Three-Dimensional Super-Resolution for Magnetic Resonance Imaging using Convolutional Neural Networks

1215088 ZHUO, Churong 【 Intelligent Informatics Laboratory 】

1 Introduction

High resolution magnetic resonance imaging (MRI) is becoming indispensable for accurate quantitative medical diagnosis. However, it is difficult to obtain high-resolution MRI images due to the medical device and other limitation. There are two kinds of super resolution methods, one is using multiple images to reconstruct the high resolution (HR) image, and the other is the single image super-resolution (SISR).

Approaches of SISR methods can be broadly categorized into three categories: interpolation methods, example-based methods, and learning-based methods. Interpolation methods often generate over smoothed methods. Example-based methods took long computation time to generate HR images, it is difficult to use it in real-time clinical application.

In this paper, we first use 2D super-resolution convolutional neural networks (SRCNN)[1] to generate the HR image in MRI images, then we introduced a new neural network architecture, 3D ResNet model to generate HR images of structural brain magnetic resonance images.

The proposed 3D ResNet networks show superior performance over the 2D SRCNN networks and interpolation methods, it have more sharp edges. The results suggest that 3D convolutional neural network could be promising and helpful in medical imaging super-resolution.

2 Super-Resolution CNN

Influenced by the success of deep learning method, which applied in computer vision fields, Dong et al. introduced super-resolution convolutional neural network (SRCNN). It uses only 3 layers network to generate HR image, and it demonstrates high quality image reconstruction in natural images.

We applied SRCNN to magnetic resonance imaging (MRI) in order to obtain high quality medical images. It contains three steps, patch extraction and representation, non-linear mapping, and reconstruction. We used the Adam optimizer instead of stochastic gradient descent (SGD) optimizer that Dong used in his paper. The SGD maintains a single learning rate for all weight updates and the learning rate does not change during training. Adam combines the best

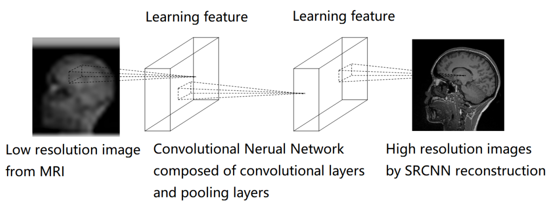

Figure 1 Overview of the SRCNN for MRI scheme

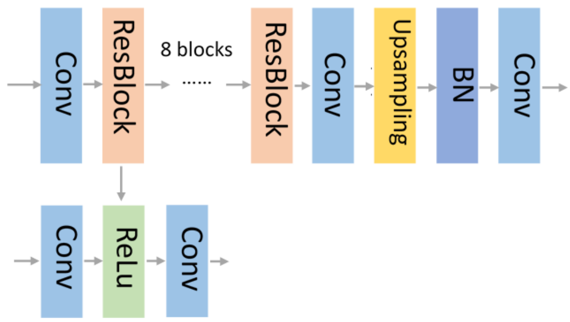

Figure 2 Structure of the 3D-ResNet for MRI scheme

properties of the AdaGrad and RMSProp algorithms to provide an optimization algorithm that can handle sparse gradients on noisy problems.

Figure 1 shows the architecture of single image MRI super resolution using SRCNN.

3 3D-ResNet SR

Inspired by the development of residual learning techniques, Bee Lim et al. introduced enhanced deep residual networks (EDSR)[2] in super-resolution fields. We propose a three-dimensional ResNet model for Super-Resolution(3D-ResNet SR). The network generally followed the EDSR but adapted for 3D volume data. The residual block is composed of 64 3x3x3 convolution kernels followed by a ReLu and another same size convolution kernel. The network we built use a total of 8 residual blocks. We also added one batch norm layer before final convolution layer.

Figure 2 shows the architecture of 3D-ResNet. The original version of the network using mean square error (MSE) loss, but the images obtained by minimizing MSE are over-smoothed since it didn't capture the perceptual difference between the output and the ground truth image. Inspired by the perceptual loss

Table 1 Comparison of NN, Bicubic, SRCNN , 3D-ResNet.

