

# Correcting for encoding field imperfections in arterial spin labeling using gradient impulse responses and concurrent field monitoring

Mustafa Cavusoglu<sup>1</sup>, Lars Kasper<sup>1</sup>, Johanna S. Vannesjo<sup>2</sup>, Benjamin E. Dietrich<sup>1</sup>, Simon Gross<sup>1</sup>, and Klaas P. Pruessmann<sup>1</sup>  
<sup>1</sup>Biomedical Engineering, ETH Zurich, Zurich, Zurich, Switzerland, <sup>2</sup>FMRI centre, Oxford University, Oxford, United Kingdom

**Introduction:** Perfusion MRI based on arterial spin labeling (ASL) methods has inherently very low signal-to-noise ratio (SNR), hence it requires fast coverage of k-space which is often achieved by using gradient-echo-EPI as the readout sequence. This typically demands the gradients to be employed at the limits of the system capabilities and to be switched rapidly during the course of the acquisitions which makes acquisition highly vulnerable to gradient field imperfections. This is due to a number of effects including eddy currents, amplifier bandwidth limitations, mechanical oscillations and delays. The resulting deviations in the gradient field time courses cause substantial artifacts on the reconstructed images. Additionally, perfusion images are calculated based on a series of control and tag images which are often repeatedly acquired for a number of delay times (TI) to sample the ASL kinetic curve for perfusion quantification. External field fluctuations or thermally related changes to the gradient system can cause actual k-space trajectories to vary over time, and each of the ASL images may thus associate with particular k-space trajectories which have potentially variable deviations from the nominal trajectories. In this work, we directly measured the gradient field evolution monitored using a dynamic field camera [1] and reconstructed all the ASL images with actual gradient waveforms. Furthermore, with the assumption that the gradient chain behaves as a linear time-invariant system it is possible to determine the gradient impulse response function (GIRF) of the system as a one-time calibration procedure [2], based on which the gradient waveforms can be predicted. We therefore additionally performed the reconstruction based on such GIRF-predicted k-trajectories. We explored the effects of gradient field imperfection driven artifacts on to the absolute perfusion weighted images.

**Methods:** All measurements were performed on a 3T Philips Achieva system (Philips Healthcare, Best, The Netherlands). The GIRF of the system was determined for each gradient axis by measuring the field response to triangular input functions [2] using a dynamic field camera with 16 transmit-receive <sup>1</sup>H NMR probes [1]. ASL data was acquired on a healthy volunteer using the EPSTAR labeling scheme followed by single shot EPI readout (TE=17 ms, FOV=220 mm, voxel size = 3x3x3 mm<sup>3</sup>, 5 slices) and for 5 TI times (TI=100,500, 900, 1200 and 1700 ms) to span the ASL kinetic curve. The tag had 130 mm width and was positioned at a 10 mm gap to the imaging region. Simultaneously with the imaging acquisition, the k-trajectory was measured up to 1<sup>st</sup> spatial order using concurrent field monitoring with 19F NMR probes [1]. GIRF-predicted trajectories were obtained by a multiplying the nominal gradient sequence with the measured GIRFs in the frequency domain. Image reconstruction was performed using (a) the nominal trajectory (without EPI phase correction), (b) the GIRF-predicted trajectory, and (c) the k-trajectory (k<sub>0</sub>-k<sub>3</sub>) measured with concurrent field monitoring. Both the GIRF-predicted and the concurrently monitored trajectories contained also 0<sup>th</sup>-order field integrals, k<sub>0</sub>(t), by which the coil data was demodulated before reconstruction. Image reconstruction was performed as a re-gridding Fourier transform inside an iterative conjugate gradient algorithm, including SENSE [3]. The reconstruction was complemented by a field-map based static off-resonance correction using multi-frequency interpolation [4]. Average perfusion-weighted images were created by calculating control-tag difference images using surround subtraction at each inversion (post label delay) time. Voxel-wise ASL kinetic curves were calculated from the set of averaged magnetization difference images and the standard model [5] were fit to each dataset using a Gauss-Newton nonlinear least-squares method to estimate perfusion images.

