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Synthesized 7T MRI from 3T MRI via deep learning in spatial and wavelet domains

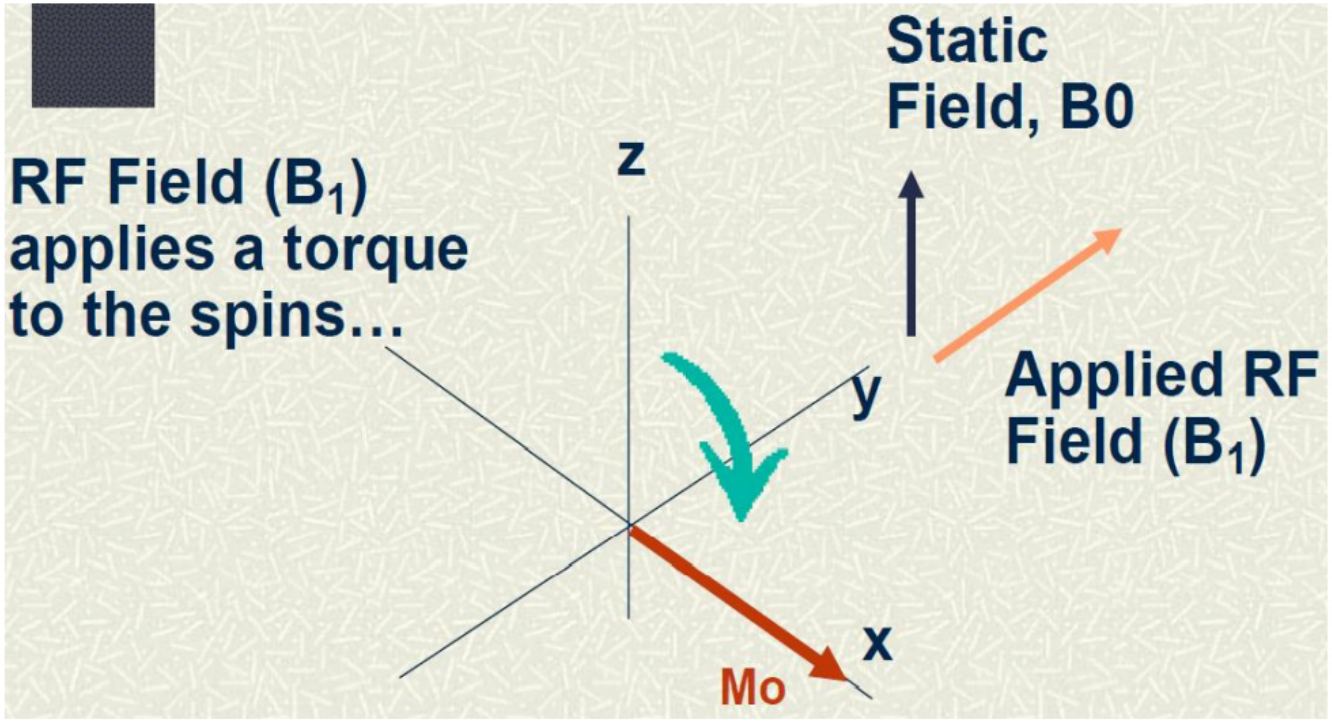
2021.02.24

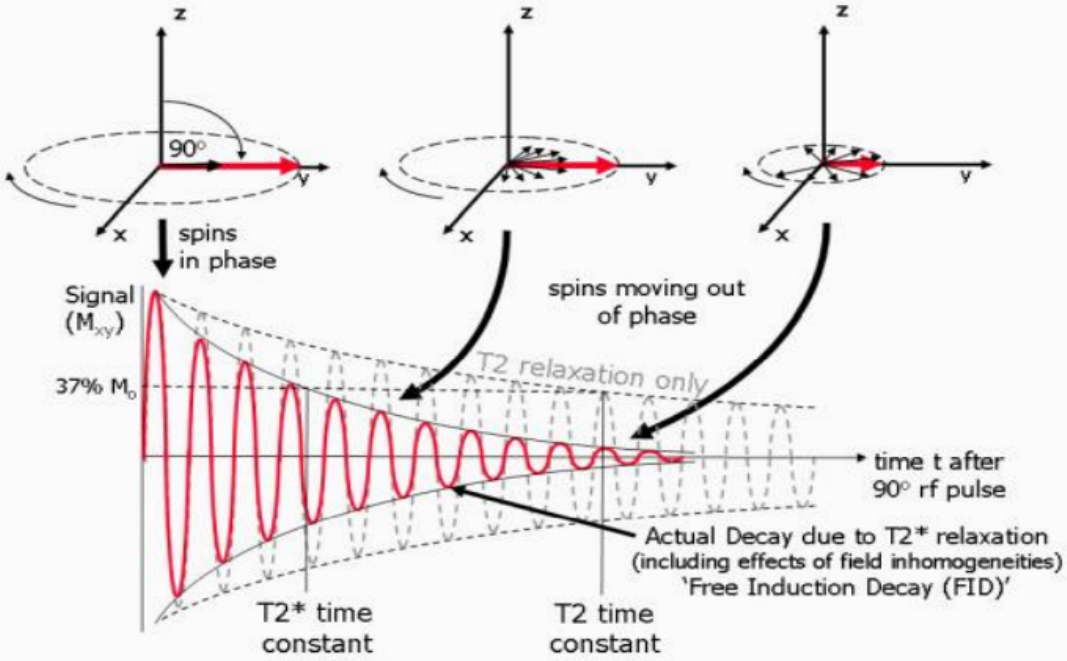
TAIL lab 정현재

Translation
Artificial
Intelligence
Lab

Contents

Magnetic Field Strength





01 Introduction - Background

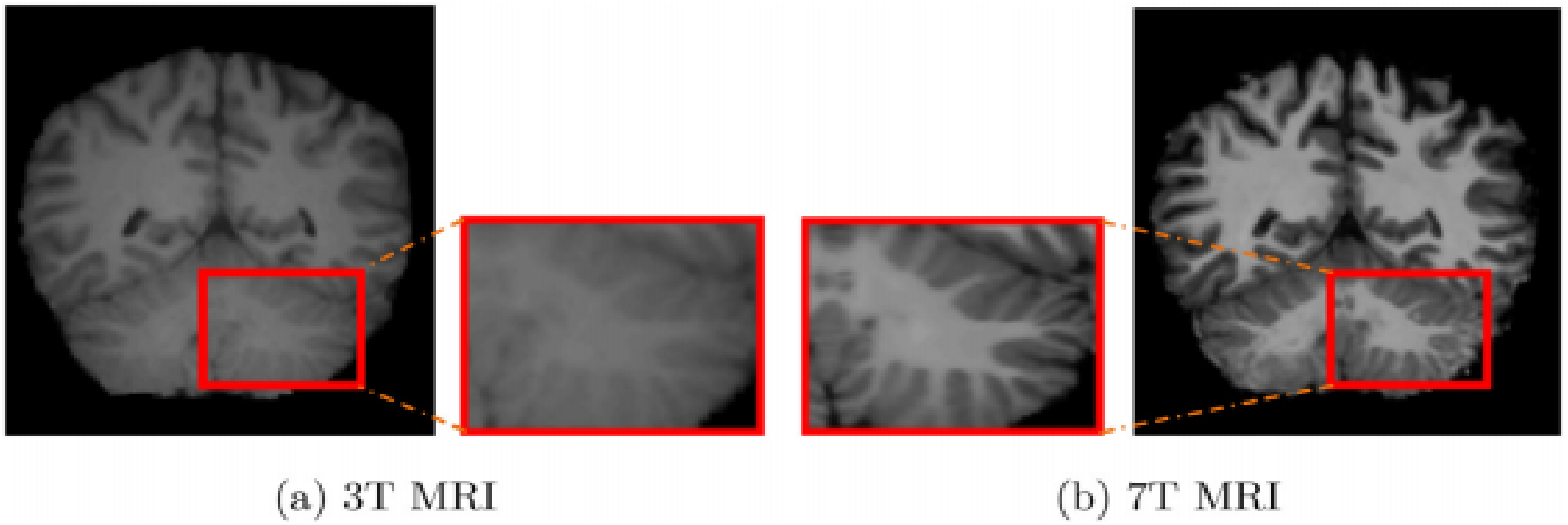


Fig. 1. 3T and 7T MRI.

