

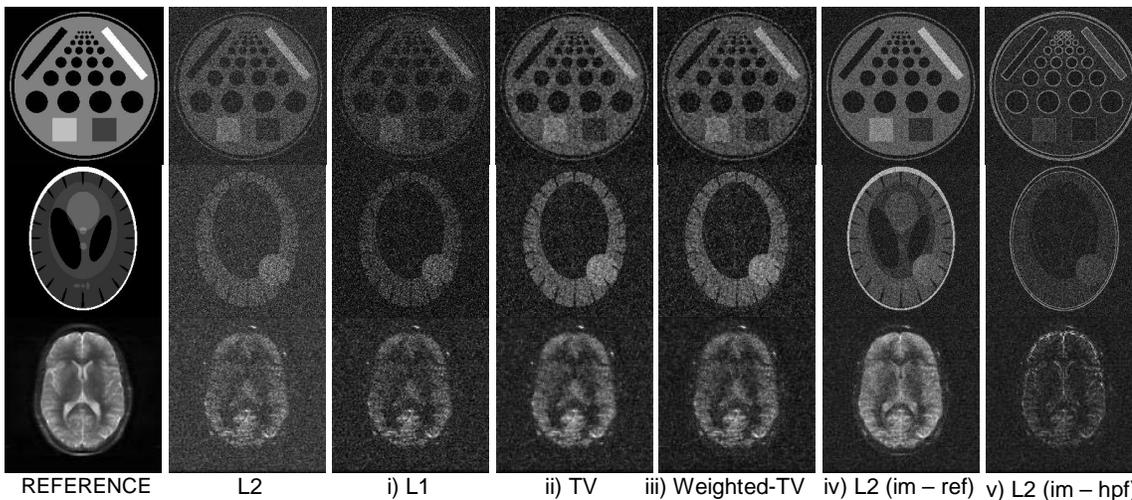
Including Prior Knowledge in the Reconstruction of ASL Perfusion Images to Reduce Noise and Improve Spatial Resolution

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INTRODUCTION: Perfusion measurements, obtained using Arterial Spin Labelling (ASL), are often limited by Signal-to-Noise Ratio (SNR), the perfusion signal being approximately a few percent of the normal signal from the tissue. Consequently, perfusion images are most often acquired at lower resolutions to increase SNR. This is often suitable where changes in tissue perfusion are themselves of low resolution. However, in the perfusion image, boundaries between tissue types where the perfusion signal changes abruptly can be blurred. It would be desirable to obtain perfusion images with higher resolution. This may be achieved with an image reconstruction which incorporates either effective noise reduction or a method to increase resolution using prior information. Image de-noising techniques exist that minimise the difference between the image and the acquired data subject to certain constraints on the reconstructed image; for example, the minimisation of the absolute image intensity, or the total variation between image pixels in the final image. A more sophisticated method involves weighting the constraint penalty by a parameter derived from prior information obtained from a reference image. Furthermore, Compressed Sensing techniques (1) exploit the constraint of sparseness in some domain to achieve image reconstruction with sub-Nyquist sampling. Quantitative perfusion measurements often include co-registered, anatomical reference images, from which tissue-T1 and M0 is measured. Thus, a conventional ASL study is well disposed to benefit from constrained reconstructions using prior information. We explore image de-noising reconstructions for obtaining perfusion images at higher resolutions than those permitted by thermal noise alone and techniques for enhancing images with prior knowledge from a reference image.

METHODS: Constrained image reconstruction was achieved by minimising the sum of the L2-norm of the difference between the image in k-space with the acquired data (data consistency), and an additional metric of the image, weighted by a regularisation parameter, L . Minimisation was achieved iteratively, using freely available conjugate gradient and line-searching algorithms based on algorithms in (2). Constraints investigated were: i) the L1-norm of the image itself, ii) the total variation (TV) of the image, iii) TV, weighted by the inverse of the TV in the reference image (3), iv) the L2-norm of the difference between the image and the reference image, evaluated in k-space, and v) the L2-norm of the difference between the image in k-space and the reference image after applying a high pass filter in k-space. Constrained image reconstruction was implemented on simulated k-space data, with white noise added, representing a resolution phantom, and a perfusion phantom that had different target and reference images, and on in vivo data from a brain perfusion image (pCASL labelling (4), with background suppression, SSFSE signal acquisition, in a 2-D slice with image matrix 128x128, and 4 label-control pair signal averages.)



RESULTS: Images were obtained with various values of the arbitrary regularisation parameter, L , and visually assessed to determine the span between “small” and “large” values of L . Images with intermediate values of L are shown in the Figure below for each of the objects. These images show the properties of each constraint. L1, TV, and weighted-TV constraints all produce

visibly de-noised images. The L2-norm constraints show a steady transition between the L2-norm perfusion image and replication of the reference image. Also shown for comparison are the reference images used in some constraints and the data-consistency L2-norm perfusion images, obtained without any additional constraint.

DISCUSSION: Constrained image reconstructions using reference images as prior knowledge show promise for reducing noise and increasing resolution of ASL perfusion images. This approach takes advantage of the simultaneous anatomic and functional capabilities of MRI. The unwise use of prior knowledge can produce images more characteristic of the reference image than the underlying ASL signal, however.

REFERENCES: 1) Lustig M, 2007, MRM, 58:1182-95, 2) Press WH, et al. "Numerical Recipes: The Art of Scientific Computing", 3) Haldar JP, 2008, MRM, 59:810-18, 4) Dai W, 2008, MRM, in press.