**Results:** Fig.1 shows a comparison of the 0<sup>th</sup> and 1<sup>st</sup> order phase coefficients (k<sub>0</sub>/k<sub>x,y</sub>) implying that the GIRF- predicted trajectory captures many features of the monitored k-space trajectory and accurately predicts oscillations in k<sub>0</sub> caused by the readout gradient. A time-linear component observed in the concurrently monitored k<sub>0</sub>, but not in the GIRF-prediction, stems from lower-order projections of concomitant field terms. As concomitant fields scale non-linearly with the gradient strength, they cannot be predicted by the GIRF-approach. Strong ghosting artifacts are clearly visible in the ASL control image when reconstructed with nominal trajectories (Fig.2). The ghosting is largely eliminated when using the GIRF-predicted or concurrently monitored trajectories for reconstruction. Due to the time linear component in k<sub>0</sub>, an image shift of about 1 pixel in the phase-encoding direction is observed between the GIRF-based and the monitoring based reconstructions. Fig.3 shows the corresponding absolute perfusion maps and their differences [%] showing that trajectory errors lead to very large inaccuracies in perfusion images. These are highly eliminated in the GIRF reconstruction which however still exhibits some discrepancy relative to the reconstructions using concurrent field monitoring. Similar effects are also observed in Fig.4 showing the ASL kinetic curves calculated and averaged in a ROI consisting just gray matter voxels in the yellow circle (Fig.3a).

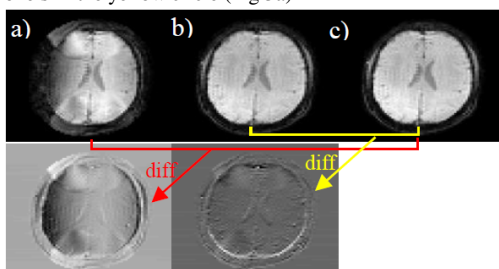


Fig.2. ASL control images reconstructed with (a) nominal, (b) GIRF predicted, (c) measured trajectories .

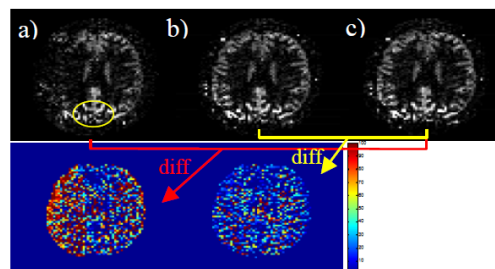


Fig.3. Absolute perfusion images reconstructed with (a) nominal, (b) GIRF predicted, (c) measured trajectories .

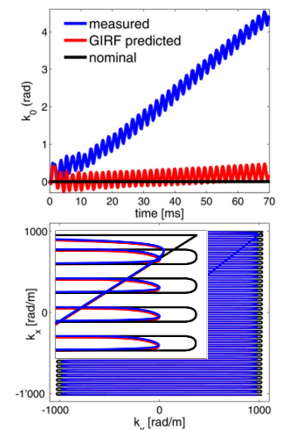


Fig.1. k-trajectory: nominal, GIRF predicted and measured k<sub>0</sub>(t) (top) and parametric first order k<sub>x</sub>-k<sub>y</sub> (bottom).

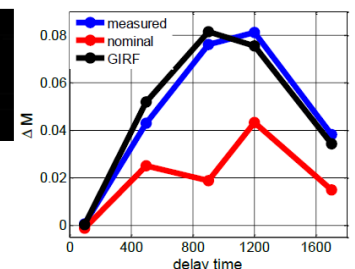


Fig.4. ASL kinetic curves calculated and averaged in the specified ROI.

**Discussion:** Gradient field imperfections can cause substantial artifacts (up to 100%) in perfusion maps and we showed that these artefacts can be eliminated by gradient field evolution using concurrent field monitoring requiring a complex hardware setup. Alternatively, GIRF reconstruction can significantly reduce the artifacts however it does not take into account non-linear gradient responses and variations over time. For certain encoding strategies existing methods such as EPI phase correction are not sufficiently robust for clinical application and they do not extend to more advanced k-space encoding schemes. We here showed that GIRF-based reconstruction significantly reduces these artifacts. The GIRF-approach has the advantage that it can be implemented for arbitrary sequences after an initial one-time system calibration. However, it does not take into account non-linear gradient responses or variations over time. To further increase reconstruction accuracy, gradient field evolutions acquired with concurrent field monitoring can be used, at the expense of requiring a specialized hardware setup. In contrast with existing trajectory correction strategies, such as EPI phase correction, both the GIRF-approach and concurrent monitoring extend to more advanced k-space encoding schemes. Spiral acquisitions would be particularly promising for ASL, due to their short echo-time and fast k-space coverage, but have hitherto not been feasible on most systems because of their vulnerability to trajectory imperfections. This could potentially be overcome by the use of GIRF- or monitoring-based reconstructions.

**References:** [1] Barmet C. (2008). MRM 60(1):187-197 [2] Vannesjo S.J. (2012). MRM 69(2):583-93 [3] Pruessmann K.P. (2001) MRM 46(4):638-651 [4] Sutton B.P. (2003). IEEE TMI 22:178-188 [5] Buxton R.B. (1998). MRM 40:383-396.