- Compared to routine 3T MRI, 7T MRI provides images with higher resolution and high signal-to-noise ratio
- However, 7T MRI scanners are often cost prohibitive and hence not always accessible in the clinics.

01 Introduction - Contribution

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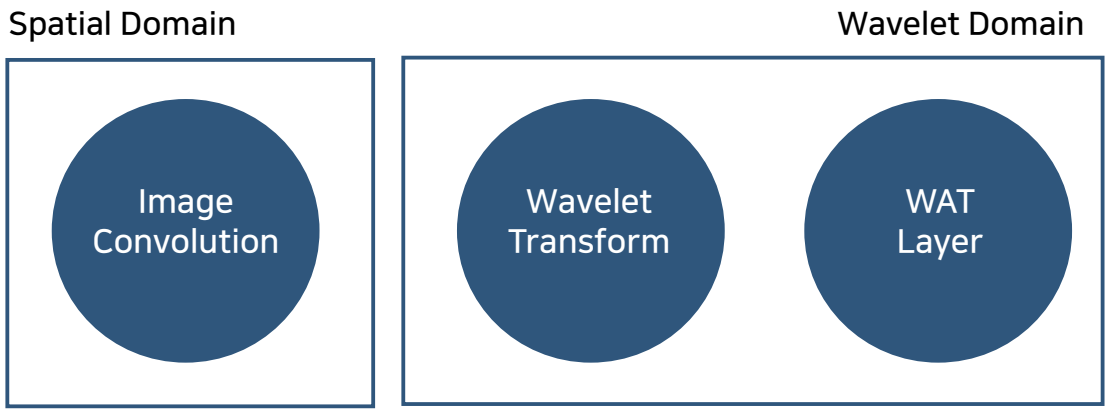
- A novel method for 7T image synthesis by leveraging complementary information of **both spatial and wavelet domains.**



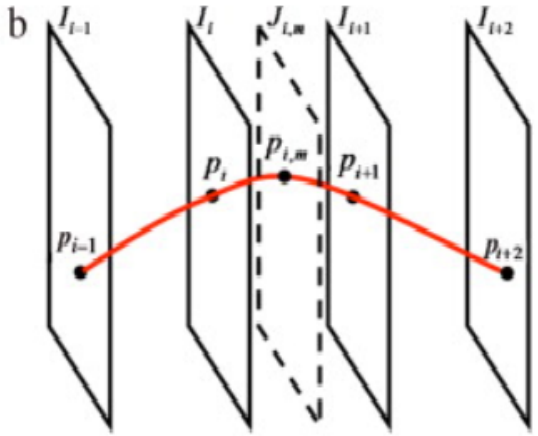
- Provide an efficient way to incorporate image priors in **deep learning** to achieve superior image synthesis performance.
  - Prior Research : Linear regression, Sparse Learning, RF (hand-crafted feature)

- A flexible and parameter-efficient WAT layer that can be embedded into a neural network to facilitate effective reconstruction with consideration of multiple frequency components.

Prior Image Synthesis Methods

<Interpolation-based>

methods are based on linear or non-linear interpola-tors, such as nearest-neighbor and bilinear. Although simple and fast, these methods. blur sharp edges and fine details
(Kim et al., 2010; Tam et al., 2010)

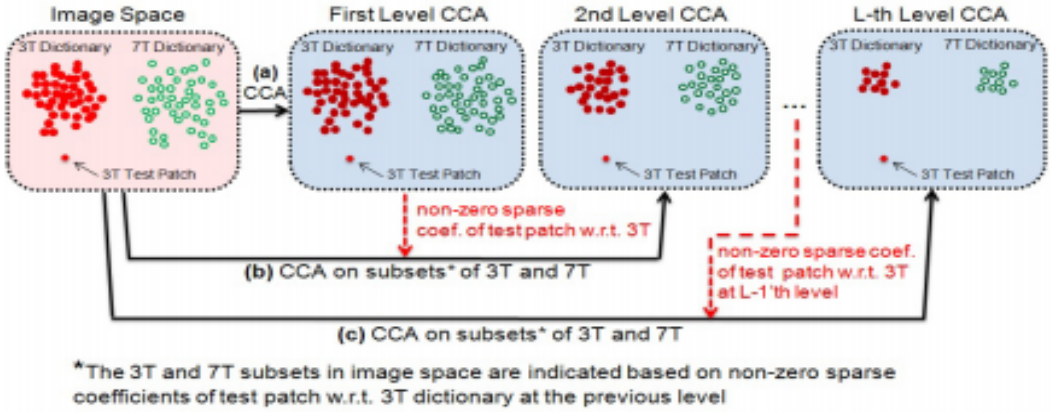


$$f(x)=\frac{d_2}{d_1+d_2}f(x_1)+\frac{d_1}{d_1+d_2}f(x_2)$$

$$P=q(\beta A+\alpha B)+p(\beta D+\alpha C)$$
$$=q\beta A+q\alpha B+p\beta D+p\alpha C$$

<Learning-based>

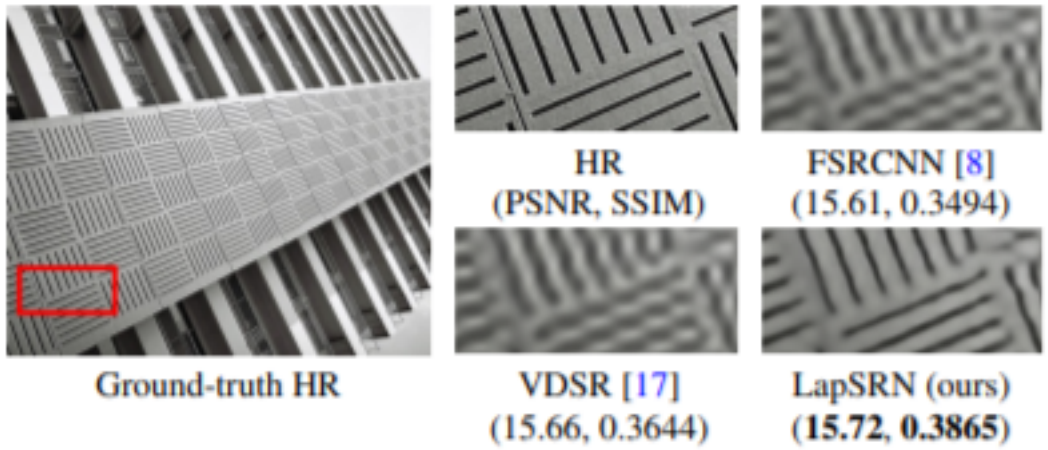
Such as sparse learning, Random Forest (LR to HR images) This form of sparse learning has also been employed in together with multi-level canonical cor-relation analysis (MCCA)
(Bahrami et al. 2017 MCCA)



