Introducing prior knowledge through the non-local means filter in model-based reconstructions improves ASL perfusion imaging

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Introduction: The arterial spin labeling (ASL) technique is an attractive alternative to contrast-enhanced methods for perfusion imaging [1]. The major disadvantage for ASL is low SNR and low spatial resolution of the resulting images, stemming from the fact that ASL is a subtractive technique with the perfusion signal typically amounting to about 1% of the component signal. The hypothesis of this work is that the SNR and spatial resolution of perfusion images acquired with ASL can be improved by incorporating side information from high-SNR anatomical images into model-based reconstructions of the data.

The incorporation of prior knowledge regarding image features is a well-known method by which image quality may be improved for many imaging methodologies, including in perfusion imaging with ASL [2]. In this case, prior information regarding the perfusion distribution exists: it should be restricted to white and gray matter and not be distributed uniformly across known anatomical boundaries. Therefore, the imposition of side information from high resolution, high SNR anatomical images has the potential to improve perfusion imaging. Here, we apply the non-local means denoising algorithm to perfusion image data, using spatial information derived from concurrently-acquired anatomical images to build the filter weights.

Methods: Anatomic side information was incorporated into perfusion reconstructions by introducing boundary information into the regularization term in a cost function used to estimate the image in iterative model-based reconstructions:

$$\hat{f} = \underset{f}{\operatorname{argmin}} \|y - Af\|_2 + \beta_{NLM} \|f - NLM(f,p)\|_2 + \beta_{TV} \|Cf\|_1$$

where C is a differencing matrix used to apply a small total variation penalty and *NLM(f,p)* is a non-local means filtered version of the image, trained on an anatomic image, *p*. Briefly, the non-local means filter works on the principle that any local image patch should look similar to other image patches present in the same image [3]. In order to apply the filter to low-SNR perfusion data (which does not contain much spatial information), we first deploy the filter on a high-SNR, high-spatial-information anatomical image, *p*. The calculated filter weights are saved and then used to guide the perfusion filter by describing, for any individual patch, which other patches in the (perfusion) image, *f*, should be similar and how to combine them.

To test this idea, a simulated experiment was first performed. A T2-weighted brain image was segmented into white matter, gray matter, CSF, and background. To this segmented image, a small amount of complex noise was added to create an “ideal”, high-SNR anatomical reference image (Fig. 1A). Next, the CSF was removed and the white matter intensity reduced to create an ideal perfusion image (Fig. 1B). This ideal data was then truncated in k-space and more noise was added in order to generate a simulated noisy, low-resolution perfusion data set. The resulting k-space data was then reconstructed with a standard inverse Fourier transform (iFFT - Fig. 1C) as well as a model-based reconstruction in which side information was imposed through the method described above (Fig. 1D). Using the “ideal” high-SNR perfusion image as the reference, the SNR, mean percent error (MPE), and peak SNR (PSNR: a measure of image similarity between each reconstruction and the reference perfusion image) was recorded for the iFFT and constrained reconstructions.

An *in vivo* experiment was carried out on 3T Trio Siemens scanner with a 12-channel head coil. A T2-weighted 3D SPACE (TR/TE = 2000/302 ms) image with isotropic 1.5 x 1.5 x 4 mm^3 resolution provided high contrast between gray and white matter in order to supply high-quality boundary information. Three-D pseudo continuous ASL [4] with background suppression was performed with a bolus duration = 2000 ms, post label delay = 1000 ms, and BIR4 adiabatic pulses to achieve intravascular flow suppression. Images were acquired with a 3D TSE stack-of-spirals sequence with 3 interleaves per slice [5]. Each interleaf had a readout duration of 6 ms and 24 slices were collected for an overall resolution 4 x 4 x 4 mm^3. TR/TE were 5000ms/22ms. Total scan time was 2 minutes. As before, the standard iFFT reconstruction was performed as well as a constrained reconstruction with a bias towards a side-information-trained non-local-means filtered version of the image.

Results: In a numerical phantom derived from a T2-weighted anatomical image, the application of model-based iterative reconstructions improves SNR, resolution, and reduces error (Fig. 1, Table 1). Compared to the standard inverse Fourier transform reconstruction, the model-based reconstruction improves SNR (in white matter by 7%; in gray matter by 225%), decreases MPE of white and gray matter image intensities, and increases PSNR by improving resolution. *In vivo*, the model-based reconstruction shown in Fig. 2 improves resolution across sharp image boundaries defined by the T2-weighted image in 2A.

Discussion: The non-local means denoising algorithm provides a simple, effective method by which side information may be leveraged in order to improve ASL perfusion MRI. These results indicate that the incorporation of anatomical side information into model-based reconstructions results in images that are closer to “truth” than standard analytical reconstructions that do not utilize this extra information.

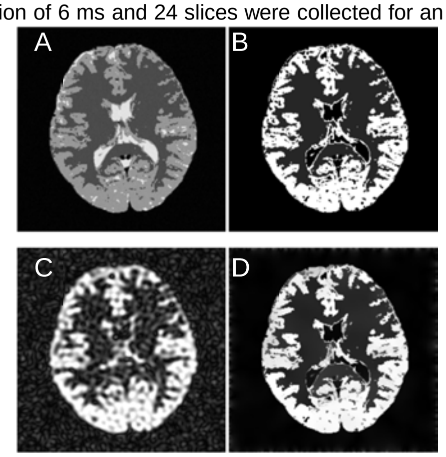

Figure 1. Reconstructions of simulated perfusion images. A) "Anatomical" image used to train non-local means filter. B) Ideal high-SNR, high-resolution perfusion image. C) iFFT reconstruction of low resolution, noisy data. D) Constrained reconstruction.

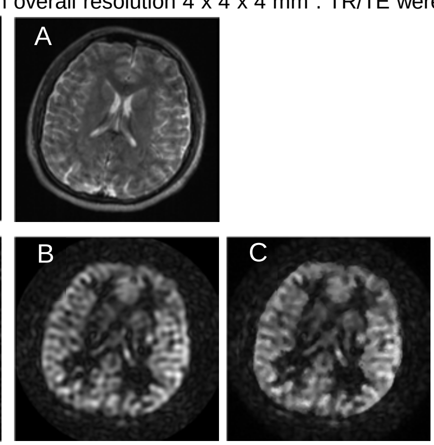

Figure 2. Constrained model-based reconstructions in the brain. A) T2-weighted image used to constrain model-based reconstructions. B) iFFT reconstruction. C) Constrained reconstruction regularized towards a side-information-trained NLM denoised image.

Table 1. Quantification of reconstruction performance from Fig. 1.

	iFFT Reconstruction			Constrained Reconstruction		
	SNR	MPE	PSNR	SNR	MPE	PSNR
White matter	1.48	12.8%	34.4	1.59	4.68%	45.6
Gray Matter	3.83	-16.5%		8.61	-7.25%	

References: [1] Detre, et al. MRM. 1992;23:37-45. [2] Robson and Alsop. ISMRM. 2009;2865. [3] Buades, et al. Multiscale Model Sim. 2005;4:490–530.[4] Dai, et al. MRM. 2008;60:1488. [5] Zhao, et al. ISMRM. 2013;2157.