MLSP Project

Synthesizing 7T MRI from 3T MRI using Wavelet-based CNN

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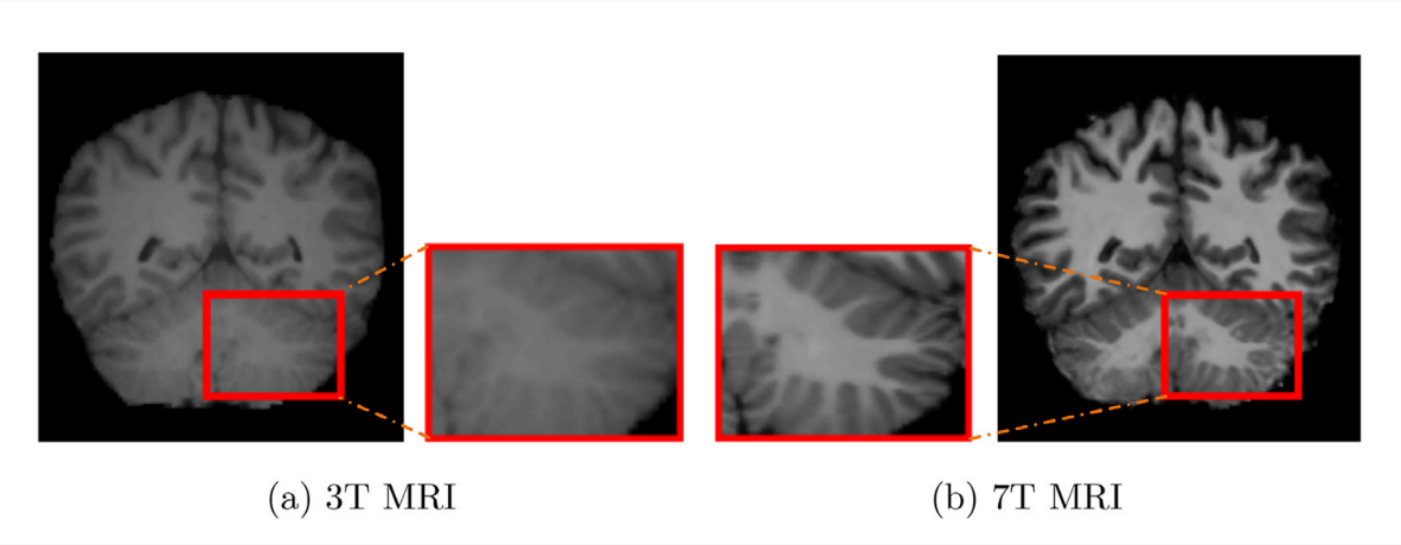
Motivation.

- Create high-resolution 7T MRI from low-resolution 3T MRI



Comparison of 3T MRI and 7T MRI

Goal.

- Compare WATNet with a basic CNN architecture

3 steps.

1. Normalise the 7T images between $[0, 1]$ using the min-max normalisation:

$$I_{\text{norm}} = \frac{I - \min(I)}{\max(I) - \min(I)}.$$

2. Artificially generate the 3T images from the 7T images.

3. Perform histogram matching on both the 3T and 7T images using one 7T reference image.

The BasicCNN model consists of 4 stacks of 2D convolutional layer, followed by batch normalization and activation layer.