Prior Image Synthesis Methods + Loss

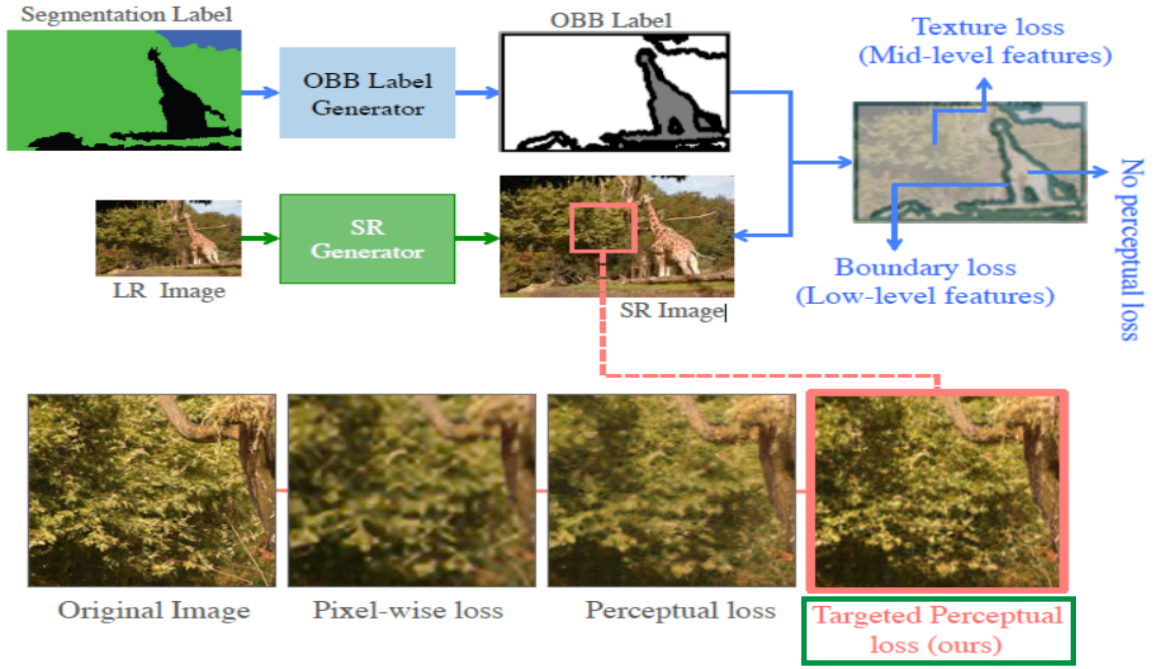
<LR-to-HR Mapping>

Multi-level canonical correlation analysis(MCCA), Residual learning, Laplacian pyramid network, Dense connection, Information distillation blocks
- high performance networks



<Learning-based>

MSE (Mean Square Error Loss) -> Perceptual loss (Blur clear, high quality reconstruction) -> Consider semantice information (SISR) and Other developed Losses



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Proposed Framework

- Given a 3T image I, our goal is to synthesize a 7T image $\hat{O}$ that is as similar as possible to the ground-truth 7T image O.

$$\hat{O} = R_\theta(I), = \quad \hat{O} = R_\theta(I|\{W_l\}),$$

< Proposed Framework >

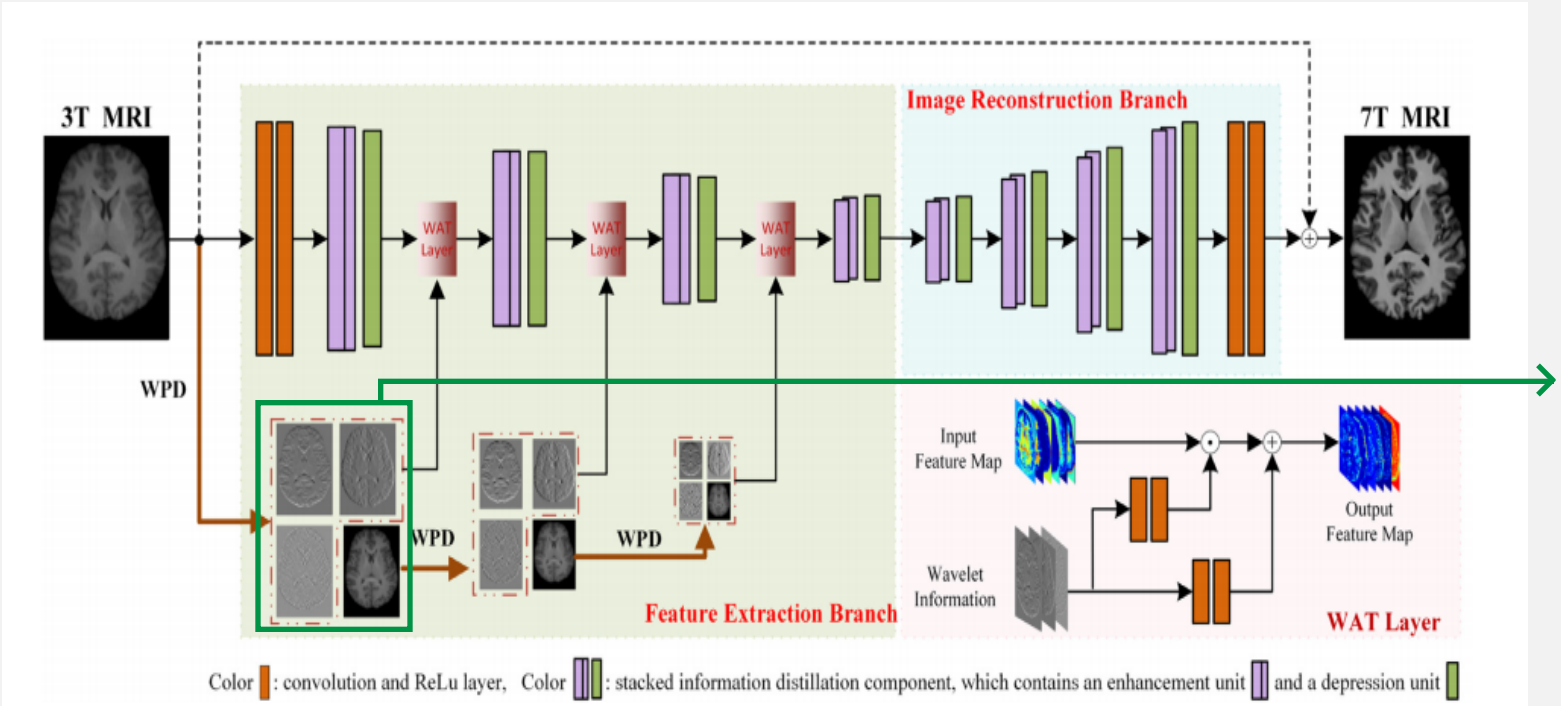
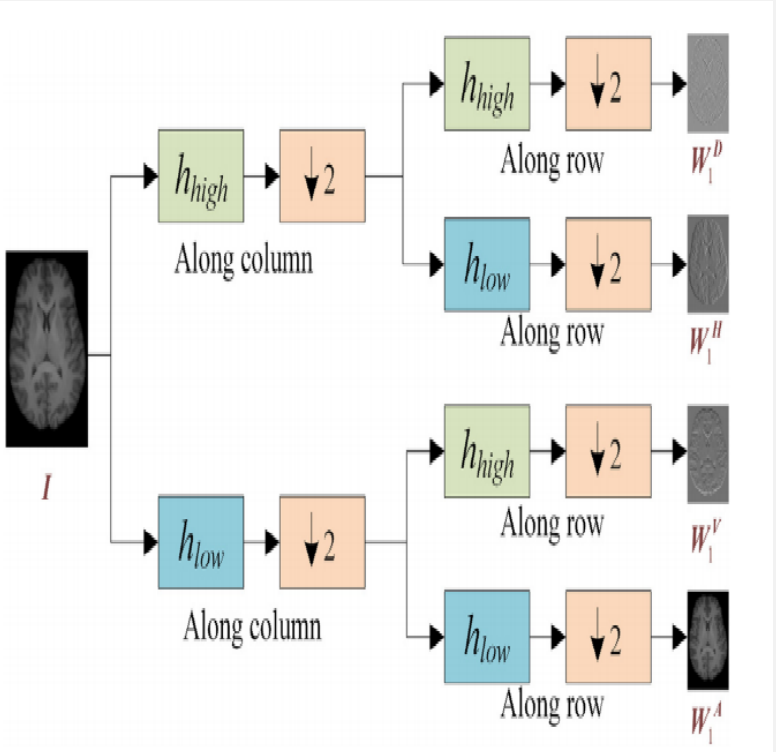


Fig. 2. WATNet predicts the 7T image using a 3T image and its wavelet coefficients.

