Robust Edge-directed MRI interpolation

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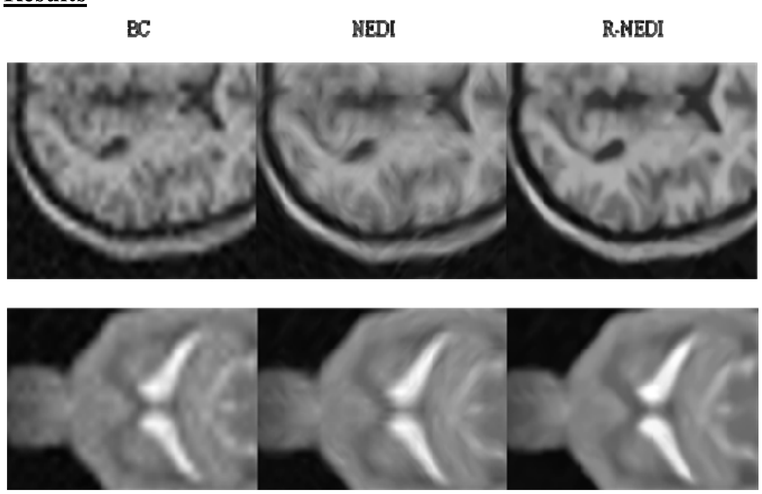
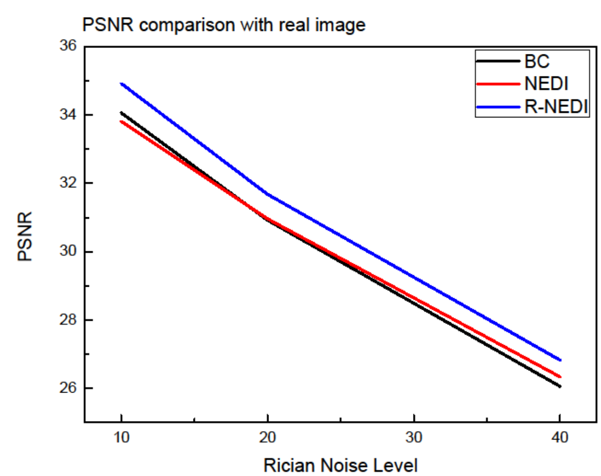
Abstract It has been demonstrated in the literature that the concept of edge-directed interpolation, e.g., New Edge Directed Interpolation [1] (NEDI), can dramatically reduce the artifacts caused by traditional interpolation methods that fail to incorporate local edge information. However, the least squares nature of NEDI hampers its performance with MR images with heavy noise. This work incorporates a robust estimation mechanism into the NEDI framework, in combination with a Non-Local Means [2] (NLM) weighting scheme to better capture local structural image information.

Introduction Image interpolation (in the upsampling sense) is essentially an ill-posed inverse problem. Traditional interpolation methods use spatially invariant models, producing artifacts as a result. One of the remedies that incorporate edge information is NEDI, which utilizes edge information via neighborhood pattern estimation. However, for pattern estimation, NEDI relies on an Ordinary Least Squares (OLS) scheme, which proves to be non-robust, especially in the presence of heavy noise. Furthermore, thinking along the logic of NEDI as neighborhood pattern estimation, we incorporate another estimator, NLM, which can help to better capture the locality of edges.

Method Suppose, for each unknown point Y in the image domain to be interpolated, we assume that Y is a weighted sum of its N-neighborhood $\{y_1, \ldots, y_N\}$: $Y \cong \vec{\alpha} \cdot \vec{y}$, where $\vec{\alpha}$ is the weight vector for each neighbor, which can be computed via an iterative reweighted least squares estimation of the neighborhood patterns,
$\vec{\alpha}_m = \arg\min_{\vec{\alpha}} \sum_i \omega_R(r_i)\omega_N(i) r_i^2$, where r_i is the residual of each pattern estimation, $r_i = y_i - \vec{\alpha} \cdot \vec{N}(y_i)$, $\vec{N}(y_i)$ is the neighbor vector of y_i, $\vec{N}(y_i) = [y_{i1} \quad \ldots \quad y_{iN}]^T$, the residual reweighting function $\omega_R(x) = \exp(-x^2 / c_r^2)$, the NLM weighting function $\omega_N(i) = \exp(-\|\vec{N}(i) - \vec{N}_{current}\|^2 / h^2)$. c_r and h are two constant parameters that control the degree of weightings. The computation is iterative since r_i is unknown initially.

Results





Above figures are the comparisons between bi-cubic interpolation (BC), NEDI and the proposed robust NEDI (R-NEDI), using both synthetic images and real images, with Rician noise. First three images from top row are synthetic images (with 20% Rician noise) interpolations for BC, NEDI, R-NEDI, respectively. The figure to the right is the PSNR graph for three interpolation methods for real images with Rician noise from 10% to 40%. The bottom row contains similar images for those of real image interpolation results.

Discussion & conclusion The results confirm that feature-directed interpolation can better preserve the shape of local image structures, as can be seen from the contrast between the non-adaptive method and adaptive ones. However, when noise is present in the image, a robust estimator of the local image pattern is needed to extract the useful structural information for interpolation, as is implemented in this work.

[1] X. Li and M. T. Orchard, "New Edge-Directed Interpolation," IEEE Trans. on Image Processing, Vol.10, No.10, pp. 1521- 1527, October 2001.
[2] A. Buades, B. Coll and J.M.Morel, "A non-local algorithm for image denoising", CVPR 2005, pp. 60-65, June 2005.