3D Brain MRI Super-Resolution with Image Gradient Tensor Feature Clustering

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Introduction

- **Motivation**: Magnetic resonance imaging (MRI) with high spatial resolution provides abundant anatomical information for diagnostic decisions. However, high spatial resolution MRI acquisition yields longer acquisition time, smaller spatial coverage and lower signal-to-noise ratio (SNR) because of hardware capacity limitations. Taking advantage of the single image super resolution (SISR), high-resolution (HR) image can be obtained by recovering super-resolution (SR) from low-resolution (LR) reducing MRI acquisition time.
- **Goal**: In this study, we propose a fully 3D SISR method for human brain MRI that constructs image gradient-based tensor and uses several linear filter models based on the features of the tensor.

Methods

- **Data**: We obtained 897 high-resolution (0.7x0.7x0.7mm) T1-weighted volumes from the Human Connectome Project 900 dataset (Van et al., 2013). We used 30 images for training and the rest for validation.
- **Preprocessing and LR generation**: We set the maximum value by clipping the upper 0.1% value, and normalized the data by adjusting the data range from 0 to 1. We downsampled the original HR volume to LR volume in factor of 2.
- **Tensor feature extraction from volume patch**: We computed the gradient matrix $\mathbf{G} \in \mathbb{R}^{9^3 \times 3}$ that represents gradients for each axis from 9×9×9 volume patch. Then we defined the 'image-gradient tensor' $\mathbf{D} = \mathbf{G}_k^T \mathbf{W} \mathbf{G}_k \in \mathbb{R}^{3 \times 3}$, where $\mathbf{W}$ is a Gaussian weighting matrix. (Romano et al., 2017). We extracted tensor shape and orientation components from each tensor (Gahm et al., 2014).
- **Clustering and training**: The tensor shape and orientation features were clustered using expectation maximization. For each combination of two centroid (label), we established the mapping between the LR patches and center HR intensities of the patches as a filter by linear regression.
- **Testing:** In test stage, for each voxel, a tensor was constructed from the surrounding patch. We selected a filter by finding the nearest label from the learned clustering models. We applied the filter to the patch to predict the HR intensity for the voxel.

Results

- Figure 2 shows an example of 3D MRI SR using tricubic, SRCNN and our proposed method. The proposed method and SRCNN (d, c) better recovered the HR details (a) especially in the gray-white matter boundary than the interpolation method (b).
- We measured the peak signal-to-noise ration (PSNR) – our method (35.97±0.88, mean±std) significantly outperformed the interpolation method (32.17±0.58) by 11.8%, and was slightly better than SRCNN (35.80±0.84). Our method produced the structural similarity index measure (SSIM) (0.9827±0.0041) that is 1.7% higher than the interpolation method (0.9664±0.0054), and comparable to SRCNN (0.9833±0.0038).

Conclusions

We developed a novel fully 3D super-resolution method for MRI by constructing tensors from volume patches and establishing the mapping between LR patches and HR intensities using the tensor features. We demonstrated that our proposed method achieved much better recovery of the HR details than the conventional methods, effectively reducing the training time. In future work, we will extend our work in different modalities of brain imaging.

References

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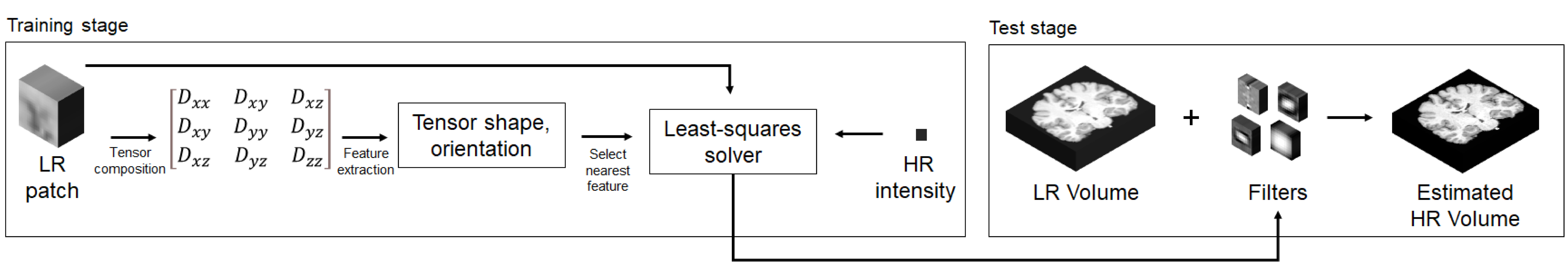