< Wavelet Transform >



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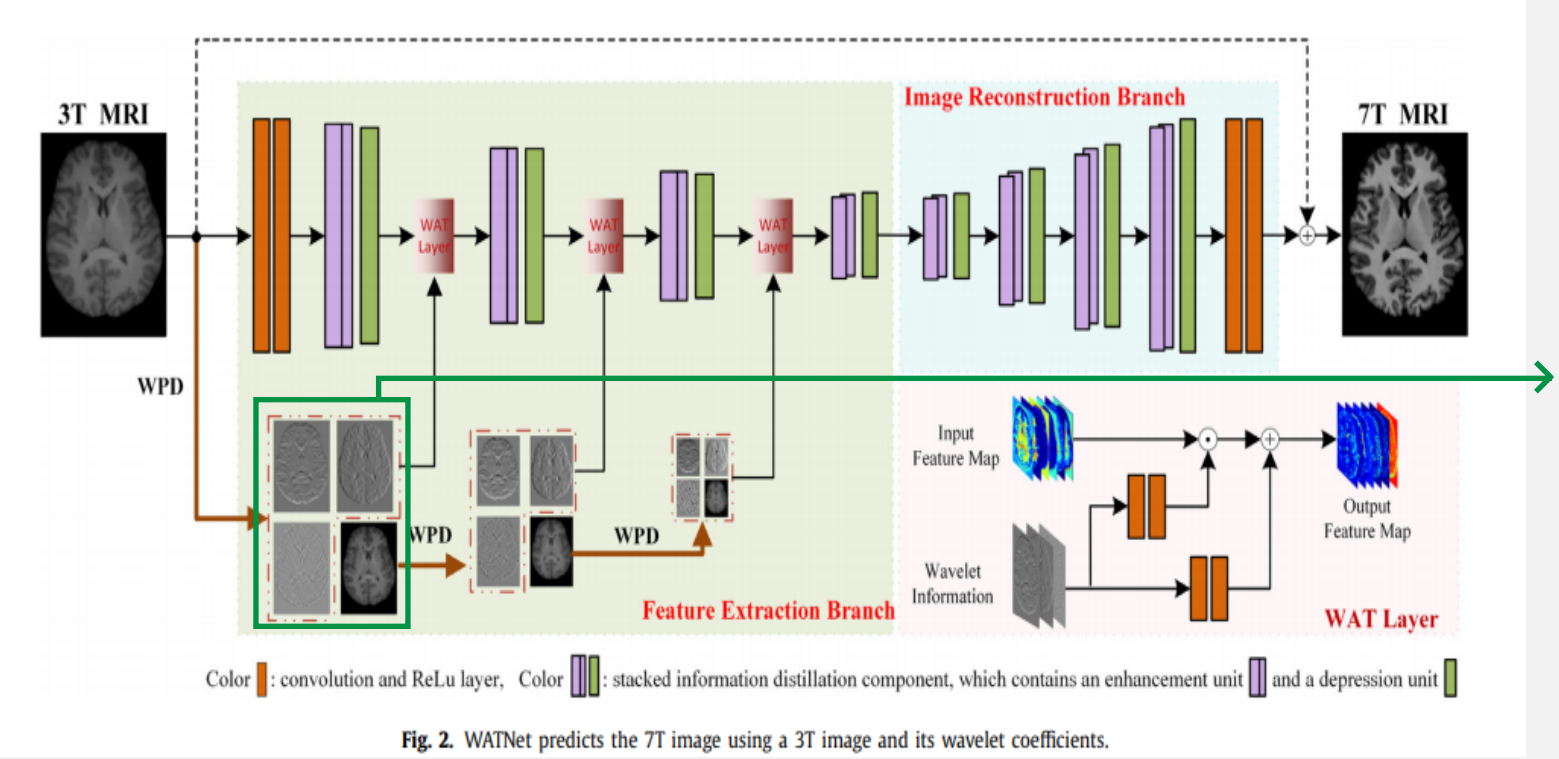

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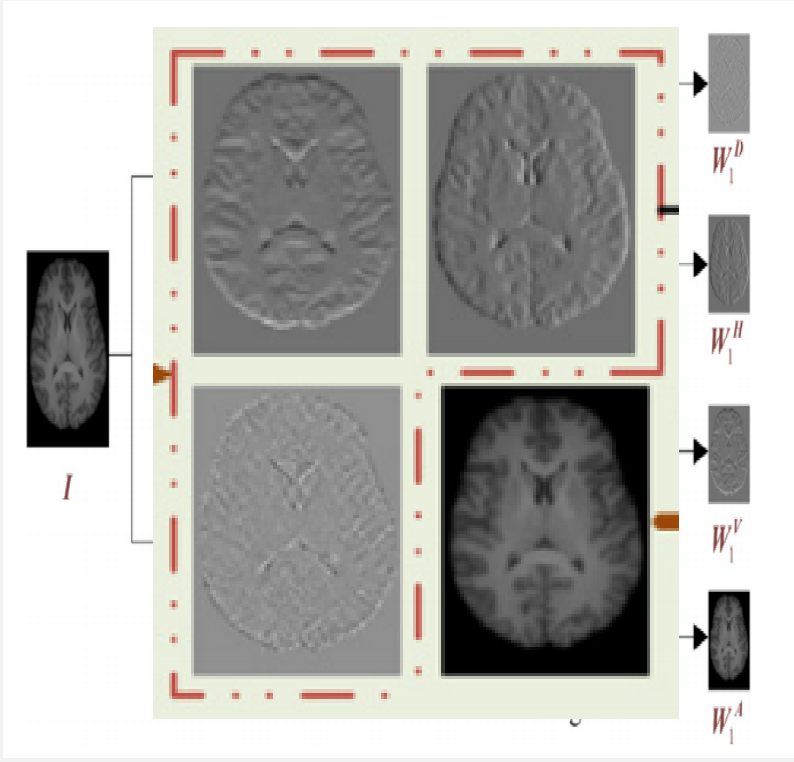

