Super-resolution of Multi-contrast MRI Images with Deep Learning

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1 Introduction

Magnetic resonance imaging (MRI), one of the medical imaging modalities, generates medical images by a strong magnetic field rather than using ionizing radiation. On account of the ability for displaying high contrast resolution of soft tissue, MRI becomes an essential detection method for the brain neurology. One problem is the cost of an MRI scanner–though high-resolution (HR) MRI images are useful, a more powerful MRI scanner is often unaffordable for a clinic. Thus, the super-resolution (SR) technique might be a practical method for creating a higher resolution MRI image.

A recent study showed that the 3D deep densely connected neural networks (DCSRN) [1] achieved state-of-the-art performance in single 3D MRI brain image super-resolution reconstruction. Inspired by the multi-contrast images of MRI and the work of DCSRN, we propose a 3D multi-contrast super-resolution network, which is shown in Figure 1.

2 Methods

The aim of this study is achieving better 3D MRI super-resolution performance with the help of multi-contrast MRI images. In our work, we use a pair of T1-weighted image and T2-weighted image as the multi-contrast MRI images.

In the proposed network, we use three kinds of images, T2wHR, T2wLR, and T1wHR.

T2wHR The high-resolution T2-weighted images used as the (correct) output data.

T2wLR The low-resolution T2-weighted images used as the network input.

T1wHR The high-resolution T1-weighted images used as a hint for improving super-resolution quality.

The workflow of multi-contrast super-resolution MRI image reconstruction could be divided into three steps: 1) Data pre-processing 2) Super-resolution cubes generation 3) MRI image reconstruction.

2.1 Data pre-processing

To keep the same setting for T1-weighted and T2-weighted images, we did co-registration by SPM12 for all T2-weighted images base on T1-weighted images. Then, we applied normalization to all the T1-weighted and T2-weighted images. The low-resolution T2-weighted MRI images are generated by the following three substeps: converting the high-resolution T2-weighted images to k-space by FFT; zeroing 75 percent of the high-frequency part in k-space; applying the inverse FFT. The training data were generated by randomly cropping 64x64x64 cubes from the pair of MRI images.

2.2 Super-resolution cubes generation

The high-resolution T1-weighted and the corresponding low-resolution T2-weighted MRI cube were concatenated as the network input data. After passing one convolution layer, the transformed input data were fed to a four-unit densely-connected block. Then the final convolutional layer and sigmoid activation function generated the super-resolution T2-weighted SR cubes.

2.3 MRI image reconstruction

We rebuild the whole super-resolution image by averaging the outputs (T2-weighted super-resolution cubes) with the 3D sliding window where stride width is 32.

3 Experiment

3.1 Experiment setup

In this study, all the T1-weighted and T2-weighted structural MRI images were generated by customized Siemens 3.0 Tesla connectom scanner and belong to 32 healthy adult subjects in the Human Connectome Project (HCP). Among the 32 subjects, the MRI images of 29 subjects were used for training, the remaining three subject's MRI images were treated as testing images. All the experiments were implemented

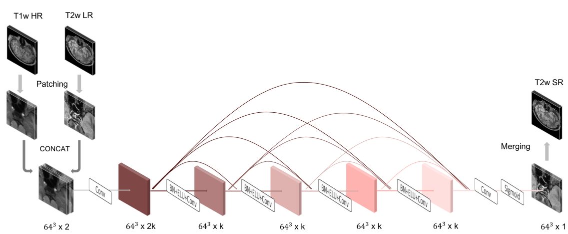


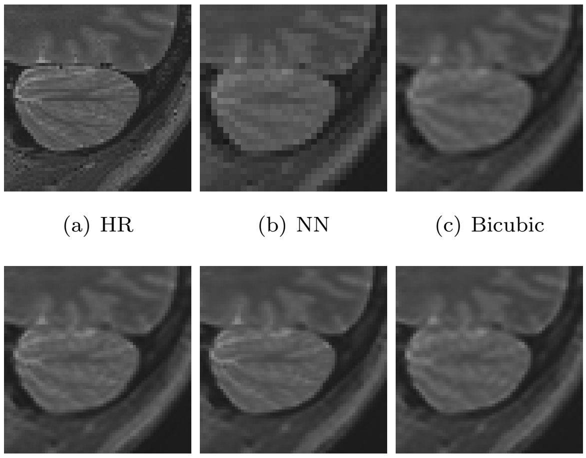
Figure 1 The architecture of 3D MRI multi-contrast super-resolution network

