Sparsity-based superresolution MR imaging using dual dictionaries

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Target Audience: Scientists and clinicians who are interested in high resolution imaging, image processing, and image reconstruction

Purpose: Clinical imaging is always longing for increased image resolution to obtain superior details of biological structural changes at micro (i.e. <100μm) levels. Unfortunately, current human MRI is limited to meet this ever-increasing need due to various restrictions including hardware technology, acquisition time, and SAR. Super-Resolution (SR) is the process of reconstructing a High Resolution (HR) image from a Low Resolution (LR) image and has been predominantly used in digital photography and picture enhancement. The most common approach to SR is to acquire a series of shifted LR images and then fuse them to obtain one HR image, which is not a practical approach. Recent SR techniques attempt to reconstruct the HR image from a single LR image by exploiting similar sparse representations under different representation basis [1, 2]. In this study, we propose to bring this idea to brain MRI for supersolved subvoxel microstructural diffraction.

Methods: The proposed method, named coupled-sparsity superresolution (CS-SR), exploits the fact that the LR and HR images share similar sparse representation α, under different representation bases. This is, $D_H\ X_H = D_L\ X_L = \alpha$, where D_H and D_L are the HR and LR representation bases (dictionaries) respectively and X_H and X_L are the HR and LR images respectively. In order to recover the HR image from the LR image, the method estimates the relationship between D_L and D_H. In general, this is an undetermined problem that can have infinite solutions. But, by constraining the problem to find the relationship of the sparse coefficients in a transform domain rather than the non-sparse coefficients in the image domain, it can be solved in an iterative fashion by training two dictionaries at HR and LR and imposing the coupled sparsity constrain (equation above) with as demonstrated in [1]. The proposed superresolution approach solves the following optimization problem:

$$\min_{D_x, D_y, \{\alpha_i\}} \sum_{i=1}^{N} \left(\|x_i - D_L.\alpha_i\|_2^2 + \|y_i - D_H.\alpha_i\|_2^2\right) + \lambda\|\alpha_i\|_1 \quad \text{s.t.}\ \|D_L(:,k)\|_2 \le 1,\quad \|D_H(:,k)\|_2 \le 1 \quad \text{with } x_i \in \mathrm{D_L}, y_i \in \mathrm{D_H}$$

where D(:,k) is the k^{th} column of dictionary, α_i is the sparse code of x_i and λ the parameter controlling the sparsity penalty and representation fidelity. To show feasibility of the proposed method, we acquired a HR brain image, downsampled it (crop the central k-space region) to obtain a LR image, apply the coupled-sparsity SR reconstruction and compare the SR results to the original HR image. The HR image was acquired at 7 Tesla using 2D GRE pulse sequence with TR/TE/FA/BW: 1600/25/35/50 FOV =180x240mm, image matrix = 768x1024, spatial resolution = $0.234mm^2$

Results: Figure 1 shows the reconstruction results using the brain image acquired at 7T. The proposed CS-SR algorithm enhanced small structures that were blurred in the LR image (see arrows) and presented results that are compatible with the HR image. The Coupled Sparsity algorithm presents residual ringing artifact, which is due to incomplete extrapolation in k-space.

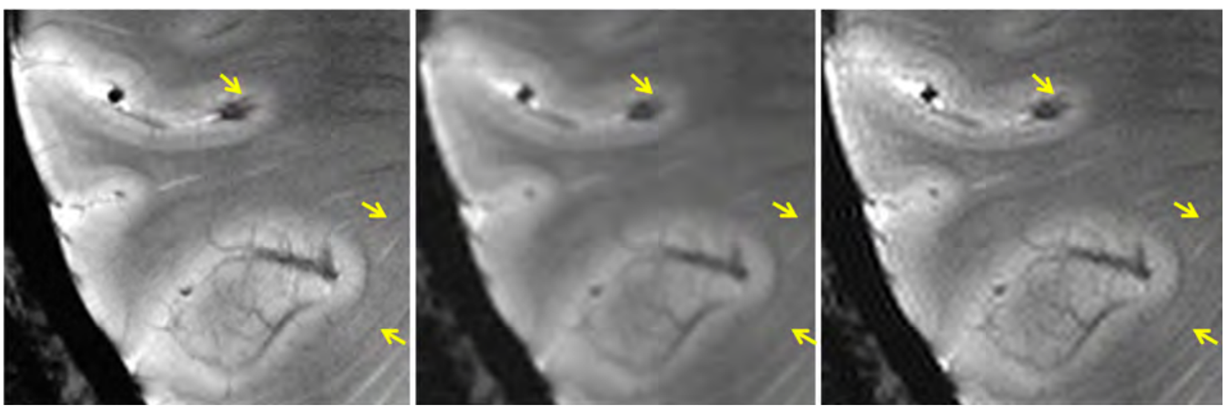

Fig.1: From left-to-right: HR brain image acquired at 7T (pixel: $0.23mm^2$), LR image ($0.47mm^2$) and SR reconstruction using the proposed CS-SR algorithm. The arrows indicate vessels that appear blurry in the LR image and are enhanced by the SR reconstruction

Conclusions: Human brain has more microstructures than we can currently observe on MRI. Superresolution techniques have been proposed previously for MRI but with limited success due to scan time and SNR challenges. The proposed sparsity-based approach has the advantages of being less sensitive to noise amplification due to the non-linear nature of the reconstruction. This study was a proof-of-principle to show feasibility of increasing resolution without increasing acquisition time. Future work will explore ways to assess the effective increase in resolution and to reduce residual ringing. The eventual goal of developing CS-SR method is to differentiate microstructures (e.g. small vessels) within a single voxel or to achieve subvoxel diffraction.

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References: [1] J. Yang, "Coupled dictionary training for image super-resolution," *IEEE Trans Image Process,* vol. 21, pp. 3467-78, 2012. [2] J. Yang, "Image super-resolution via sparse representation," *IEEE Trans Image Process,* vol. 19, pp. 2861-73, 2010.