Parameter-Free Compressed Sensing Reconstruction using Statistical Non-Local Self-Similarity Filtering

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Introduction:
Compressed Sensing (CS) MRI [1] enables image reconstruction from highly undersampled data by exploiting image sparsity and incoherent sampling. In CS, sparsity is typically enforced by minimizing the ℓ_1 norm in a chosen transform domain, such as wavelets or finite differences [1]. The choice of regularization parameters is crucial for the balance between artifact removal and structure preservation. However, these parameters depend on the sparsity in the transform domain and can be calibrated only to a limited degree by optimizing them for a given type of images with similar sparsity. Recent work has shown that using adaptive transforms such as learned dictionaries and non-local self-similarity constraints can lead to improved image reconstruction [2-5]. Although these methods can achieve superior results, their success also depends on the choice of a number of parameters, which need to be tuned for the specific problem and are often difficult to adjust.
In this work, we present a CS reconstruction based on statistical non-local self-similarity filtering (STAINLeSS), in which the parameters are entirely determined by the noise estimation in the receive channels obtained from a standard noise measurement.

Methods:
Image reconstruction is performed using a POCS algorithm**,** by iteratively refining the estimates in two alternating steps: artifact reduction by image filtering and projection onto the undersampled k-space data. The STAINLeSS filter proposed in this work is related to the non-local means filter [6]. Each pixel p_i of the filtered image is computed as a weighted average of pixels $p_i = \sum_j w_{ij}\, p_j$ that are not necessarily spatially local to p_i.
The weights w_{ij} are computed as $w_{ij} = d_{ij}^{(N-1)/2} e^{-d_{ij}/2}$, where
$d_{ij} = \sum_k (p_{i+k} - p_{j+k})^2 / (\sigma_{i+k}{}^2 + \sigma_{j+k}{}^2)$ is a measure of the distance between small image patches centered around pixels p_i and p_j, σ_i is the noise standard deviation at pixel p_i and N is the number of pixels in the patch. The analytical formula for the weights computation is statistically motivated and derived for Gaussian noise. Complex images obtained from a single coil element have spatially constant Gaussian noise in the real and imaginary part. The noise standard deviation can be estimated from standard noise measurements performed in the beginning of each acquisition. For SENSE based multi-coil reconstruction the spatially varying noise in the combined image is estimated using noise propagation analysis.
Starting with an initial image x_0 and k-space data $y_0 = y$, the reconstruction algorithm for multi-coil data consists of repeating the following steps until convergence:

1) $y_i = \mathcal{F}Cx_i;\ y_i|_{acq} = y$ data fidelity constraint
2) $x_i = \frac{C^H\mathcal{F}y_i}{C^HC}$ coil combination
3) $x_{i+1} = S(x_i, \sigma)$ STAINLeSS filtering

Here $\mathcal{F}$ is the Fourier transform, C is the coil sensitivity matrix, and S is the STAINLeSS filter. 3D brain and phantom data were acquired on a 1.5T clinical scanner (Philips Healthcare, Best, The Netherlands) using 8-channel head coil for the brain and body coil for the phantom data (TE/TR=4.5/12.5ms, FOV=240x240x176mm^3, 1mm isotropic voxel). The data were retrospectively undersampled using variable density Poisson disk sampling [7] and reconstructed using the proposed method. CS reconstruction using iterative soft thresholding in the wavelet domain (Daubechies 4) and manually tuned threshold was performed for comparison.

Results:
Figure 1 shows reconstruction results in the phantom using wavelets and the STAINLeSS filter for reduction factor of 5. Figure 2 shows the reconstruction results for the brain data with reduction factors of 4 and 9. Magnified areas of each image are shown for better visualization. The reconstruction with the STAINLeSS filter shows clearly improved image quality with reduced noise and aliasing artifacts as well as better preserved features. At high reduction factors the signal is reduced and features that fall under the noise level cannot be recovered, but no additional artifacts are observed, such as in the wavelet-based reconstruction.

