Heavily undersampled radial acquisition of dynamic vessel-encoded arterial spin labelling angiograms reconstructed in a compressed sensing framework

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Introduction

Magnetic resonance angiography (MRA) can guide clinical decisions in cerebrovascular diseases. Vessel-encoded ASL (VE-ASL[1,2]) provides vessel specific and dynamic angiograms in a non-invasive and SNR-efficient manner, but the process of vessel-encoding increases scan times compared to standard ASL angiography. However, angiograms are spatially sparse, especially when they are vessel-selective, making them well-suited to accelerated acquisition and compressed sensing (CS) reconstruction, which relies on image sparsity in some domain[3]. In this work we exploit highly undersampled radial trajectories, which satisfy the CS requirement for incoherent artifacts, to significantly accelerate the acquisition of VE-ASL dynamic angiograms.

Methods

Three volunteers were imaged with a Siemens Verio 3T scanner with a 32-channel head coil. Labelling was performed using pseudo-continuous ASL (pCASL) and a 4-cycle Hadamard vessel-encoding scheme to separate blood supply from the right and left internal carotid arteries (ICA), and the basilar artery (labelling time: 1000 ms). A 2D radial golden angle SPGR readout[4] was applied for 1260 ms after each pCASL preparation (TR/TE = 12/6 ms). The images were reconstructed with 1.1 mm in-plane resolution and 105 ms temporal resolution (12 frames, slab thickness: 50 mm). 34 acquisitions for each encoding cycle were required to reach the Nyquist limit of 306 spokes per frame. Total scan time was 5.5 min. Subsets of the raw data were used in reconstruction yielding acceleration factors up to R = 34 (a single acquisition for each encoding cycle, scan time 9.6 seconds). Reconstruction was carried out with CS using a fast iterative soft thresholding algorithm (FISTA[5]). The encoding model used in the reconstruction included the vessel encoding, the coil sensitivities, and the k-space trajectory. The coil sensitivities were estimated directly from the time-averaged data used for each reconstruction. The reconstructed images were compared with the fully sampled time-averaged reference image using a structural similarity index (SSIM[6]). Temporally the reconstructions were compared with the fully sampled time series with a pairwise calculated correlation coefficient for each vessel component.

Results

High SSIM values (range: 0.91–0.99, high perceptual spatial correspondence, see Fig 1, top row for an example) were achieved across all acceleration factors. The temporal correlation coefficients between fully sampled and the undersampled timeseries were generally high (range: 0.92–1.00, see Fig 1, bottom row for an example), except for the basilar artery in one subject which had very little signal (correlation coefficient: -0.28 at R = 34). The regularisation factor for reconstruction was optimised on a subject by subject basis (range: 7.0e-6–1.2e-5). The narrow range suggests generalisability.

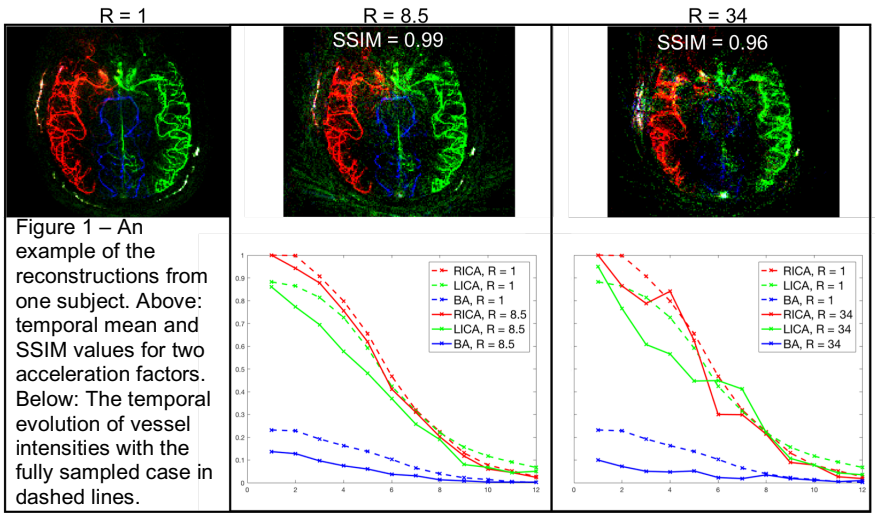

Figure 1 – An example of the reconstructions from one subject. Above: temporal mean and SSIM values for two acceleration factors. Below: The temporal evolution of vessel intensities with the fully sampled case in dashed lines.

Discussion

These preliminary in-vivo results are consistent with the results obtained previously from simulations[7]. Reconstruction can be further improved by representing the smoothly varying temporal signal in a sparse domain by using either total variation or sparsity under a Fourier transform. Extension to dynamic 3D acquisitions will also be explored.

Conclusion

We have presented a method for acquiring dynamic vessel-selective angiograms in as little as 9.6 seconds whilst maintaining spatial and temporal information, greatly improving the clinical applicability of this approach.

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