Arterial Spin Labeling Improvement by Incorporating Local Similarity with Anatomic Images

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Target Audiences: Radiologists and researchers, who are interested in arterial spin labeling and multiple contrast imaging.

Purpose: Arterial spin labeling (ASL) perfusion MRI has shown research and diagnostic value [1], but it suffers from relatively low SNR and spatial resolution [2]. Fortunately, high quality anatomic images are routinely collected with other contrasts (e.g. T1 and T2). It may be possible to exploit the spatial information of these anatomic images to improve ASL images. Here, we introduce a method, which enhances the resolution and SNR of ASL images by exploiting their local similarity with T1 weighted images. Importantly, it preserves the quantitative perfusion values in larger regions of the image.

Method: The proposed method tries to improve ASL images by reducing the dissimilarity between ASL and anatomic images. ASL images (X) are decomposed into two orthogonal parts: one represents the similarity (S) with the anatomic image (Y), and the other is the dissimilarity (D). Local similarity ($S_{M,n}$) is rapidly calculated within a smoothing kernel M by the Fourier transform and convolution theorem, then it is removed from the dissimilar image D iteratively with index n. ϵ is a relaxation factor, which controls the convergence of the algorithm. By removing the dissimilarity (D_N) from the original ASL image, the enhanced image ($\hat{X}$) preserves most similarities between ASL and anatomic images.

$$D_{M,n+1} = D_{M,n} - \epsilon S_{M,n}$$
$$= D_{M,n} - \epsilon \left(\frac{\langle D_{M,n}, Y_M \rangle}{\langle Y_M, Y_M \rangle} Y_M \right)$$
$$\hat{X} = X - D_N$$

CNR	Lesion1	Lesion2
original	28.4	62.7
wavelet	20.8	53.7
proposed	43.5	97.7

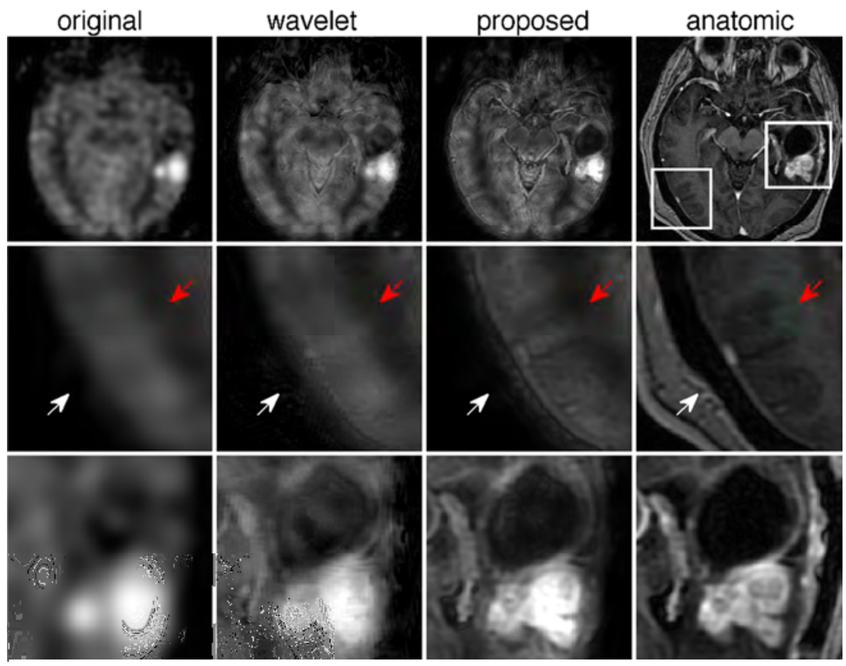

Figure 1. ASL image enhancement by anatomic information on 3D tumor patents. Both wavelet and the proposed method can preserve low resolution ASL contrast (highlighted by arrows) and improve the resolution of ASL images by anatomic information in T1 weighted image. In the tumor lesions, the proposed method provided both anatomic resolution and ASL contrast. It doesn't requires tradeoff between approximation and detail coefficients as chosen wavelet fusion method.

Five patients with high grade glioma were scanned with a 3T GE MR VH/I as part of their clinical evaluation. ASL was performed using background suppressed continuous arterial spin labeling with a stack of variable density spiral readout. Images were acquired at a 48x48x64 on an 18x18x24 cm FOV. Three ASL averages were acquired over 5 minutes. ASL 3D volumes were reconstructed offline and interpolated to matrix size 512x512. They were registered to match the contrast enhanced T1-weighted scans using the scan coordinates of the images. Further registration with SPM coregistration was optionally performed. A wavelet-based fusion method [3] was chosen for comparison. Wavelet coefficients were combined by weighted average for approximation coefficients and choose-max for detail coefficients.

Results: Figure 1 shows one selected slice of a 3D scan in a selected patient. Both methods preserved the low resolution information and original contrast between gray and white matter, as highlighted by arrows. In the tumor region (bottom), the proposed method provided both detailed structural information as in the anatomic image and perfusion contrast from the ASL image. It also suppressed noise and revealed higher contrast-to-noise (CNR) ratio, as shown in the table. The proposed method is simpler than the chosen wavelet method, which requires tradeoff coefficients between ASL and anatomic images.

Conclusion: We presented a novel method, which enhances ASL images by local anatomic information. It preserves the original ASL contrast and improves the ASL image quality for diagnostic purposes. Further work is required to assess the relative performance with anatomic images with different contrasts.

References: 1. Detre et al, JMRI, 2011;54:2066-2078. 2. Alsop et al, MRM. 2014. DOI: 10.1002/mrm.25197. 3. Pajares et al, Pattern Recognition. 2004;37(9):1855-1872.