An Unsupervised Method to Enhance both SNR and Edges for PPI

W. Guo[1], and F. Huang[2]

[1]Department of Mathematics, University of Alabama, Tuscaloosa, AL, United States, [2]Advanced Concept Development, Invivo Corporation, Gainesville, FL, United States

Introduction: Partially parallel imaging (PPI) techniques [1-2] reduce acquisition time at the cost of signal to noise ratio (SNR). Regularization techniques [3-4] can be used to improve image quality by balancing SNR and residual aliasing artifact/spatial resolution through a regularization parameter set. In this work, an unsupervised adaptive method is proposed to reduce noise and artifact level, as well as to sharpen edges. This method is based on Non-local Means (NL-Means) introduced by Buades et al. [5]. Results of the application to GRAPPA [2], with both phantom and in vivo data, demonstrate that the proposed method is able to increase SNR, to preserve the fine structures, and to sharpen the edges at the same time.

Methods: Let $v = \{v(i) \mid i \in I\}$ be the noisy input, NL-Means [4] uses weighted average of image values in **non-local** neighbors, instead of conventional spatial neighbors, to smooth the image. A pixel *j* is an non-local neighbor of a pixel *i* if they have statistically similar neighborhood, where the similarity is defined by a measure $w(i, j) = \frac{1}{z(i)} e^{-\frac{\int_T G_a(t)(v(x+t)-v(j+t))^2 dt}{h^2}}$ where *T* is a similarity window centered at origin for a 2D input, G_a is a Gaussian kernel with parameter *a*, *h* controls the overall smoothing amount, and *z(i)* is a normalizing constant such that $\sum_j w(i, j) = 1$. The smoothed value at *i* is defined as $s(i) = \sum_{j \in N(i)} w(i, j) v(j)$, where the size of searching window *N(i)*, denoted by *k*, is fixed as a constant. Because *v(j)* contributes only when *j* has a statistically similar neighborhood as *i*, NL-Means is able to better preserve structures and textures. To deal with unevenly distributed noise in images by PPI, the knowledge of edge locations and noise/artifact distribution in *v* can be learned by comparing *v* and a *regulating* image *u* reconstructed using the data for sensitivity maps (or GRAPPA convolution kernel). This information is then used to define adaptive *h* and *k* to enhance edges and to sufficiently remove noises. As in [5], we compare patch-wisely the noisy input *v* with *u* to locate edges; local variance is used to find areas with high noise/artifact level. Piecewise constant *h* and *k* are set to be low near edges and high at regions deteriorated more. Values of *h* and *k* in each piece are determined automatically using background noise variance and interior patch variance, k-mean segmentation is utilized to distinguish different pieces fully automatic.

Results: The proposed method was applied to two data sets. One data set was simulated with Shepp-Logan phantom and sensitivity maps from a 4-ch cardiac coil. One brain data set was acquired on a 1.5 T system (GE, Waukesha, WI) with an 8-ch head coil (Invivo, Gainesville, FL). GRAPPA with a kernel of size 4×5 was used for reconstruction. The acceleration factor was 4; number of auto-calibration signal (ACS) lines was 56. The proposed method was applied to both real and imaginary part of each channel individually before the generation of the composite image. For better view, only partial regions are shown. In Fig.1, the removed noise (as shown in d) matches well with the true noise as shown in (b). By comparing Fig. 1a and Fig. 1c, it is clear that noise level was dramatically reduced while edges were perfectly preserved. Fig. 2 shows the results of the brain image. The edges were clearly enhanced while the noise was thoroughly removed. In the map of the removed noise (Fig. 2c), no structure information was observed. Mean values of SNR of 10 different areas have been improved from 11.8 to 46.2, 4.2 to 16.2 for phantom and brain data respectively.

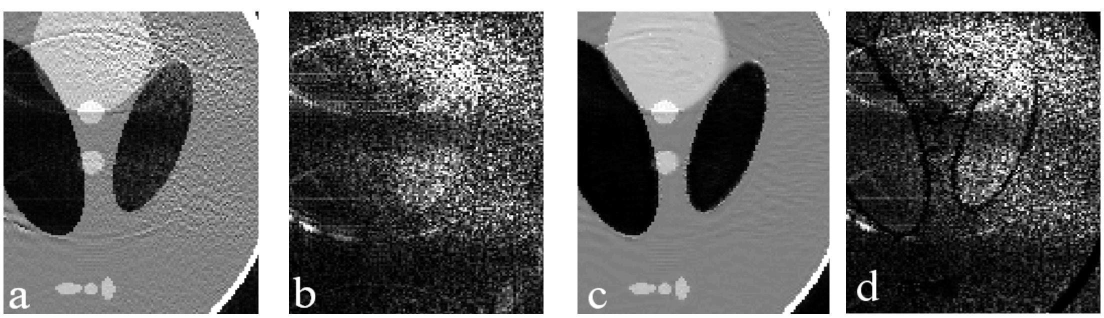

Fig. 1 Noisy input　Real residual　Enhanced output　Removed residual

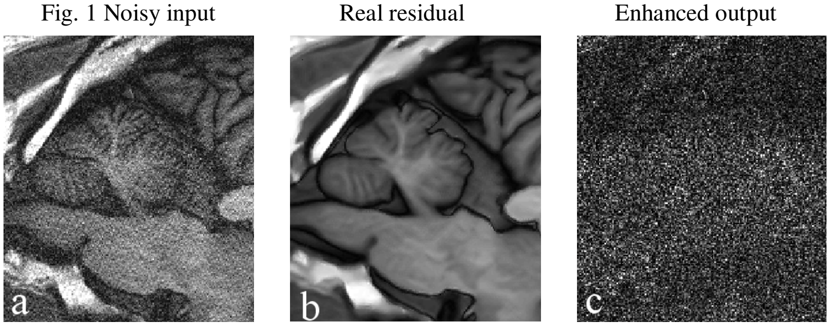

Fig. 2 Noisy input　Enhanced output　Removed residual

Conclusion and Discussion

An unsupervised adaptive NL-Means method was proposed to enhance images with non-evenly distributed noise/artifact. Adaptive parameters were chosen automatically through learning from the input image and a *regulating* image. Quantities we used include patch mutual information and local variance, k-mean segmentation was applied to define parameters fully automatically. Results have shown that the proposed model is able to significantly improve SNR and edges definition.

Reference: [1] Prussmann, K.P. et al., 1999; MRM 42: 952-962. [2] Griswold M. A., et al. MRM 2002; 47: 1202-1210. [3] King, K. F. et al. ISMRM 2001, P 1771. [4] Lin F-H et al., 2004; MRM 51:559-567 [5] Buades A et al., CVPR 2005;2:60-65. [6] Guo W. et al. MICCAI 2008; 2:939-947.