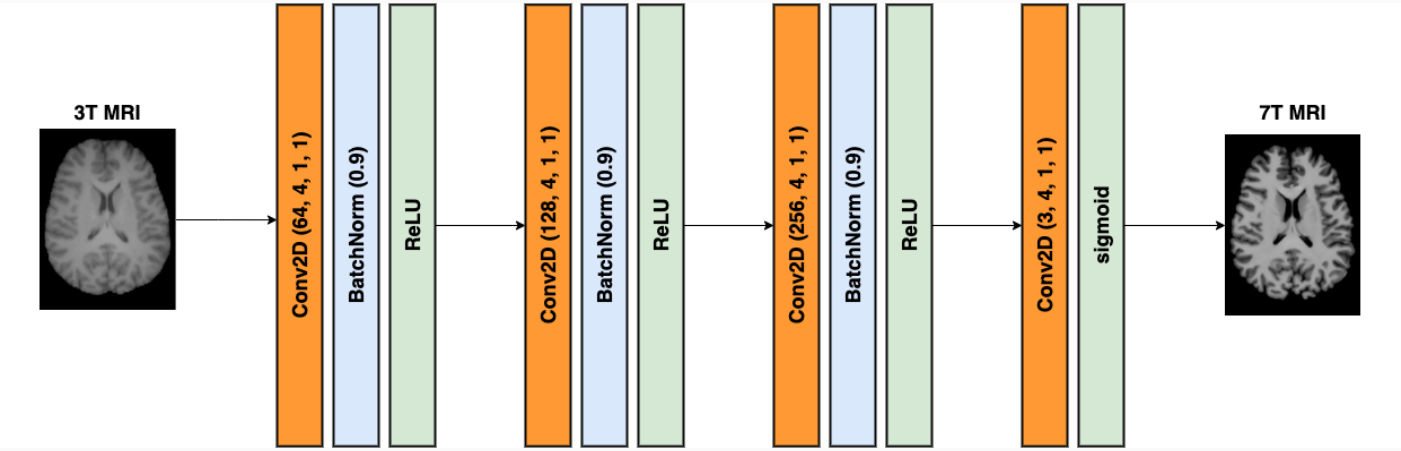
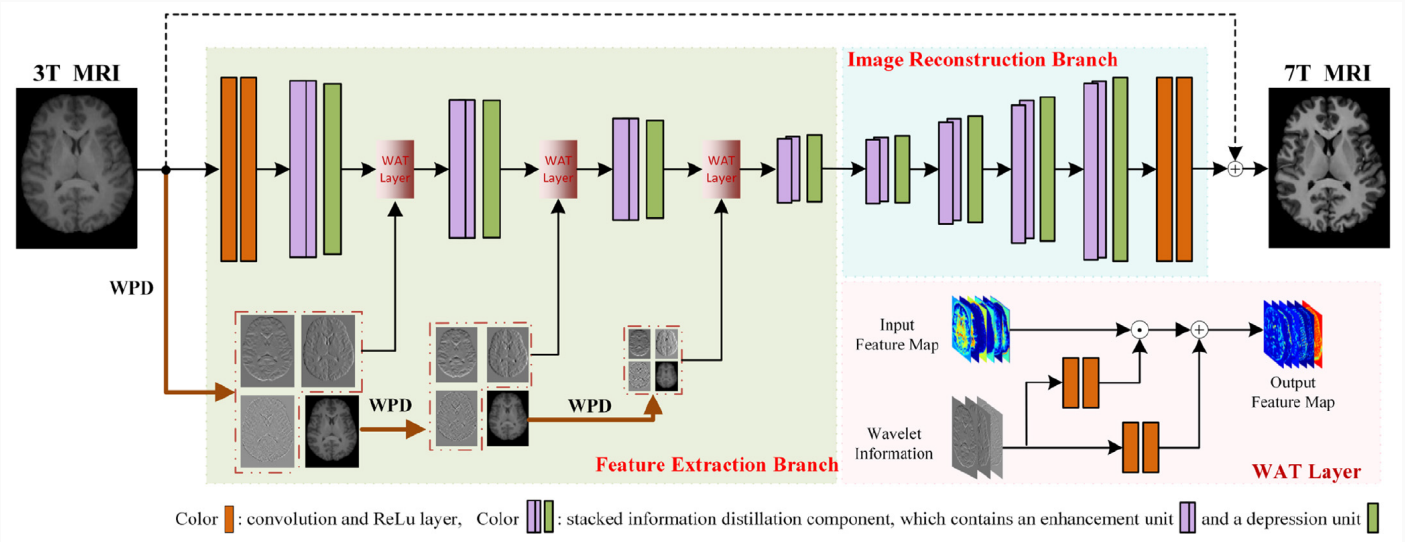
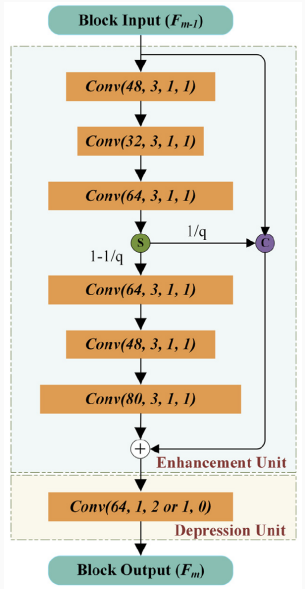


Figure: Architecture of the BasicCNN model.

