Strategies for the implementation of Compressed Sensing on Arterial Spin Labeled Data: a retrospective study

Stanislas Rapacchi[1], Robert X. Smith[2], Danny J.J. Wang[2], and Peng Hu[1]
[1]*Radiology, UCLA, Los Angeles, CA, United States,* [2]*Neurology, UCLA, Los Angeles, CA, United States*

Introduction: Arterial Spin Labeling (ASL) is a perfusion imaging technique of long history[1–4]. However it suffers greatly from low signal compared to his rival Contrast-Enhanced Imaging, thus averaging over multiple repetitions is a requirement. As a consequence ASL acquisitions can be very demanding in time. Many recent developments[5,6] proposed to accelerate MRI using Compressed Sensing (CS) to benefit from the inherent sparsity of MR images to reduce the amount of data acquired while maintaining signal-to-noise ratio (SNR). The important sparsity of the ASL signal due to the subtraction of the background (unlabeled images) to blood-labeled image makes ASL a perfectly suited technique for CS acceleration. We propose here to investigate the potential implementation of CS to accelerate ASL acquisitions by undersampling using two different strategies: 1) To under-sample each acquisition independently then to apply CS individually and subtract the reconstructed images. 2) To use the same pattern for both acquisitions in order to perform the subtraction in the k-space domain.

Theory: All pixels of an MR image are represented in a vector X. ASL consists of the acquisition of the same slice twice, once with a saturation pulse labeling blood spins upstream: X_L, and once without: X_{NL}. The second acquisition is then subtracted to the first: $X_{ASL} = X_L - X_{NL}$. The purpose of strategy 2) is to benefit from the inherent sparsity of the images after background subtraction. Thus images are reconstructed from $Y_{ASL} = Y_L - Y_{NL}$, where Y is the corresponding k-space vector for image X. However the image difference in ASL is usually performed by the magnitude difference. Because if complex subtraction were performed, global phase differences between the 2 acquisitions would prevents proper cancellation of the background and hide small arteries and capillaries (Fig. 1 & 2). We correct global phase differences by deleting the phase of the center point of k-space prior to k-space complex subtraction. For both strategies, we define the image reconstruction as the L1 norm minimization problem similar to Lustig and al.[5] approach: $X_{ASL} = \arg\min_X \|FX - Y\|_2^2 + \lambda_1 \|TV(X)\|_1 + \lambda_2 \|W(X)\|_1$, where F is the 2D Fourier transform and a mask to match acquired data Y, TV is the total variation transform and W is the wavelet transform. The L1 norm minimization problem is solved using a conjugate gradient approach.

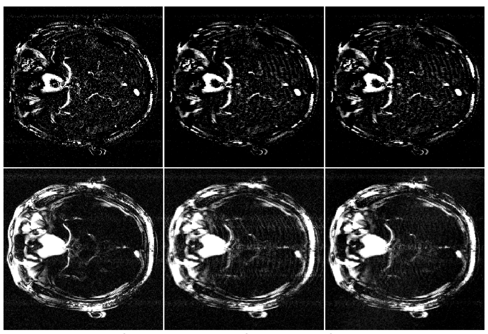

Figure 1: Left to right: Reference (full k-space), under-sample (2X) and CS reconstructed (2X) image. Magnitude subtraction of ASL acquisitions (strategy 1, Top) and complex k-space subtraction reconstruction (strategy 2, Bottom).

Material & Methods: Multi-slice multi-repetition ASL data were acquired on the brain of one volunteer with fully sampled k-space. Data were under-sampled retrospectively so that CS reconstruction could be evaluated in regards to reference images. Acquisition parameters using a balanced-SSFP sequence at 1.5T (Siemens, Avanto) were: 10 slices, 10 repetitions, 224x222 matrix size with 0.98x0.98 mm^2 in-plane resolution and 4mm slice thickness, TE: 2.2 ms, TR: 4.4 ms, 25 segments. Under-sampling was done using random sample lines in the $k_x - k_y$ plane. Half the number of lines was distributed in the center of k-space and the other half was randomly distributed in higher frequencies. Data were under-sampled using true rates of 2X and 4X. Minimization was performed using parameters λ_1 = 0.00001 and λ_2 =0.00001 optimized empirically.

Qualitative evaluation was assessed from magnitude images and maximum intensity projection (MIP) reconstructed images. CS-reconstructed images were compared to references images (using full k-space).

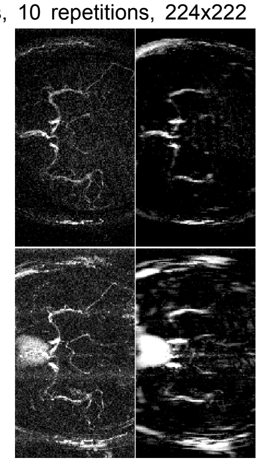

Figure 2: MIP images. Full k-space (left) and CS (4X) reconstruction (right). Top: strategy 1. Bottom: strategy 2.

Results: K-space under-sampling impacts greatly ASL images, affecting the delineation of all arteries, even at low acceleration rates (Fig. 1, Mid.). However under-sampling artifacts can be reduced using compressed sensing. The strategy 1) where each acquisition is under-sampled and reconstructed independently provides great contrast of labeled arterial blood but individual CS reconstruction does not compensate fully for under-sampling artifacts (Fig. 1 & 2). The strategy 2) enables better CS reconstruction but suffers a great contrast loss (Fig. 2). The complex subtraction let anatomical features appear which hamper small arteries visualization due to phase differences between acquisitions.

Discussion and conclusion: ASL appears a potential application for compressed sensing acceleration beyond parallel imaging acceleration factors. However the option to perform background subtraction in the k-space domain does not appear beneficial. A more advanced phase correction could be considered and could be integrated to CS reconstruction. The separated CS reconstruction of the 2 acquisitions seems more appropriate for ASL although it prevents CS to benefit from the sparsity of images after subtraction. We have proposed here a study of CS application to ASL. Prospectively under-sampled data acquisition seems promising and would enable to measure in-situ the benefits of CS to ASL acquisition and its influence of perfusion detection accuracy.

References: 1. Alsop DC, Detre JA. *Radiology*. 1998;208(2):410 -416; 2. Detre JA et al. *Neurology*. 1998;50(3):633 -641; 3. Wang J et al. *Radiology*. 2005;235(1):218-228; 4. Yang Y et al. *MRM*. 1998;39(5):825-832; 5. Lustig M, et al. *MRM*. 2007;58(6):1182-1195; 6. Gamper U et al. *MRM* 2008;59(2):365-373.