Dynamic 3D ASL in 20 Seconds Per Frame with Model-Based Image Reconstruction

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Target audience: Researchers and clinicians interested in cerebral perfusion imaging and arterial spin labeling.

Purpose: Arterial spin labeling (ASL) yields maps of cerebral blood flow (CBF), which are useful in the management of stroke, tumors and other disorders. Dynamic ASL using multiple observation times (OTs) reveals rich dynamic perfusion information, such as arterial transit time (ATT). However, the inherently low SNR makes dynamic ASL time-consuming and parameter maps less reliable. In this work we use sparse image reconstruction methods, not primarily to fill in missing k-space, but to improve parameter map accuracy.

Our strategy is as follows[1]: (1) 3D TSE stack-of-spirals readouts[2] for efficiency; (2) dual-density spirals for autocalibration and motion robustness; (3) SPIRiT [3] and spatial total variation constraints for single-shot 3D imaging; and (4) sparse model-based reconstruction [4] to enforce prior information about the temporal evolution of the dynamic ASL signal at multiple OTs, acquired by varying both tagging duration and post label delay (PLD).

The first goal of this work was to validate that model-based reconstruction improves image quality and parameter map accuracy. The second goal was to demonstrate fast and robust dynamic ASL acquired in 20 seconds per frame.

Methods: A model-based dynamic ASL reconstruction can be described by the following objective function:

$$\hat{x} = \arg\min: \|Fx - y\|^2 + \lambda_1 |(G - I)x|_2 + \lambda_2 |TV(x)|_1 + \lambda_3 |M(x)|_0$$

The first part of the equation enforces data fidelity. x is the target image, y is the sampled data, and F is the Fourier transform, including the spiral trajectory and an undersampling mask. The latter part of the equation enforces prior knowledge: G is the SPIRiT kernel, TV is spatial total variation, and M is the perfusion model based on a K-SVD dictionary of possible perfusion signals.

All experiments were performed on Siemens Magnetom Trio 3T scanner using an in-house sequence. The validation of model-based reconstruction was performed on six volunteers. The ASL blood bolus was tagged by balanced PCASL. k-space was sampled by a 3D stack-of-spirals trajectory with single-shot dual density readouts. 24 slices covered the whole brain. In-plane resolution=4.5mm×4.5mm, slice thickness=4.5mm, TR=5s. ASL images were averaged 12 times at each perfusion phase and were acquired at 9 successive OTs. The scan time was 18 minutes.

Fast dynamic ASL imaging was performed on volunteers with similar parameters, adding background suppression for additional artifact suppression. Data was acquired at 9 successive OTs, with 12 averages acquired at each OT. Total scan time was 3-9 minutes, depending upon number of averages included.

Images were reconstructed in MATLAB, with conventional non-Cartesian gridding reconstruction, SPIRiT parallel reconstruction and model-based reconstruction. CBF and ATT maps were quantified by least squares model fitting (M-CBF and M-ATT) and weighted averaging (W-CBF and W-ATT) [5].

Results and Discussion: Fig. 1 shows statistical analysis of the six volunteers' images. With model-based reconstruction, SNR of ASL images was significantly improved (Fig. 1a) and model fitting residual of CBF estimation was significantly reduced (Fig. 1b). Using the high-SNR CBF map from all available data (12 averages) as a gold standard, the CBF maps from only 1/3 of data (4 averages) were evaluated by similarity index (Fig. 1c). The proposed method resulted in significantly higher similarity to the high-SNR results. Fig. 2 shows results from a fast dynamic ASL volunteer scan. Compared to gridding reconstruction, the proposed method reduced the background noise and model regression residual in the 60 s per OT scan. It largely maintained the image quality and accuracy of the CBF map when the scan time was reduced to 40 s per OT. Further acceleration to 20 s per OT resulted in somewhat more error in the CBF calculation. Nonetheless, the proposed method yielded high quality dynamic 3D ASL images and parameter maps from 9 perfusion phases in 3 minutes.
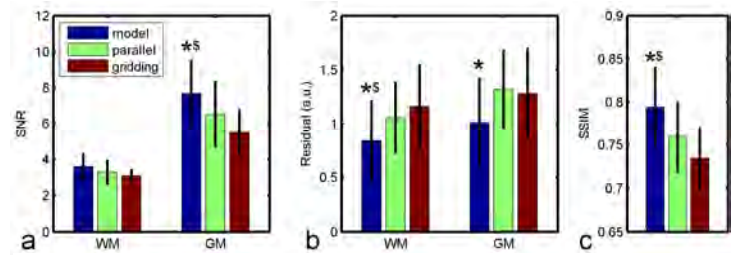