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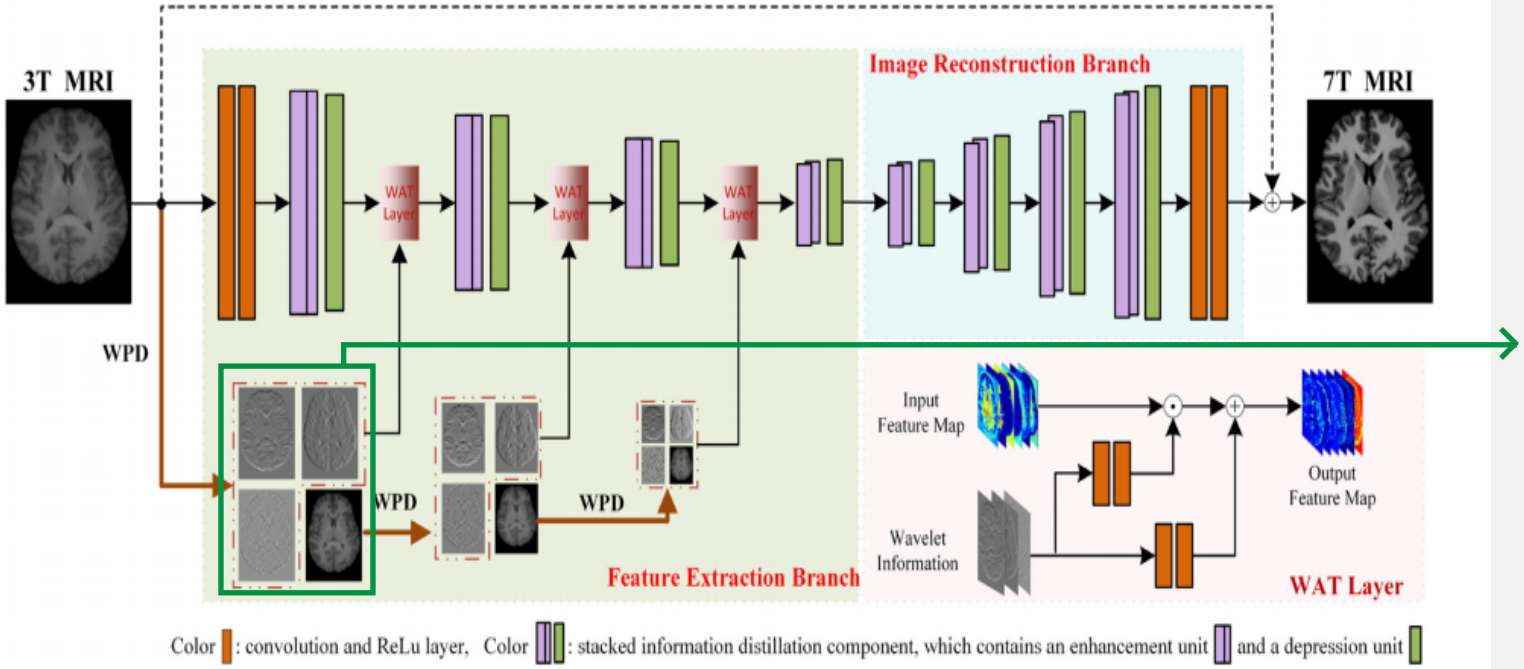

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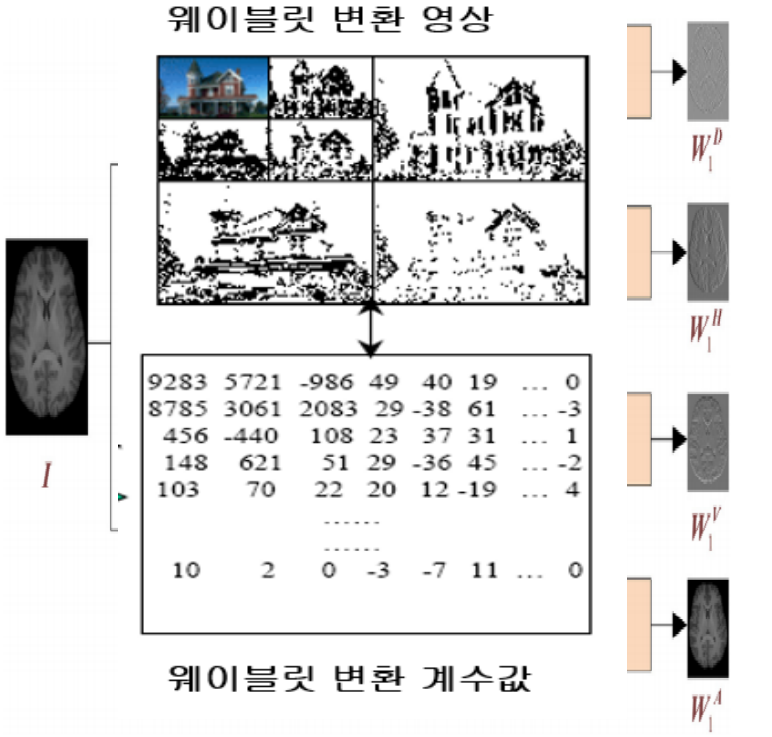

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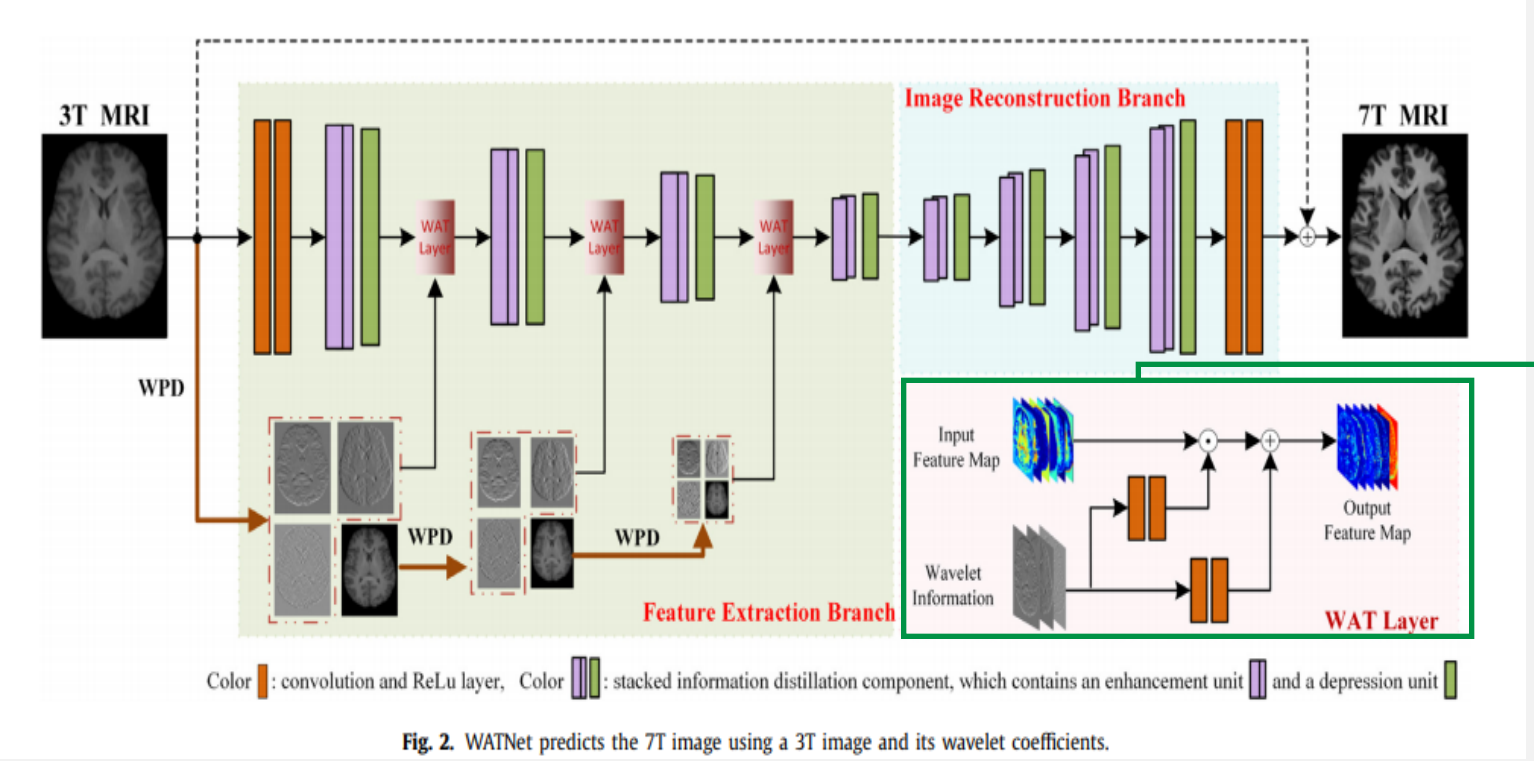

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< WAT Layer >

$$\gamma_l = U(W_l),$$

$$\beta_l = V(W_l),$$

$$\mathrm{WAT}(F|\gamma_l, \beta_l) = \gamma_l \odot F + \beta_l,$$

Feature Extraction Branch

- 2-layered Conv layer - 1개, information distillation blocks - 4개, WAT layers - 3개

