Structural and functional magnetic resonance imaging super-resolution using deep convolutional neural network

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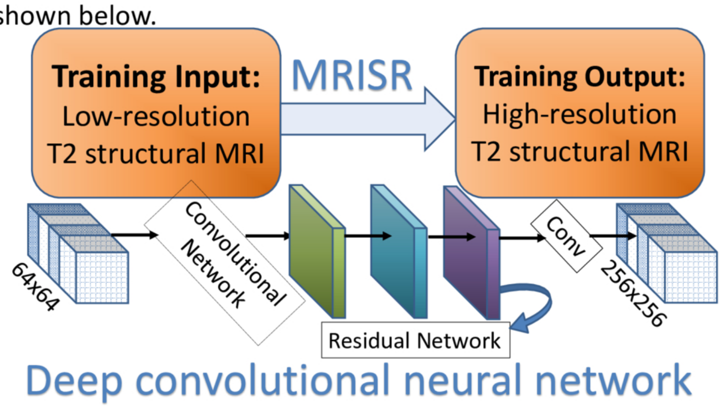
Motivation

Magnetic resonance imaging (MRI) is proved to be a safe, non-invasive and effective way of evaluating brain anatomy and function. MRI techniques for functional brain mapping utilizes different magnetic properties of hydrogen atoms (protons) comprising water molecules ubiquitous throughout the body. Both techniques do not use ionizing radiation as X-ray or CT, and are far more objective compared to the traditional questionnaire methods of psychological evaluation. However, the trade-off between image quality, motion artifact and image acquisition time has been a problem for researchers. This study tackles the MRI optimization problem by integrating image details learned from structural MR images and generating high-quality structural and functional MRI.

Materials and Methods

The MRI dataset were downloaded from an in-house rodent imaging project which included 23 subjects and their corresponding T2 structural MRI and functional MRI slices (234 and 65 slices for training and validation dataset, respectively). Imaging data was acquired using an 11.1 Tesla Magnex Scientific 40 cm horizontal magnet (Bruker BioSpin, Billerica, MA) with RRI BFG-240/120-S6. Acquisition sequences were prepared and controlled using ParaVision (Version 6.0.1). We used a deep convolutional neural network in order to maintain the functional MR image quality as well as reducing the subject motion artifacts in scenarios where long acquisition time is not preferable. The algorithm diagram is shown below.



Results – Neural Network Training and Testing

Validation Curve

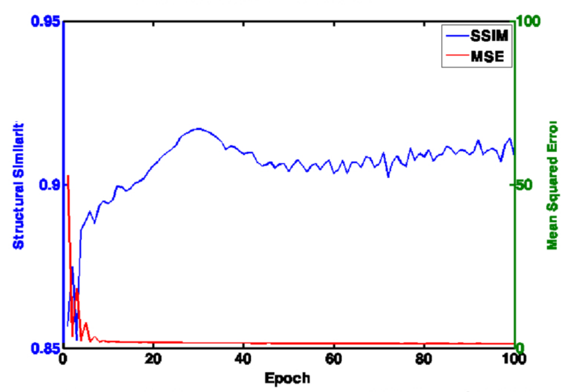


Figure 1. Fast convergence SSIM and MSE.

Table 1. Test Summary

Methods	SSIM	MSE	PSNR(dB)
Bicubic	0.906	1.83	29.8
MRISR	0.940	1.45	32.8

Table 1. Comparison of 2 image upscaling methods. Structural similarity – SSIM; Mean square error - MSE

