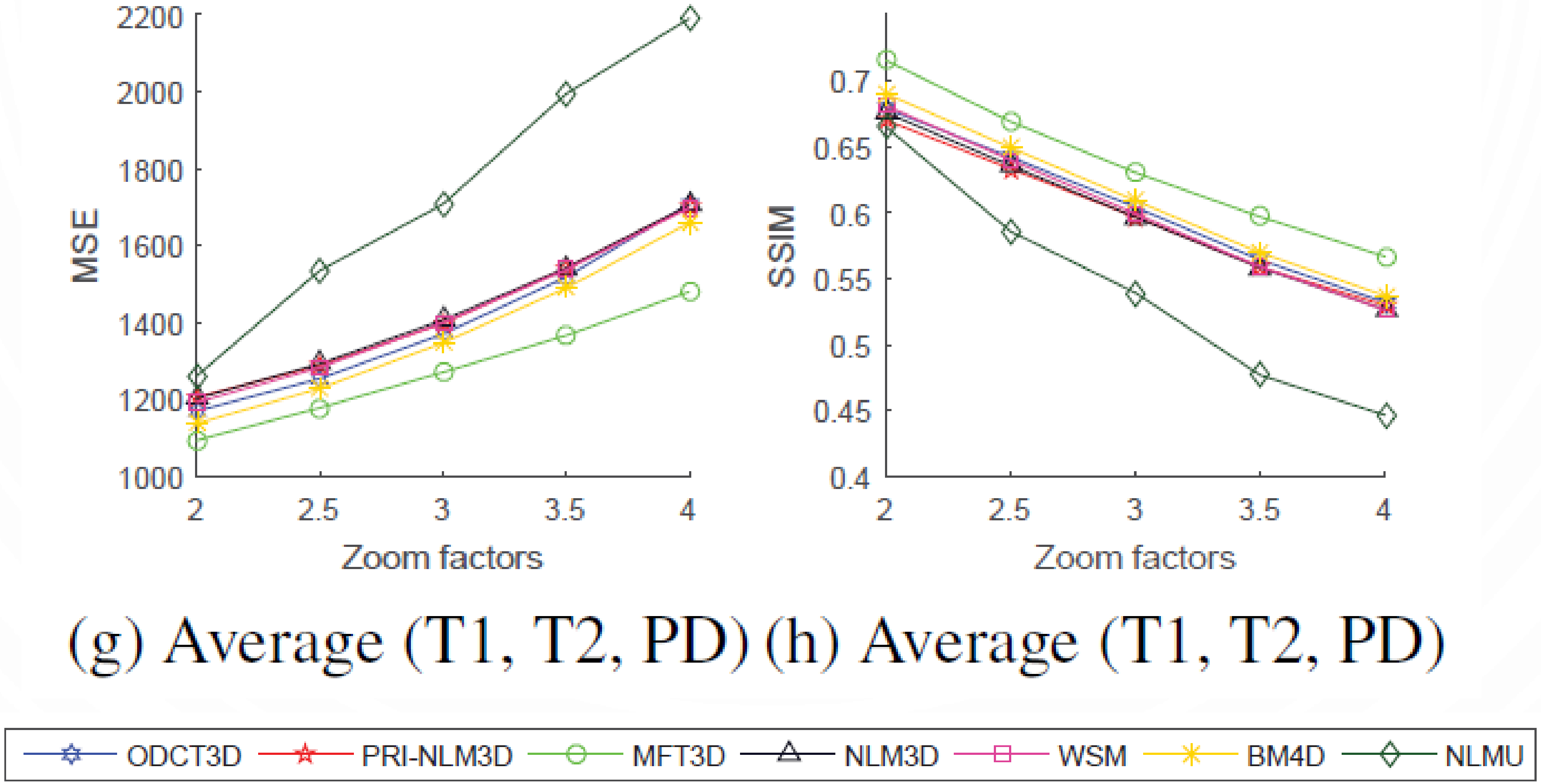
	$\alpha = 2$	$\alpha = 2.5$	$\alpha = 3$	$\alpha = 3.5$	$\alpha = 4$
T1	1.6	2.55	3.15	3.6	4.1
T2	1.6	2.2	2.75	3.2	3.75
PD	1.6	2.4	2.95	3.4	3.95