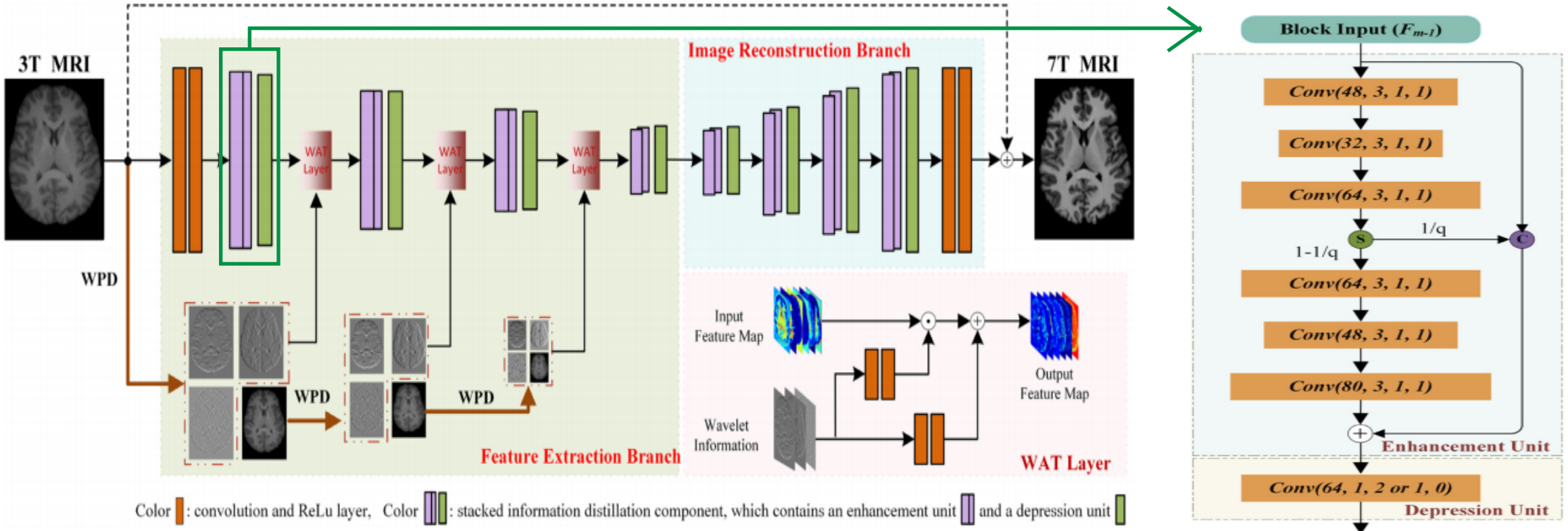
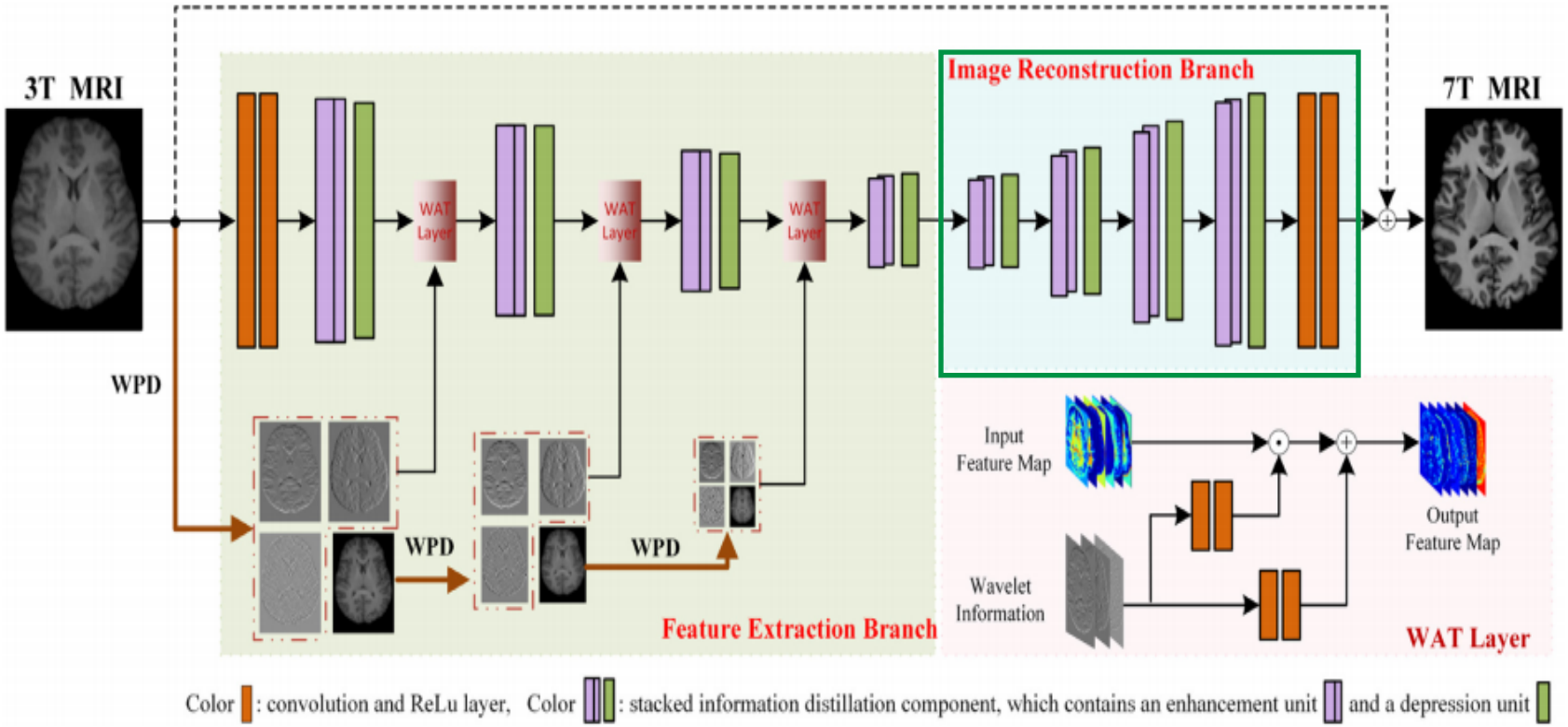


Fig. 2. WATNet predicts the 7T image using a 3T image and its wavelet coefficients.

Image reconstruction Branch, oss function

- the wavelet modulated feature maps and generates the residual image that is added to the 3T image for generating the 7T image.



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< Loss Function >

Mean Absolute Error

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n}.$$ [1]

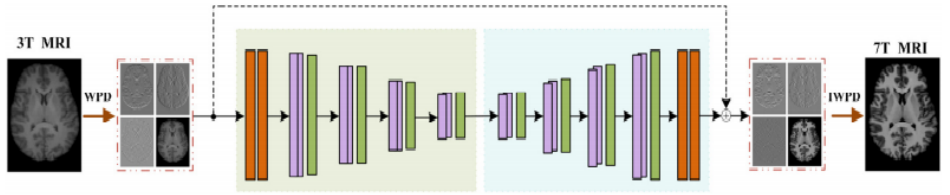
$$L^{MAE} = \sum_{i}^{N} \| O^i - \hat{O}^i \|_1.$$

Experiments

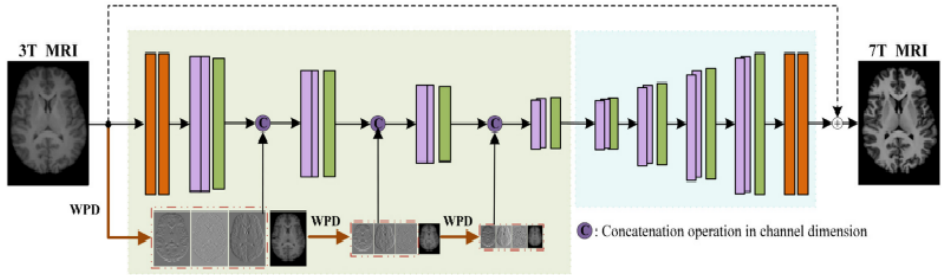
- Compared WATNet with several state-of-the-art 7T image synthesis methods
- we used 15 pairs of 3T and 7T brain images in our experiments. For 3T MRI, T1 images with 224 coronal slices were acquired using a Siemens Magnetom Trio 3T scanner, with voxel size 1 × 1 × 1 mm3, TR = 1990 ms, and TE = 2.16 ms

Table 1
Quantitative comparison of different methods utilizing wavelet information. Mean PSNR and SSIM values of leave-one-out cross validation are shown.