Conclusion:
A practical CS reconstruction based on statistical non-local self-similarity filtering is proposed. The method achieves improved image quality compared to wavelet based CS reconstruction in particular in SENSE based multi-coil reconstruction due to its adaptivity to spatially varying noise**.** The proposed method provides improved robustness due to the lack of free parameters which is crucial for the clinical applicability of CS.

References:
[1] Lustig M et al, MRM 2007 58:1182-95 [2] Doneva M et al, MRM 2010 64: 1114-20[3] Ravishankar S, ISMRM 2011 #2830 [4] Adluru G et al., JMRI 2010 32:1212-27 [5] A kcakaya M et al., MRM 2011 66:756-67 [6] A. Buades et al., Multiscale Model. Simul. 2005 4: 490-530

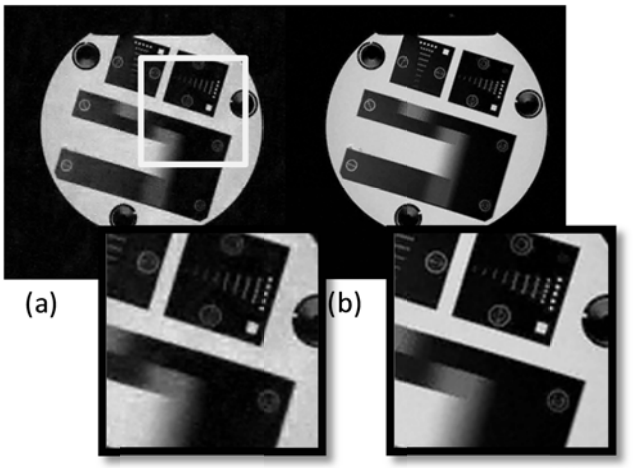

Figure 1 *CS reconstruction using wavelets (a) and the STAINLeSS filter (b) for single coil acquisition and reduction factor of 5.*

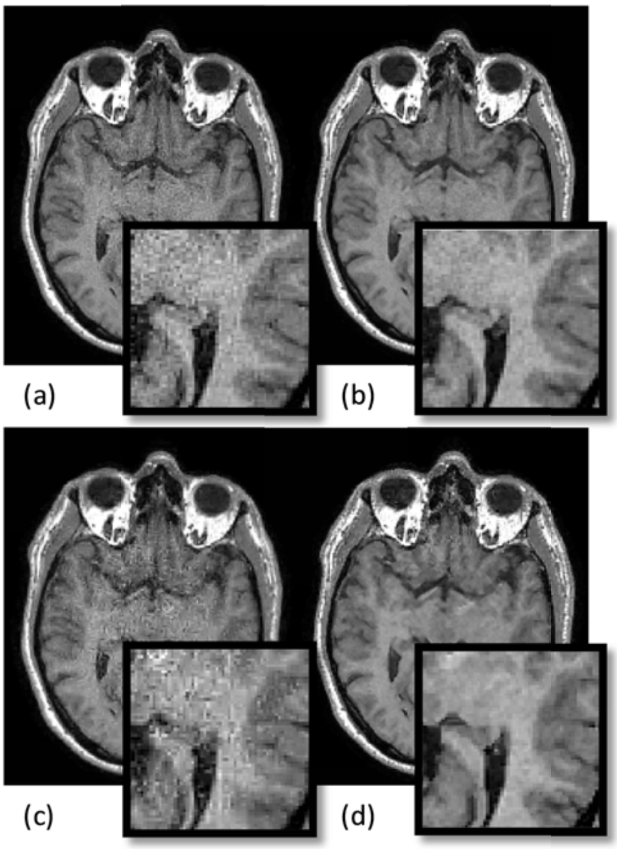

Figure 2 *CS-SENSE reconstruction of brain data using wavelets (a,c) and the STAINLeSS filter (b,d) for reduction factors of 4 (top) and 9 (bottom).*