- Conv2D(F, K, S, P) denotes a 2D convolutional layer with F filters of size K, a stride of S and a padding size P
- The model has a total number of parameters: 672 963
- The first 3 layers have respectively 64, 128, and 256 filters



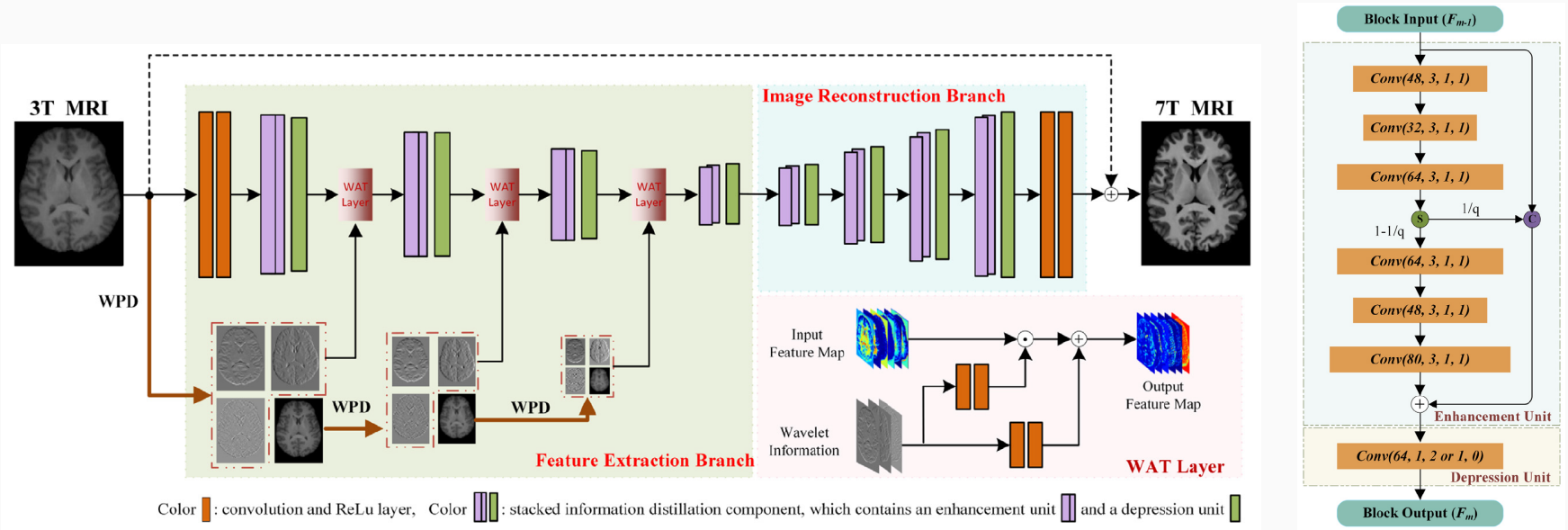
(a) WATNet



(b) DBlock

Feature extraction.

- DBlocks: suppressing unnecessary information
- WAT layers: refining feature maps by incorporating high-frequency details



(a) WATNet (b) DBlock

Image reconstruction.

- Construct residual image from the output of the feature extraction branch
- Last layers: Conv2D+ReLU and Conv2D+*tanh*
- *tanh* is used for faster convergence

Experimental Setting

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Dataset.

- 10 images of real 7T MRI and corresponding artificially generated 3T MRI

Loss function. MAE

- No need for MSE which penalizes large errors

Parameters setting.