	Wavelet prediction	Feature concatenation	WATNet
PSNR	27.43	27.83	**28.27**
SSIM	0.8479	0.8717	**0.8782**



< Wavelet prediction >



<Feature concatenation>

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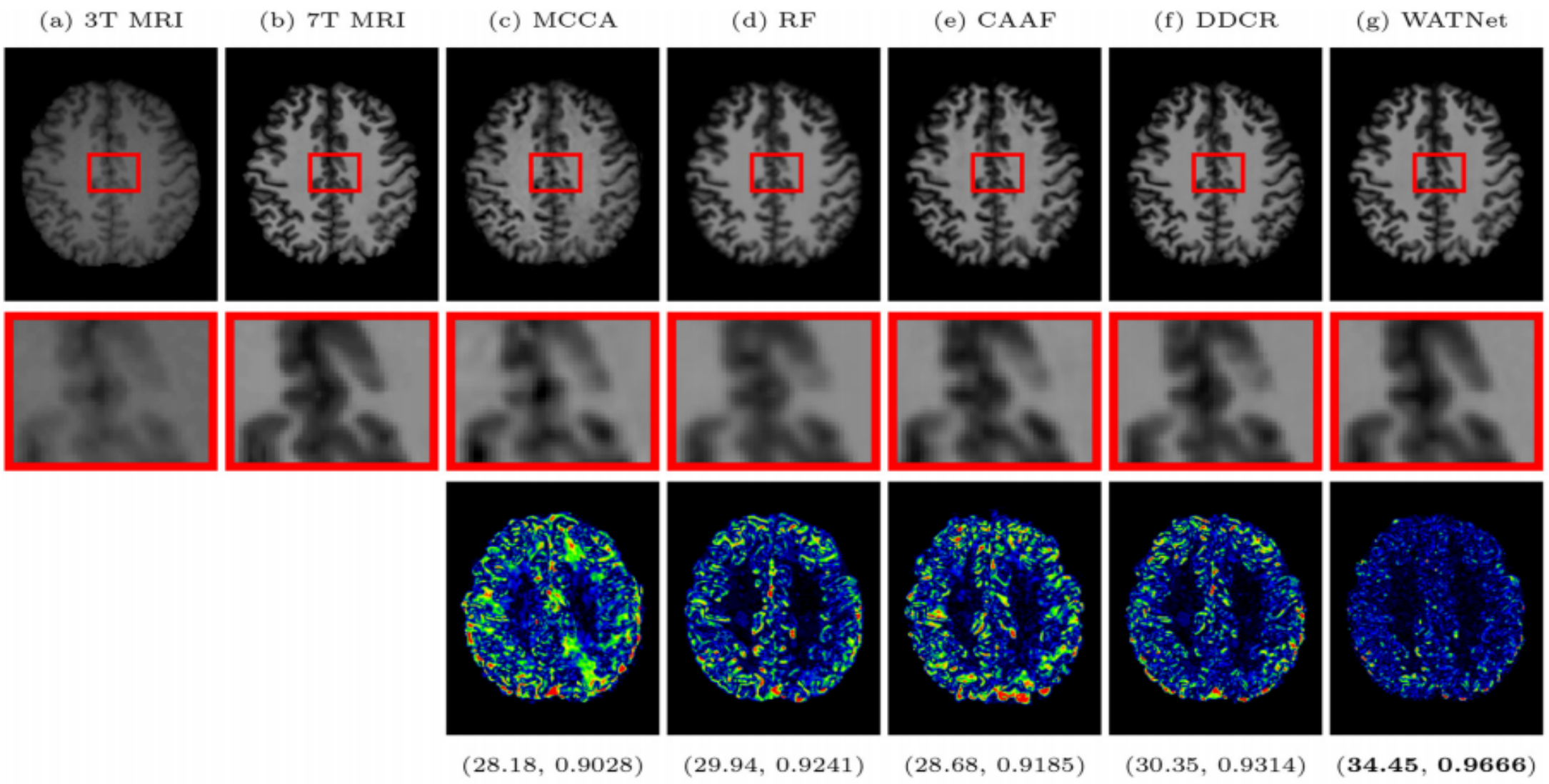
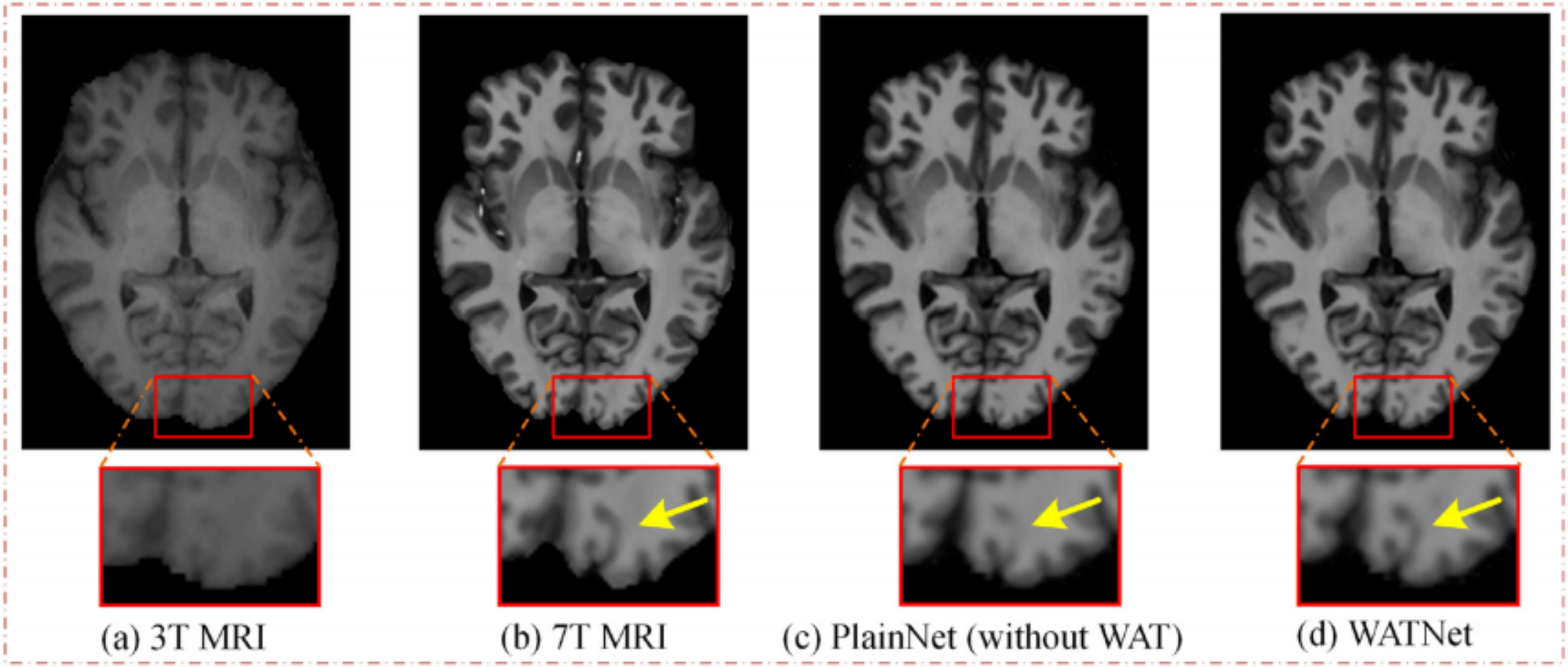
Table 2
Comparison of average ratings of the original 3T images, the real 7T images, and the synthesized 7T images given by WATNet.