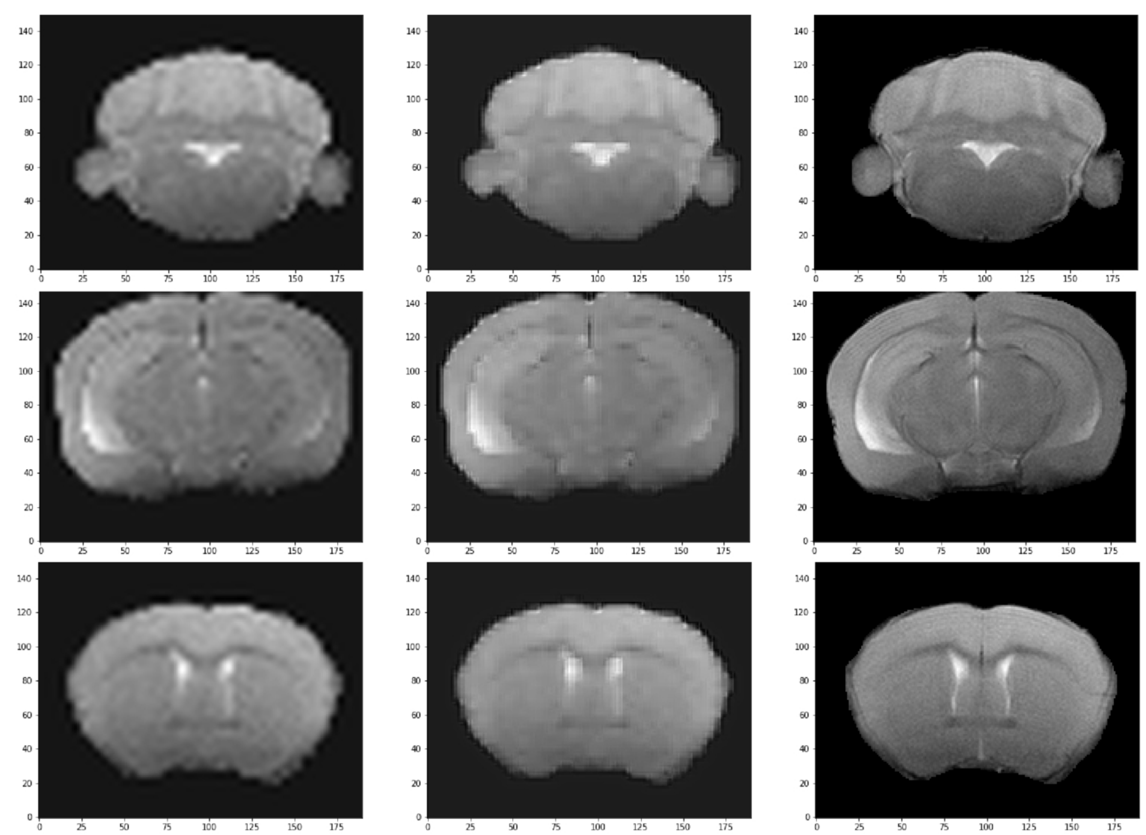


Figure 2. Test images - MRISR versus Bicubic Scaling (Scale factor = 4.0). Each row shows a different slice (slices 3, 7, 11, from up to down) and the column (from left to right) each shows the test images from bicubic upscaling and MRISR deep neural network-based methods.

Results – Prediction from FMRI

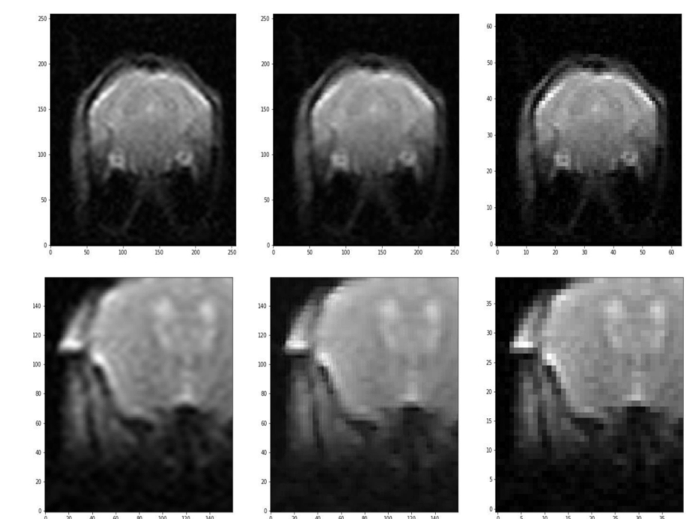


Figure 3. Prediction from low-resolution resting-state fMRI (rsfMRI scans were acquired using the following sequence: TR = 2,000 ms; TE = 15 ms; repetitions = 180; flip angle = 90; dummy scans = 2; slices = 13; orientation = coronal; thickness = 0.9 mm; gap = 0 mm; FOV = 15x15 mm; data matrix = 64x64 in-plane.) by scaling factor of 4.0. Compared to third-order interpolation method (bicubic), MRISR deep neural network showed better image quality and image detail restoration with less motion artifacts.

Discussion & Acknowledgement

Image quality are significantly improved for transferred-learning MRI compared with traditionally resampled or normalized images. Our MRISR method also compares favorably in terms of the structural similarity index with bicubic interpolation method. The results indicate that using deep convolutional neural network can effectively improve multimodal MRI image quality within a reasonable acquisition period. Thus, our method provides a practical solution for multimodal MR image super-resolution and serve as a potential enhancement tool for non-invasive, structural and functional neuroimaging. Further investigations are proposed to perform MR phantom study and prospective human imaging studies using deep convolutional neural network-based method.

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