RESULTS



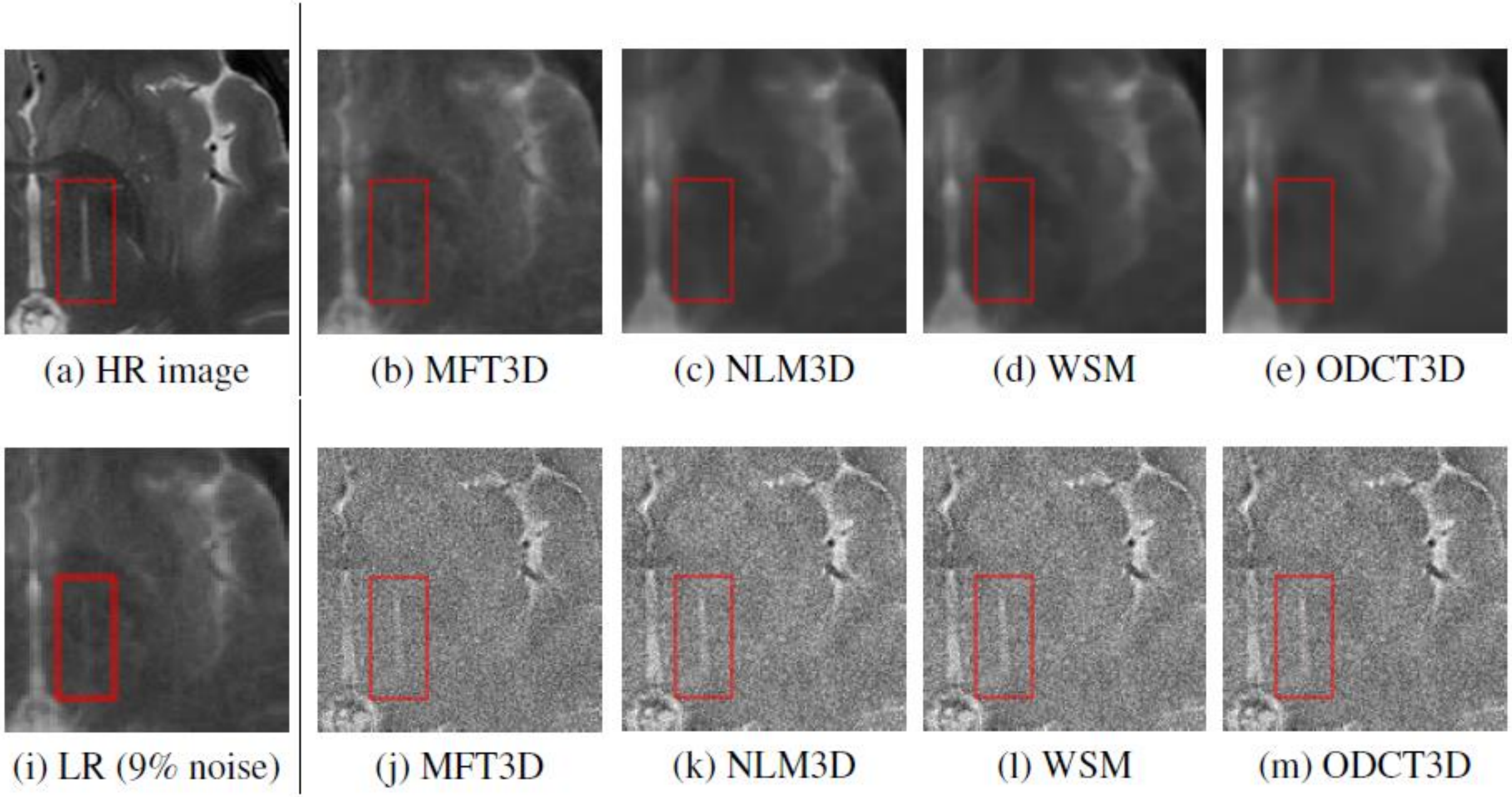
MSE
Noise Level
(a) $\alpha = 2$ (T1 image)
MSE
Noise Level
(b) $\alpha = 3$ (T1 image)
MSE
Noise Level
(c) $\alpha = 4$ (T1 image)
ODCT3D
PRI-NLM3D
MFT3D
NLM3D
WSM
BM4D
NLMU
SSIM
Noise Level
(d) $\alpha = 2$ (T1 image)
SSIM
Noise Level
(e) $\alpha = 3$ (T1 image)
SSIM
Noise Level
(f) $\alpha = 4$ (T1 image)