Figure 1. Overall flowchart of the proposed method

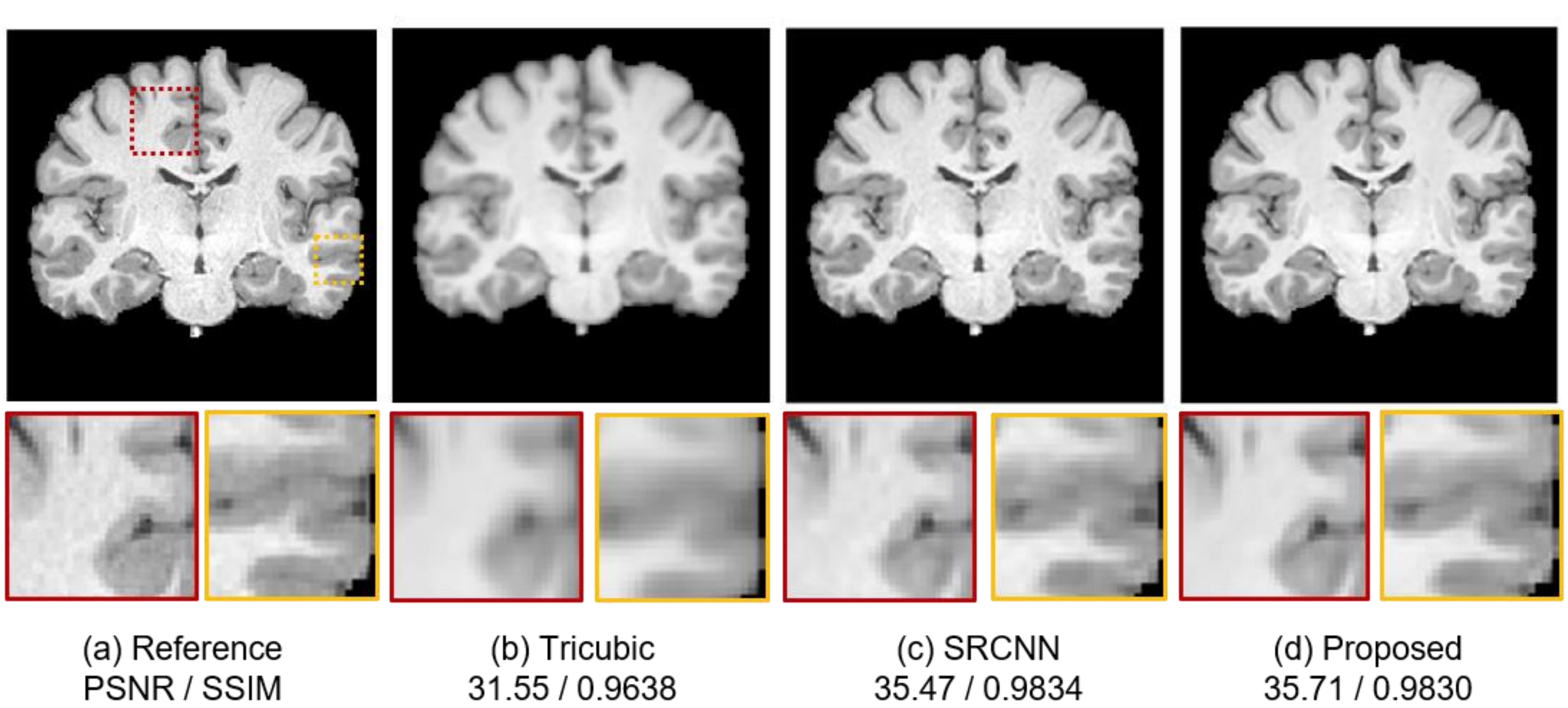

Figure 2. Visual comparison in axial view with interpolation and SRCNN methods in the upscaling factor of 2. **(a)** Original HR image, **(b)** Interpolated image from downscaled (a) **(c)** applied SRCNN from (b)

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