Fast non-local means reconstruction for multi-contrast compressed sensing

Kourosh Jafari-Khouzani[1], Berkin Bilgic[1], Jayashree Kalpathy-Cramer[1], and Kawin Setsompop[1]
[1]*Athinoula A. Martinos Center for Biomedical Imaging, Massachusetts General Hospital, Charlestown, MA, United States*

Target audience – Medical physicists and computer scientists interested in accelerated imaging.

Purpose – Multi-contrast MRI is routinely used for clinical diagnosis, wherein the same anatomical cross section is scanned under multiple contrast settings. Compressed sensing (CS) imposes sparsity or compactness priors on the reconstructed images to allow faster acquisitions by undersampling the k-space [1]. The previously proposed joint Bayesian CS (jBCS) [2] and M-FOCUSS [3] algorithms exploit the mutual information across the multi-contrast data for improved image quality in accelerated acquisitions where each contrast is undersampled. While jBCS outperforms the M-FOCUSS formulation thanks to probabilistic modeling that allows idiosyncratic signal components in each contrast, it suffers from prohibitively long reconstruction times [2]. In this contribution, we propose a fast non-local means (NLM) image reconstruction method that uses a fully-sampled contrast as prior estimate to reconstruct other undersampled contrasts. Compared to the M-FOCUSS technique that employs a joint Total Variation (TV) prior, our proposal is up to **30× faster** while achieving more accurate results with **20% reduction** in normalized root-mean-square error (NRMSE). The proposed method also attains **50% NRMSE reduction** and **20× speed-up** relative to the sparseMRI algorithm [1], which imposes TV constraint on each contrast separately, without the aid of a prior estimate.

Methods – NLM upsampling has been previously used to improve the resolution of low-resolution (LR) images [4]. In this method, a high-resolution (HR) image is used as a guide to interpolate a LR image with a different contrast. Partial volume information is extracted by a feature-based NLM method from the HR image and is applied as a constraint to the LR image in an iterative optimization. Here we apply NLM method in a similar framework to reconstruct an undersampled image. In this method, intensity of a voxel is assumed to be a linear combination of intensities of voxels in a neighborhood expressed by $\mathbf{x}(\mathbf{v}) \approx \sum_{\mathbf{k}\in\Omega(\mathbf{v})} w(\mathbf{v},\mathbf{k})\mathbf{x}(\mathbf{k})$, where $\mathbf{x}$ is the image intensity function and $\Omega(\mathbf{v})$ is a neighborhood of voxel $\mathbf{v}$. The weights $w(\mathbf{v},\mathbf{k})$ are calculated based on the similarity of feature vectors calculated for each voxel as $w(\mathbf{v},\mathbf{k}) = 1/N \exp\left(-\|F(\mathbf{v})-F(\mathbf{k})\|^2\right)$, where F is a feature vector representing tissue property of a voxel and N is a normalization factor such that $\sum_{\mathbf{k}} w(\mathbf{v},\mathbf{k}) = 1$. The weights $w(\mathbf{v},\mathbf{k})$ are estimated from the fully sampled image $\mathbf{z}$ registered to the undersampled image with $F_{\mathbf{z}}(\mathbf{v}) = \left[\mathbf{z}(\mathbf{v}), |\nabla \mathbf{z}(\mathbf{v})|, \mathbf{z}*\mathbf{g}_1|_{\mathbf{v}}, \mathbf{z}*\mathbf{g}_2|_{\mathbf{v}}, \ldots, \mathbf{z}*\mathbf{g}_k|_{\mathbf{v}}\right]^T$ where ∇ is gradient operator, * is convolution operator, $\mathbf{g}_i$, i=1,2,…,k are Gaussian kernels, and k is the number of kernels. This feature vector is designed based on the assumption that brain tissues form laminar structures and has shown to outperform patch-based NLM approaches in brain MRI [4]. The undersampling is modeled by $\mathbf{y} = H\mathbf{x} + \mathbf{n}$, where $\mathbf{y}$ is the undersampled image, $\mathbf{x}$ is the fully sampled image of the same contrast, H is a matrix incorporating undersampling, and $\mathbf{n}$ is the observation noise. The image may then be reconstructed by $\hat{\mathbf{x}} = \arg\min \|\mathbf{y} - H\mathbf{x}\|^2 + \lambda R(\mathbf{x})$, where $R(\mathbf{x})$ is a regularization term that applies prior information and is defined by $R(\mathbf{x}) = \sum_{\mathbf{v}} \left|\mathbf{x}(\mathbf{v}) - \sum_{\mathbf{k}\in\Omega(\mathbf{v})} w(\mathbf{v},\mathbf{k})\mathbf{x}(\mathbf{k})\right|^2$. An iterative approach may be used to perform the above minimization [4]. This minimization enforces the reconstructed and the fully sampled images to have regionally similar patterns.