	PSNR	SSIM	MOS
Nearest Neighbor	25.94	0.7124	1.76
Bicubic	26.14	0.7439	2.07
SRCNN	**28.12**	**0.7841**	2.51
3D-ResNet	26.43	0.7405	**3.69**
Ground Truth	/	1	4.32

idea in neural style transfer, it use the image feature representation extracted from pretrained CNN instead of the output itself. VGG Net is one of the most influential networks. VGG16 contains 13 convolution layers and 3 full-connected layers. The weight configuration of the VGGNet is publicly available and has been used in many other applications and challenges as a baseline feature extractor. We tried using perceptual loss based on the first three convolutional layers of VGG16.

4 Experiments and Results

In this paper, we use the MRI image provided by the hospital. We have 280 MRI dicom images, we randomly selected 224 of it as training set, 56 as test set. We first tried 2D SRCNN model to generate HR images, then used the 3D-ResNet network we built to generate HR images. For each dicom images, we first used Gaussian function to blur the ground-truth images, process it as 3 channel images, and normalized it to intensities between 0 and 1. Store the data into 32x32x32 volumes for training. VGG16 expects a 3-channel RGB image, so here every 2D slice of the 32x32x32 volume data is transformed into a 3x32x32 image, and the appropriate means and standard deviations are set for the RGB channels.

The performance of 2D-SRCNN and 3D-ResNet is compared to those of two interpolation methods. Peak signal-to-noise ratio (PSNR), structural similarity (SSIM), and mean opinion score (MOS)[3] are used to evaluate the results. For the MOS testing, we asked 10 raters to rate the results from 1 (low quality) to 5 (high quality). The experimental results are summarized in Table 1.

Figure 3 illustrates an example of the resulting HR images using the two interpolation methods and deep learning methods. interpolation methods, SRCNN scheme and 3D-ResNet model.

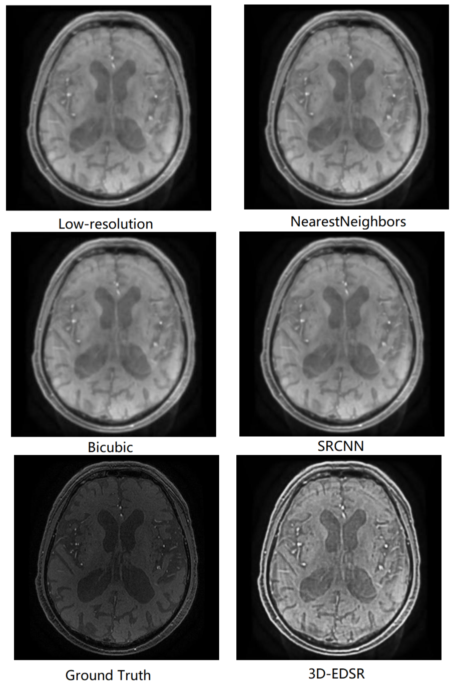

Figure 3 Visual Results

5 Conclusion

In this paper, we applied 2D-SRCNN and deep residual network 3D-ResNet in MRI. We evaluate with the widely used PSNR and SSIM measure. However, PSNR and SSIM are not improved, however they does not accurately assess image quality with respect to the human visual system, for example edge quality. We then used the MOS testing, which Christian Ledig et al. proposed, it shows that 3D-ResNet outperform 2D-SRCNN and interpolation methods.

References

[1] Dong C, Loy CC, He K, Tang X: Learning a deep convolutional network for image super-resolution. In European Conference on Computer Vision: 184–199, 2014

[2] Lim, B., Son, S., Kim, H., Nah, S., Lee, K.M. (2017). Enhanced Deep Residual Networks for Single Image Super-Resolution. 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPR), 1132-1140.

[3] Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., Aitken, A.P., Tejani A., Totz, J., Wang, Z., Shi, W. (2017). Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 105-114.