RESULTS

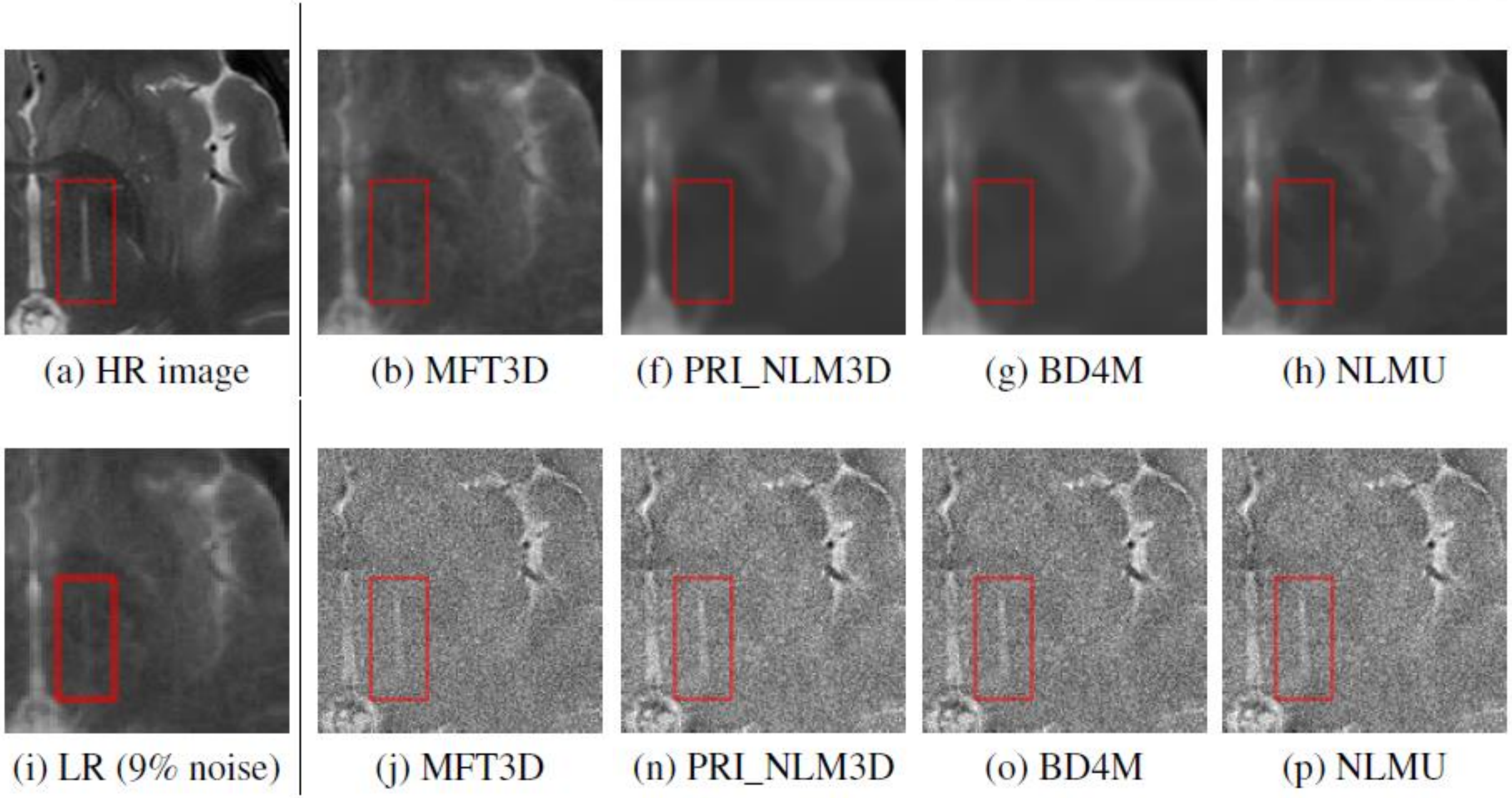


2200
2000
1800
1600
1400
1200
1000
MSE
2
2.5
3
3.5
4
Zoom factors
0.7
0.65
0.6
0.55
0.5
0.45
0.4
SSIM
2
2.5
3
3.5
4
Zoom factors
(g) Average (T1, T2, PD) (h) Average (T1, T2, PD)
ODCT3D
PRI-NLM3D
MFT3D
NLM3D
WSM
BM4D
NLMU

RESULTS


(a) HR image
(b) MFT3D
(c) NLM3D
(d) WSM
(e) ODCT3D
(i) LR (9% noise)
(j) MFT3D
(k) NLM3D
(l) WSM
(m) ODCT3D

RESULTS

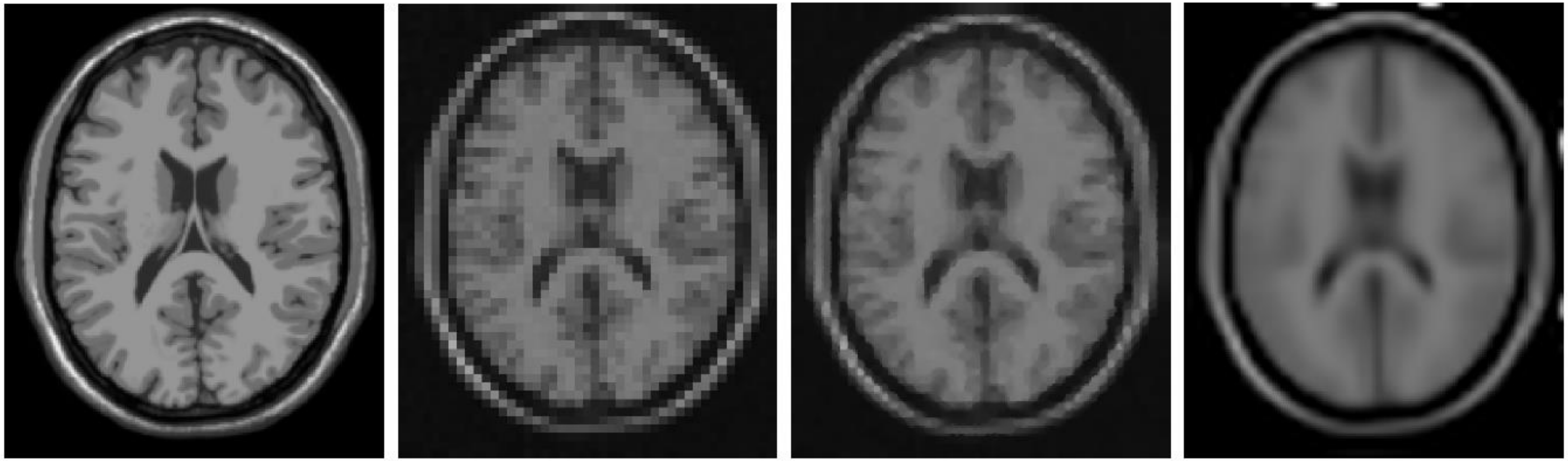


(a) HR image (b) MFT3D (f) PRI_NLM3D (g) BD4M (h) NLMU

(i) LR (9% noise) (j) MFT3D (n) PRI_NLM3D (o) BD4M (p) NLMU

RESULTS

- Hallucinations are avoided: MFT3D only takes into account the voxels which are neighboring to the estimated one



(a) HR (b) LR (c) MFT3D (d) BD4M

CONCLUSIONS

- Method for **3D MR image super-resolution and noise removal simultaneously**
- Based on a two-step **mid-sample median** filters
- **Convergence** is demonstrated and the noise distribution in the image is not relevant
- Great results with integer and fractional zooms and heavy noise
  - **Finer details are preserved**
  - **Over-smoothing and hallucinations are avoided**
- Integration of the median filter transform into SR deep networks

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