Fig. 1. ASL image SNR, CBF estimation residual and structural similarity index in six volunteers. Model-based reconstruction improved SNR (a) and reduced estimation residuals (b) significantly, compared to gridding and parallel reconstruction. Using 1/3 of the signal averages, model-based reconstruction provided better structural similarity to high-SNR images that used all of the averages (c). ROIs of grey matter (GM) and white matter (WM) were chosen based on T1 values. Wilcoxon signed-rank test was performed using these ROIs. * = P<0.05 versus parallel reconstruction. $ = P<0.05 versus gridding.
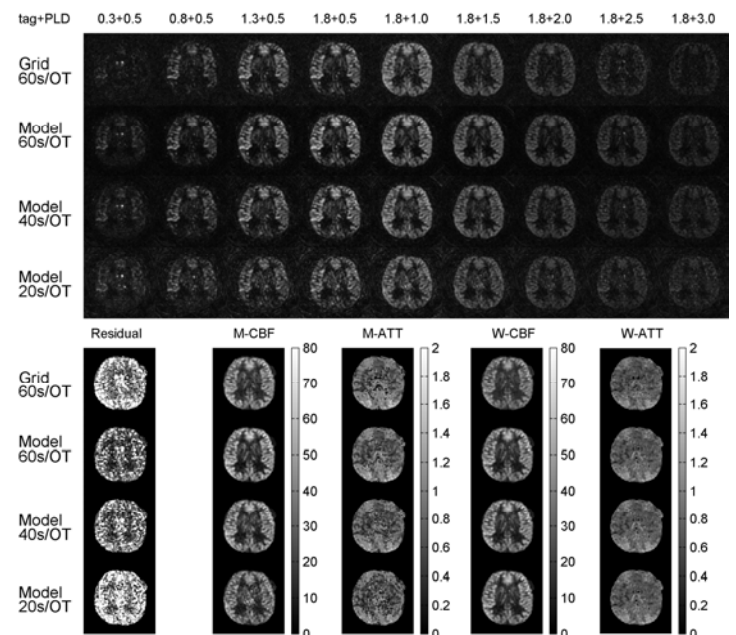

Fig. 2. Fast dynamic ASL with model-based reconstruction, single-shot 3D spiral scanning and background suppression. With a scan time of 60 s per phase (6 averages), the model-based reconstruction reduced the background noise and model residual (mean residual = 4.6e-6), compared with conventional gridding reconstruction (mean residual = 7.1e-6). With 4 averages, the proposed method maintained the image quality with a scan time of 40 s per phase (mean residual = 5.7e-6) and provided good image quality with 20 s per phase (2 averages, mean residual = 9.5e-6). Units: Dynamic model fitting residual (a.u.). CBF maps (ml/100g/min). ATT maps (seconds).

Conclusion: We demonstrated that model-based image reconstruction improves dynamic ASL image quality and parameter map accuracy. The method yields dynamic whole-brain ASL in 20s per perfusion phase, with high image quality and accurate parameter maps.

Reference: 1. Zhao. ISMRM. 2013;2157. 2. Fielden. JMRI 2014; 39(6): 1468-1476. 3. Lustig MRM. 2010; 64:457-471. 4. Doneva. MRM 2010; 64(6):1114-1120. 5. Dai et al, MRM. 2012;67:1252-1265.