- 10 epochs
- Linear learning rate decay: $0.001 \rightarrow 0.0001$ (decay steps of 10)
- Adam optimizer
- HeNormal kernel initializer: draws from a gaussian with variance inversely proportional to the input layer size

Performance metrics.

- Mean Absolute Error (MAE)
- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index Measure (SSIM)

	Worst case	Basic CNN	WATNet
	(mean ± standard deviation)		
MAE	**0.012** ± 0.004	0.014 ± 0.004	**0.012** ± 0.004
PSNR	28.759 ± 2.887	28.028 ± 2.020	**28.890** ± 2.882
SSIM	0.949 ± 0.017	**0.953** ± 0.016	0.949 ± 0.018

- WATNet slightly outperforms the BasicCNN in terms of MAE and PSNR
- Despite that WATNet incorporates high-frequency details from the wavelet transform to reconstruct the 7T images, this latter was outperformed by the BasicCNN in terms SSIM

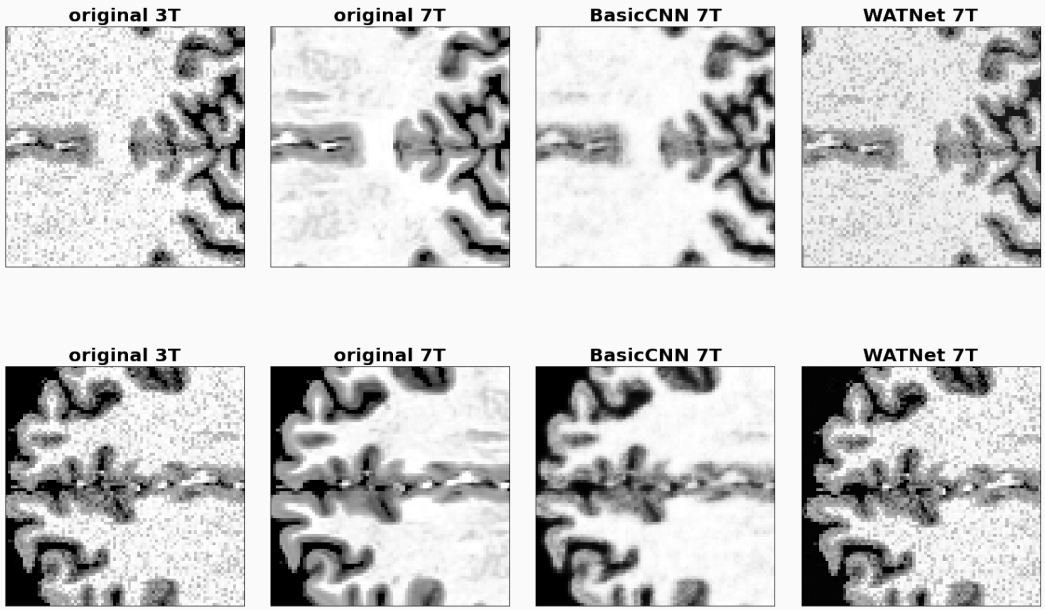

Figure: Comparison of 2 patches from the synthesized 7T MRI images.

- BasicCNN removes the noise and smoothes out the borders better than WATNet
- No large difference between original 3T MRI and the WATNet-synthesized 7T MRI synthesized
- WATNet performance inconsistent with the one in the original paper

- WATnet did not result in the same performance as described in the paper

  $\rightarrow$ The added noise does not incorporate any prior on the structure of the brain tissues

- Lack of accurate details necessary for results reproducibility: values of the hyper-parameters, last Conv2D details

- BasicCNN performs better: the WATNet is a complex model that requires more data to train

- Applying a mask to inferred 7T images before computing the loss to focus on the brain voxels only (not the dark background)
- Fine-tuning hyper-parameters for optimal performance
- Using WATnet in an adversarial setting with a PatchGAN discriminator that penalizes structure at the scale of local image patches
- Data augmentation (flipping, random scaling and/or rotation, etc.)

Thank you for your attention!

