

Robust SENSE reconstruction using non-local regularization

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Introduction: Regularization can effectively improve the signal-to-noise ratio (SNR) of SENSE reconstructed images (1). Current regularization techniques are generally model-based, which rely on some specific assumptions of the desired images (1, 2). If the model matches the image well, the regularization performance is excellent. If not, the regularization may cause additional artifacts or detail loss. This restricts the applicability of regularization. In this study, we propose a new regularization technique based on the non-local mean filter (3) for SENSE. The proposed method does not rely on any specific image model or prior image acquisition. It utilizes the information redundancy of an image and maximizes the consistence and similarity of pixel values within the image. The phantom simulation and *in vivo* experiments results demonstrate that this method can effectively suppress noises in SENSE reconstruction while preserving image details. The image quality is better than the popular Total variation regularization.

Theory: Regularized SENSE can be formularized as

$$\bar{\mathbf{u}}^\lambda = \arg \min_{\mathbf{u}} \{ \|\mathbf{A}\bar{\mathbf{u}} - \bar{\mathbf{f}}\|_2 + \lambda \Omega(\bar{\mathbf{u}}) \}$$

where \mathbf{A} is the encoding matrix, $\bar{\mathbf{u}}$ is the desired image, $\bar{\mathbf{f}}$ is the under-sampled k-space data, and λ is the regularization parameter, $\Omega(\bar{\mathbf{u}})$ is the penalty function that stabilizes the solution. In the proposed non-local regularization, the penalty function is represented as (4):

$$\Omega(\bar{\mathbf{u}}) = \int (\bar{\mathbf{u}}(x) - \bar{\mathbf{u}}(y))^2 w(x, y) dx dy \quad \text{Eq.1}$$

, where x and y are two different pixels of the image, $w(x, y)$ is a weight based on the similarity between two pixels x and y . In this study, the weight function is defined as

$$w(x, y) = \frac{\exp(-\|p(x) - p(y)\|_2^2 / \sigma^2)}{W_x}, W_x = \sum_{y \sim x} w(x, y) \quad \text{Eq. 2}$$

where $p(x), p(y)$ are patches centered at x and y , and σ^2 the thresholding parameter which controls the strength of regularization. The notation $y \sim x$ means that pixel y is in the neighborhood of pixel x .

W_x is the normalization factor for pixel x which is a sum of the weights from all neighbor pixels around x . The weight $w(x, y)$ represents the similarity between two patches at x and y . Similar patches have a large weight, while different ones have a small weight. The function $\Omega(\bar{\mathbf{u}})$ measures the self-similarity and self-consistence of an image by computing the weighted intensity difference between different pixels of the image. For a desired image without any artifacts or noises, $\Omega(\bar{\mathbf{u}})$ has tendency to be relatively small, because the pixel intensity differences $\bar{\mathbf{u}}(x) - \bar{\mathbf{u}}(y)$ and weight $w(x, y)$ cancel out each other. However, in presence of noises and artifacts, this cancel-out effect no longer exists, and $\Omega(\bar{\mathbf{u}})$ increases. Therefore, minimizing $\Omega(\bar{\mathbf{u}})$ enforces the similarity and consistence of pixel intensities across the image and thus penalizing noises and artifacts. Since $\Omega(\bar{\mathbf{u}})$ is non-convex, a proximal forward-backward splitting algorithm is used to iteratively approximate the minimization of the cost function (5).

Method: The non local regularization is applied to both simulated and *in vivo* brain data to demonstrate its feasibility. For simulation, a numerical Shepp-Logan phantom and an 8-channel receiving coil sensitivity were used to simulate the under-sampled k-space data at a reduction factor of 4. A spatially uniform and uncorrelated Gaussian white noise was added to data from each simulated channel. The *in vivo* anatomical brain images were acquired from a healthy volunteer using a 3T scanner (SIGNA EXCITE, GE healthcare) with an eight-channel head coil. A 3D IRfSPGR sequence was used to acquire the axial brain images with the following parameters: TR = 6.052 ms, TE = 2.844 ms, flip angle = 20°, FOV = 240 mm×240 mm, and the acquisition matrix = 256×256.

Results: Figure 1 compares the simulated phantom image reconstructed by un-regularized SENSE, Total Variation (TV) regularization and non-local regularization. The CG-SENSE image is severely degraded by noises. TV regularized image reduces this noise at the expense of staircase artifacts, while the image reconstructed by non-local regularization successfully removes the noise. Figure 2 compares the *in vivo* results. TV causes structure loss in the result image (Fig. 2b). However, the non-local regularization effectively suppresses the noise while image contrast and details are well-preserved. This can be further confirmed in the difference images (Fig. 2c).

Discussion and Conclusions: An adaptive non-local regularization is developed for SENSE reconstruction. By measuring the natural information redundancy of images, the non-local regularization adapts itself to different local structures of an image and enforces the similarity and consistence within the image. The phantom simulation and *in vivo* experiments results demonstrate that this method can effectively improve SNR with well-preserved image details for SENSE, even in the presence of both a high noise level and high reduction factors.

References: 1. Lin FH et al, MRM, 51:559-567(2004). 2. Rudin LI et al., Physica D 60:259-268(1992). 3. Buades A et al, Multiscale Model. Simul. 4:490-530(2005). 4. Gilboa G et al, UCLA CAM Report 06-57(2006). 5. Peyré G. et al, ECCV 57-68(2008).

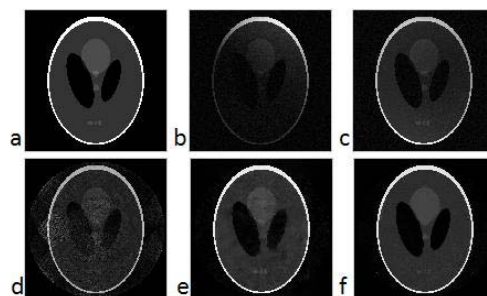


Fig.1: Phantom simulation result.(a)original phantom image; (b)single coil image with synthetically added noise.(c)sum-of-squares image. The bottom row shows images reconstructed at a reduction factor of 4. (d)CG-SENSE; (e)TV regularization; (f) non local regularization.

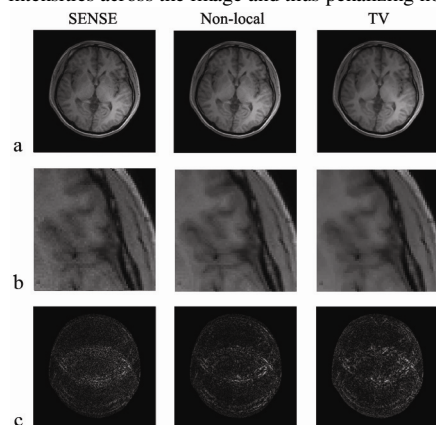


Fig.2: Brain images reconstructed by CG-SENSE, non-local regularization and TV regularization at a reduction factor of 4. (a) reconstructed images for the different methods; (b) zoomed-in parts of (a); (c) difference maps relative to the SENSE