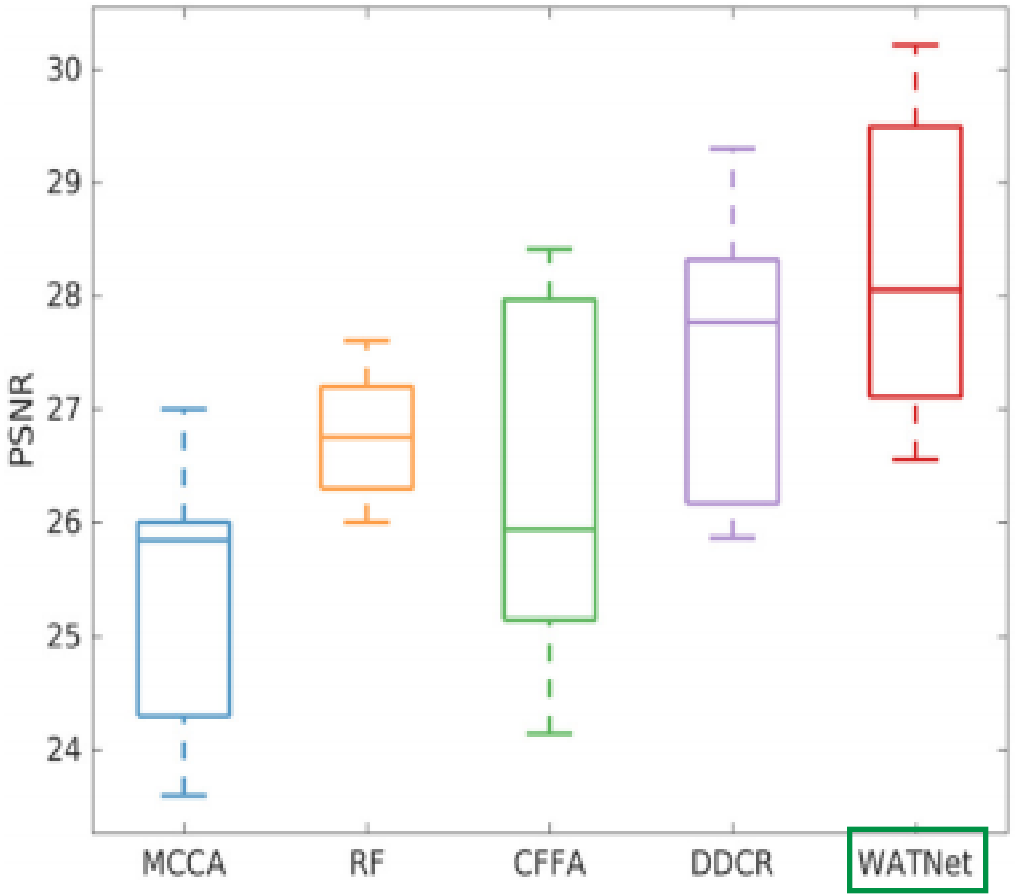
	Ratings (mean ± standard deviation)			*p*-value w.r.t. WATNet	
	3T MRI	WATNet	7T MRI	3T MRI	7T MRI
Quality	2.9 ± 0.3	4.6 ± 0.489	4.9 ± 0.3	2.65×10^{-5}	0.029
Contrast	2.75 ± 0.43	4.8 ± 0.4	5 ± 0.0	1.8×10^{-5}	0.023
Outline	1.8 ± 0.4	2.75 ± 0.43	3 ± 0.0	1.7×10^{-5}	0.0126

04 Methods and Experiments

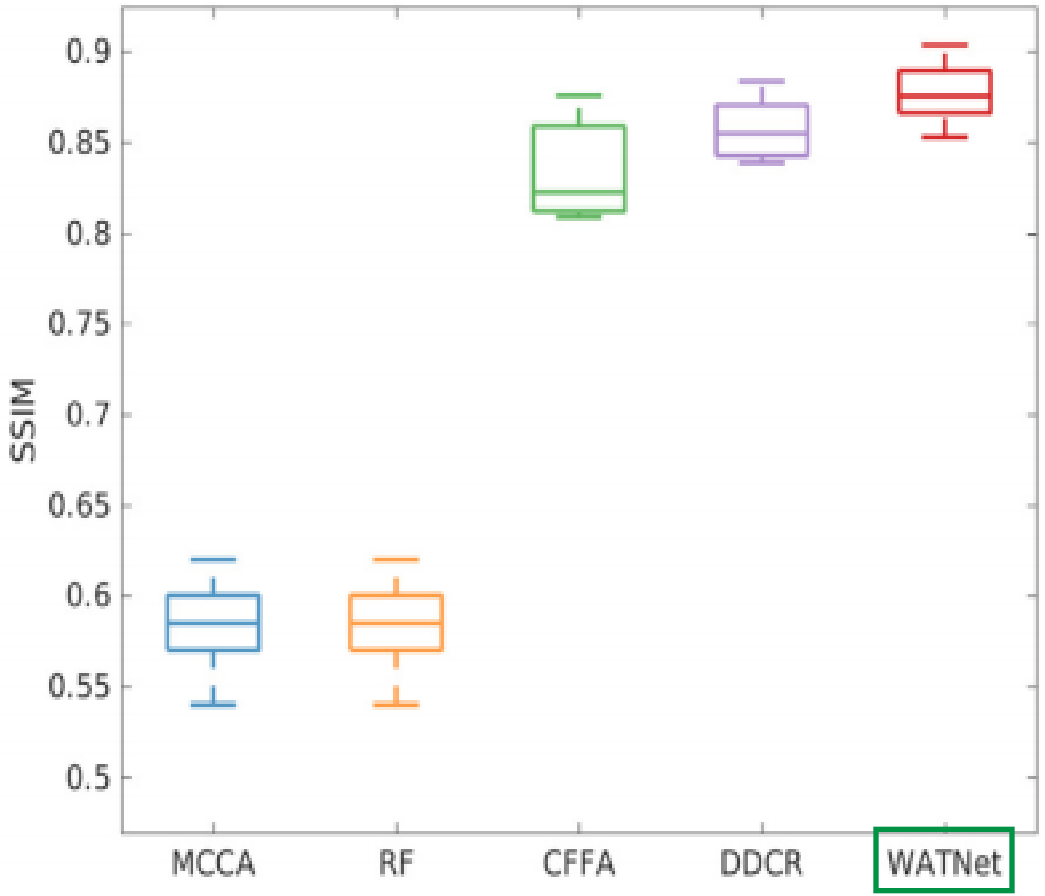



(a) 3T MRI
(b) 7T MRI
(c) PlainNet (without WAT)
(d) WATNet

04 Methods and Experiments



< PSNR >



< SSIM >

05 Conclusion

- Efficient deep learning method for 7T image synthesis by harnessing information from both spatial and wavelet domains
- Capable of synthesizing 7T images with better tissue contrast and greater anatomical detail
- Both qualitative and quantitative results demonstrate that WATNet performs favorably against the existing 7T image synthesis methods.
- Handle more general medical image synthesis tasks, such as MRI to CT and T2 images from T1 images.