Table 1 The input data detail for experiment 1 (MC-small), experiment 2 (MC-large), and experiment 3 (SC-small)

Experiment	Image type	Input cube number
MC-small	T1w and T2w	29x100x2
MC-large	T1w and T2w	29x400x2
SC-small	T2w	29x100

Table 2 The average result of PSNR, NRMSE and SSIM for nearest-neighbor (NN) interpolation, bicubic interpolation and experiment 1 (MC-small), experiment 2 (MC-large), and experiment 3 (SC-small)

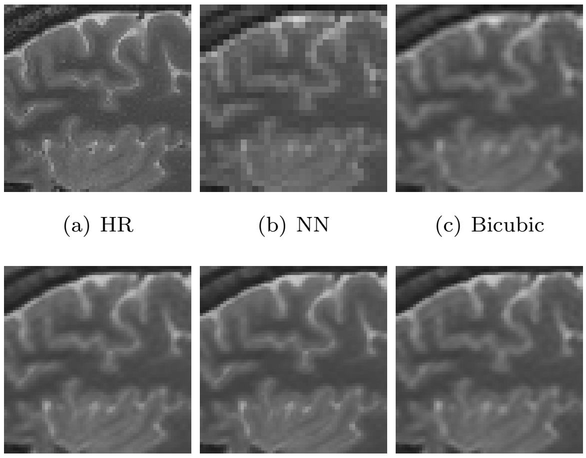
Method	PSNR	NRMSE	SSIM
NN	31.2101	0.1313	0.8928
Bicubic	32.5267	0.1128	0.9153
MC-small	35.2543	0.0822	0.9451
MC-large	35.9975	0.0755	0.9532
SC-small	34.7401	0.0874	0.9438



(a) HR (b) NN (c) Bicubic

(d) MC-small (e) MC-large (f) SC-small

Figure 2 Sample from cerebellum area (a–f) in high resolution, nearest-neighbor (NN) interpolation, bicubic interpolation, experiment 1 (MC-small), experiment 2 (MC-large), and experiment 3 (SC-small) images



(a) HR (b) NN (c) Bicubic

(d) MC-small (e) MC-large (f) SC-small

Figure 3 Sample from the juncture of white matter and grey matter in HR, NN interpolation, bicubic interpolation, experiment 1 (MC-small), experiment 2 (MC-large), and experiment 3 (SC-small) images

by TensorFlow 1.12.0 and conducted on a computer with Intel Core i3-8100 3.6GHz processor, GeForce GTX 1080Ti GPU, and 16G memory. For measuring image quality, we adopt peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and normalized root mean square error (NRMSE) as the image metrics.

3.2 Experiment design

To demonstrate the performance of the proposal network, we designed three experiments. The experiment 1 (MC-small) and experiment 2 (MC-large) were designed to demonstrate the network performance in different training data number. The experiment 3 (SC-small) intended to confirm the usefulness of adapting multi-contrast images. The input detail of each experiment is shown in Table 1. For comparing the network performance with the interpolation method, we conducted nearest-neighbor (NN) interpolation and bicubic interpolation as the other two references. The final results are shown in Table 2, with experiments 1 to 3 trained for 200 epochs. In addition, the enlarged images of randomly selected areas in the reconstructed MRI images are shown in Figures 2 and 3.

4 Conclusions

According to the results displayed in Table 2. The idea of using T1-weighted high-resolution image as a hint to improve the T2-weighted super-resolution image quality works. We can also confirm that the multi-contrast input network provides better performance than using only a single-contrast image as input.

References

[1] Y. Chen, Y. Xie, Z. Zhou, F. Shi, A. G. Christodoulou, and D. Li. Brain MRI super resolution using 3D deep densely connected neural networks. CoRR, abs/1801.02728, 2018.