Results – The proposed NLM method was applied to in vivo data acquired on a healthy volunteer at 3T, which was also reconstructed with M-FOCUSS joint TV solver [3] and sparseMRI [1] with an optimal regularization parameter that yielded the smallest NRMSE. The set consisted of a proton density (PD) image and a T2-weighted ($T2_W$) image (200×200 pixels, 1×1×1.5 mm^3, TR=3980 ms, TE=36/107 ms for PD/$T2_w$). The PD was retrospectively undersampled with a 1D pattern using acceleration R=3 while the $T2_W$ image was kept fully sampled to serve as prior. Fig. 1 shows the two fully sampled images, sampling pattern with R=3, and the reconstructed image by zero filling. Fig. 2 shows the images reconstructed by sparseMRI, M-FOCUSS, and the proposed method. As shown, the proposed method has improved accuracy compared to M-FOCUSS (NRMSE=6.9% versus NRMSE=8.76%) while being significantly faster (3.3 s versus 94.4 s). Both M-FOCUSS and the proposed method outperformed sparseMRI which uses TV penalty without the aid of prior information from the fully-sampled contrast.

Discussion – The proposed method uses prior information from a fully sampled image to guide reconstruction of the undersampled image. This is desirable when acquisition of the fully sampled contrast is faster. In particular, the rapid MPRAGE [5] and FLASH [6] sequences may serve as prior to reconstruct undersampled images with different contrasts, especially for $T2_W$ acquisitions that require long TR's to provide pure T2 contrast. The assumption our proposal exploits is that the guide and the undersampled images have regionally similar patterns. The proposed algorithm is significantly faster than two algorithms that are based on the minimization of the TV constraint.

Conclusion – The use of prior information from a fully sampled image in a NLM framework provides faster reconstruction compered to TV minimization and is comparable to joint M-FOCUSS reconstruction with prior estimate in terms of NRMSE. Further directions include addition of parallel imaging capability to further accelerate the acquisition speed by synergistic combination of SENSE [7] and NLM.

References – [1] Lustig et al., MRM 2007. [2] Bilgic et al., MRM 2011. [3] Cotter et al., IEEE TSP 2005. [4] Jafari-Khouzani, IEEE TMI, 2014. [5] Mugler et al. MRM 1990. [6] Haase et al. JMR (1969) 1986. [7] Pruessmann et al., MRM 1999.

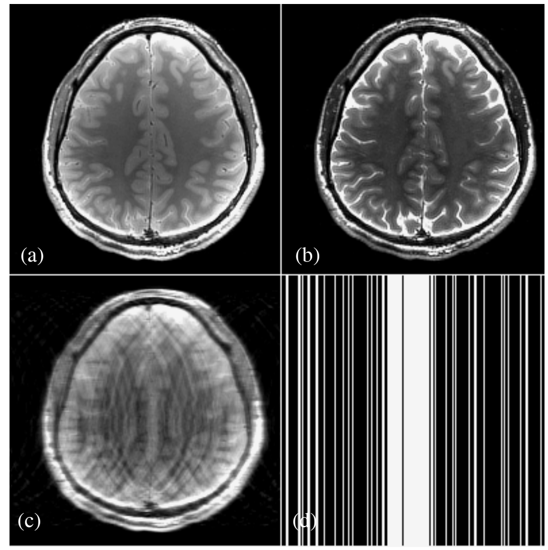

Fig. 1. (a) Fully sampled PD MRI, (b) fully sampled $T2_W$ MRI, (c) undersampled PD image reconstructed by zero-filling, (d) R=3 sampling pattern.

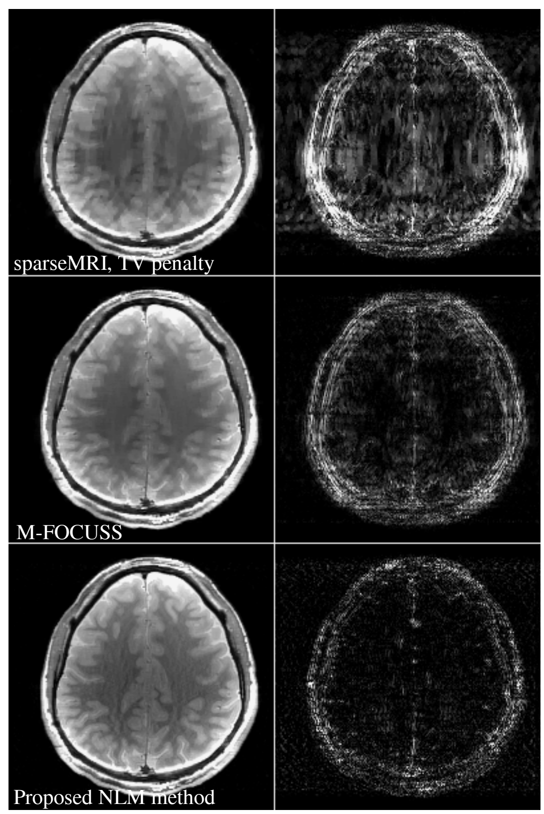

Fig. 2. Reconstructed images (left column) and error maps (right column). The error maps are scaled 5×. sparseMRI algorithm yielded NRMSE=14.22% in 70.5 seconds, M-FOCUSS yielded NRMSE=8.76% in 94.4 seconds, and the proposed NLM method with prior yielded NRMSE=6.90% in 3.3 seconds.