High resolution 3D intracranial ASL angiography using automatically tuned Compressed Sensing

Huimin Wu[1], Walter Block[1,2], Patrick Turski[3], Charles Mistretta[1], and Kevin Johnson[1]

[1]Medical Physics, University of Wisconsin-Madison, Madison, WI, United States, [2]Biomedical Engineering, University of Wisconsin-Madison, Madison, WI, United States, [3]Radiology, University of Wisconsin-Madison, Madison, WI, United States

INTRODUCTION: Assessment of the intracranial vasculature requires flow insensitive techniques with high spatial resolution. This is challenging to achieve with contrast enhanced MRA and 3D time of flight (TOF), due to rapid bolus passage and flow saturation artifacts respectively. 3D angiography techniques using arterial spin labeling (PCASL) in combination with accelerated radial acquisition have demonstrated whole head coverage with 0.7 mm isotropic resolution and reduced sensitivity to flow [1]. This resolution is still inferior to TOF and may be insufficient for visualization of small intracranial aneurysms. Achieving higher resolution is challenging due to currently high acceleration levels. PCASL angiography is, in principle, highly amenable to compressed sensing (CS) which may provide additional acceleration. However, considerable challenges exist including selection of CS tuning parameters and computational complexities arising from Non-Cartesian sampling. In this work, we investigate the use of fully 3D compressed sensing using data-driven tuning for high resolution 3D intracranial ASL angiography.

METHODS: Compressed sensing methods rely on minimization of the objective function: $\Phi(\mathrm{f}) = \|\mathbf{E}\mathrm{f} - \mathrm{d}\|_2^2 + \gamma\|\Psi(\mathrm{f})\|_1$. The first term represents data consistency ($\mathbf{E}$ = encoding matrix; f = image, d =data) while the second term encourages sparsity (Ψ is a sparsifying transform). γ is a free parameter to balance the two terms which can be challenging to determine. This function can be recast as iterative soft thresholding (IST) [2] in which, the image is iteratively updated by a gradient descent step followed by thresholding: $\mathrm{f}^{(n+1)} = \Psi^{-1}\mathrm{T}_\lambda\Psi\left[\mathrm{f}^{(n)} + \mathrm{E}^{\mathrm{H}}(\mathrm{d} - \mathrm{E}\mathrm{f}^{(n)})\right]$ Here, $\mathrm{f}^{(n)}$ denotes the solution at the n^{th} iteration and T_λ is the thresholding operator with threshold of λ. T_λ is written as: $\mathrm{T}_\lambda(\mathrm{x}) = \max(|\mathrm{x}| - \lambda, 0)\cdot e^{\mathrm{i}\arg(\mathrm{x})}$

When wavelet transforms are utilized, at each iteration, near optimal thresholds in sense of minimizing Mean Square Error (MSE) can be calculated based on Stein's Unbiased Risk Estimator (SURE) [3]. This method analyzes the wavelet coefficients at each dyadic resolution level and sets thresholds so noise is optimally suppressed while preserving signal.

Human feasibility studies were performed on a 3T MRI scanner (MR750, GE Healthcare, Waukesha, WI) with a 32-channel head coil (MR Instruments, Hopkins, MN, USA). Images were collected with a PCASL-VIPR sequence with the following parameters: Tagging duration = 3 s, sampling window length = 1 s, FOV = 220x220x160 mm^3, isotropic resolution = 0.43 mm, flip angle = 9. A total of 8906 projections, approximately 20x accelerated, were acquired in a scan time of 8 min. Data acquired for the label and control phases were first subtracted in k-space then reconstructed using a standard non-iterative method (labeled as PILS) and IST based CS. In both cases, individual coil images were reconstructed using an optimized gridding routine and combined using coil sensitivities estimated from the center of k-space [4]. For CS, manually selected and SURE based threshold were applied and compared.

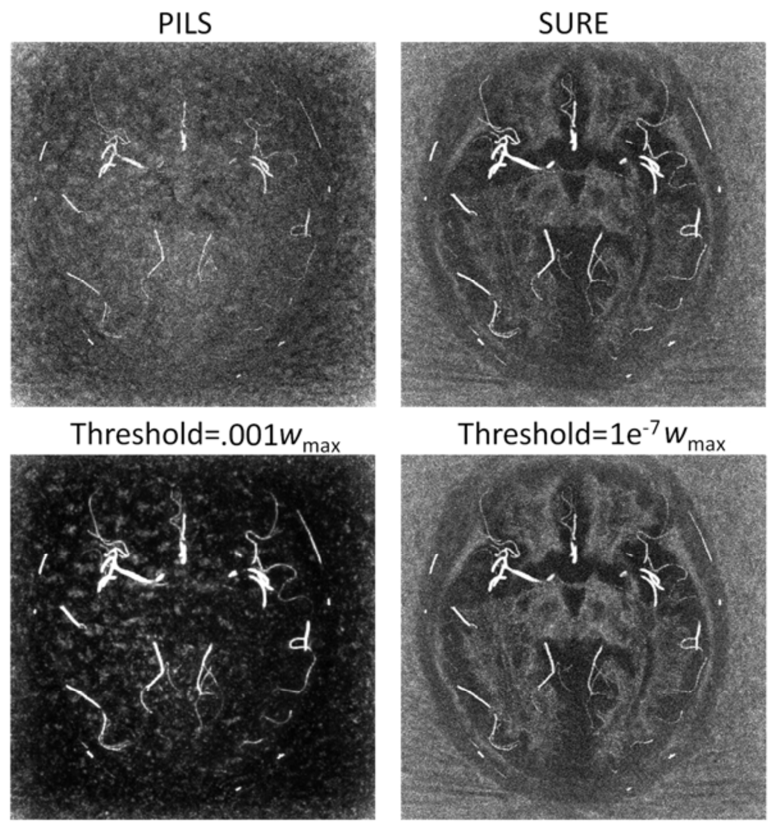

Figure 1. Limited axial MIPs of thickness 8 mm reconstructed by standard non-iterative method (PILS), CS with auto-tuned threshold (SURE), CS with manually defined threshold (the low thresh = 1e-7w_{max}, the high thresh = .001w_{max})

RESULTS: Four reconstructions are presented in Figure 1. Substantial improvements can be observed with CS (SURE and low threshold) compared to PILS in terms of SNR and vessel visualization. However, CS images reconstructed with high threshold are lower in resolution and show wavelet artifacts that may interfere with diagnosis.

DISCUSSION AND CONCLUSIONS: In this work, we combine compressed sensing, parallel imaging and 3D Non-Cartesian sampling to improve image quality and apparent SNR in high resolution 3D ASL angiography. Furthermore, we demonstrate the use of data driven tuning which created high quality images. As shown in the preliminary study, SURE tends to calculate a relatively conservative threshold. Further work will include applying and comparing other data-driven tuning methods.

ACKNOWLEDGEMENTS: We gratefully acknowledge GE Healthcare and NIH Grant 1R01NS066982-01A1 for their assistance and support.

REFERENCES: [1] Wu et al. MRM 2012 Apr 24(doi: 10.1002/mrm.24298) [2] Daubechies et al. Comm. Pure Appl. Math. 2004; 57(11):1413 [3] Donoho and Johnstone, J. Amer. Statist. Assoc. 1995; 90(432):1200 [4] Griswold et al. MRM 2000; 44:602