References I

[1] L. Qu, Y. Zhang, S. Wang, P.-T. Yap, and D. Shen.
Synthesized 7t mri from 3t mri via deep learning in spatial and wavelet domains.
Medical Image Analysis, 62:101663, 2020.

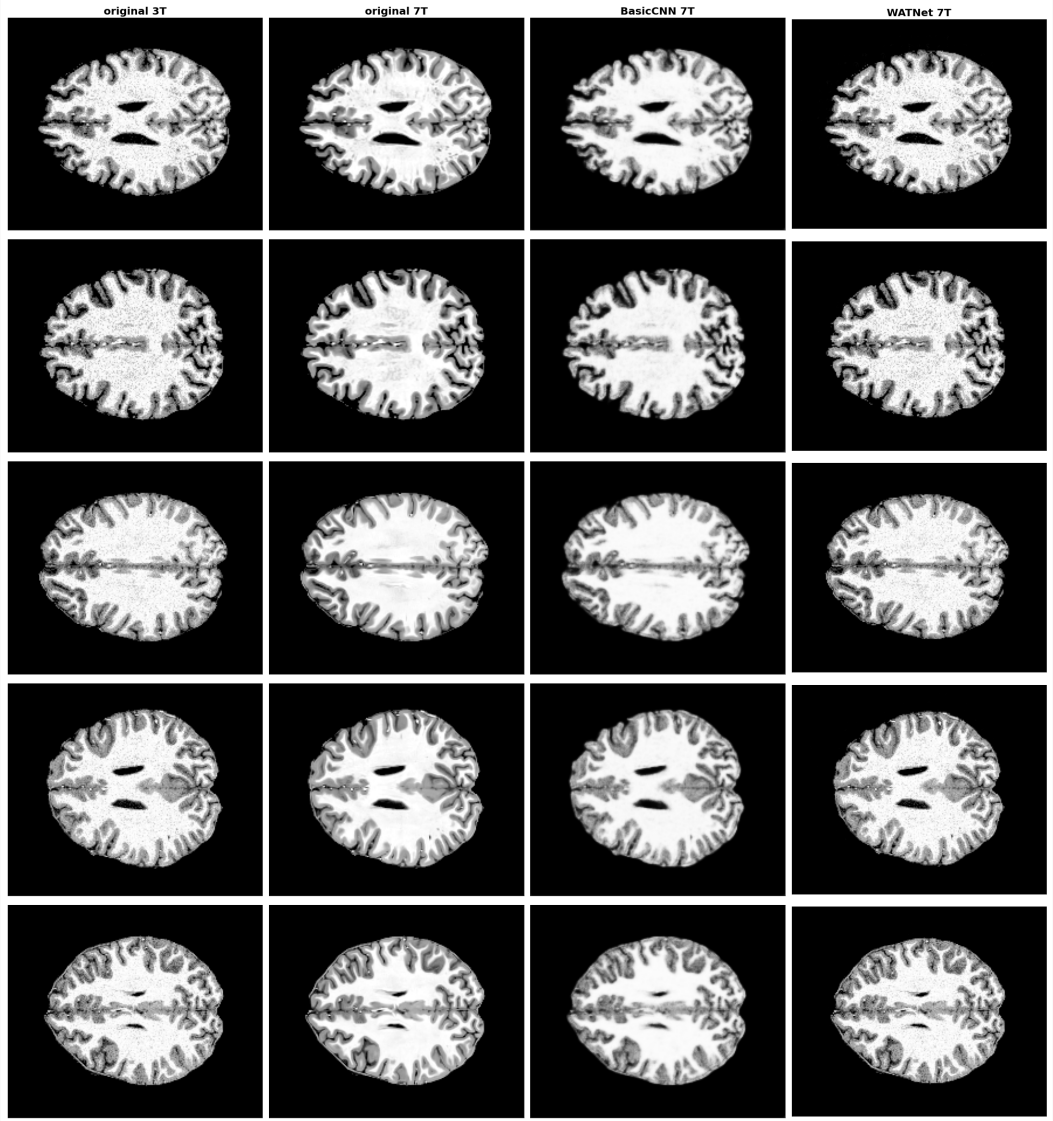

Figure: First 5 subjects

Appendix A

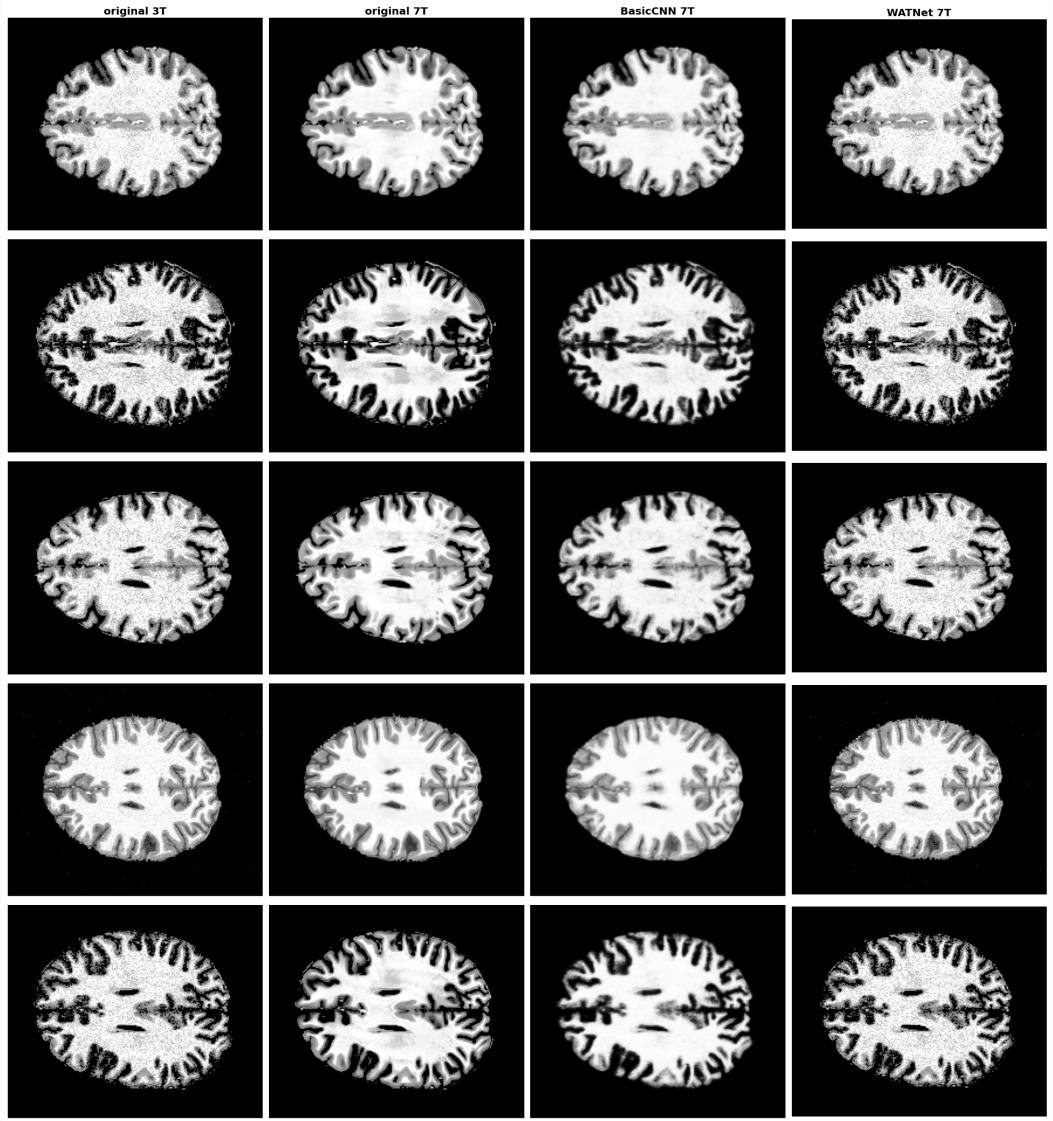

Figure: Last 5 subjects