Automatic Rigid-Body Motion Correction via Phase Retrieval and Sparsity Constraints

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PURPOSE: There has been much advancement in reducing motion corruption especially for rigid-body motion. Many of these correction methods require specific setup and/or modifications to the data acquisition. Even with these methods, there may be residual artifacts due to motion measurement error. Automatic correction methods can be applied without any motion information. We propose a novel automatic approach using the k-space magnitude constraint. This new element is incorporated with parallel imaging and compressed sensing to help guide the correction.

METHOD: For rigid-body in-plane motion, the corruption manifests as inconsistent phase. The translational motion can be represented by linear-phase for motion in the readout direction (*dx*) and a bulk-phase shift for motion in the phase-encode direction (*dy*). Additionally, small rotations can be modeled as k-space shearing (*dr*) – in other words, a linear-phase with respect to x in the (x,k_y)-hybrid-space. Conventional methods (such as least-squares [1] and cross-correlation [2]) can be used to estimate the linear phases. In summary, the magnitude of the acquired k-space data is uncorrupted by motion. This k-space magnitude constraint is described in Fig. 1c.

Algorithm: The parallel imaging (SPIRiT [3]) and sparsity (minimizing the L1-norm of its wavelet transform [4]) constraints are enforced to help guide the automated correction. These constraints can be used individually (Fig. 1a) or together (Fig. 1b). We used a generalized-projections algorithm to solve the correction problem.

Step 1: The data is projected onto the parallel imaging or sparsity set. This step reduces the motion-artifacts and gives an estimate of the true image ($\hat{m}$).

Step 2: The data is then projected onto the k-space-magnitude-constraint set. This step estimates and applies the motion parameters *dr*, *dx*, and *dy* (Fig. 1c).

Step 3: The first two steps are repeated until a reasonable convergence is found.

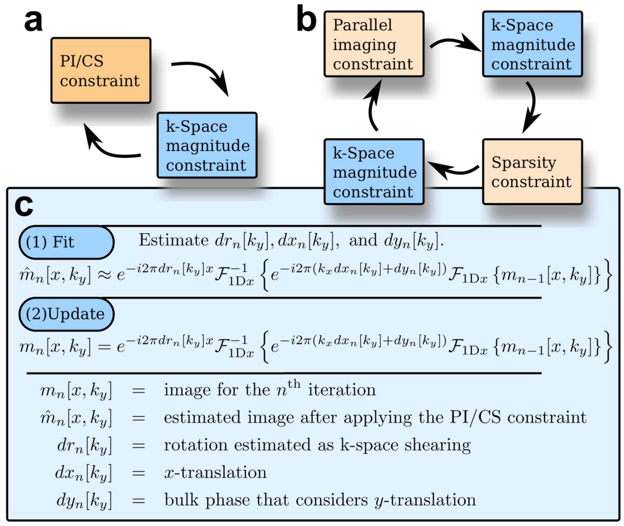

FIG. 1: *Method overview.* **a:** Basic method – either the parallel-imaging (PI) or the sparsity (CS) constraint can be applied during each iteration. **b:** Inclusive method – alternate between applying the parallel-imaging constraint and the sparsity constraint. **c:** Steps and equations to enforce the k-space magnitude. Note that $m[x, k_y]$ is the image in hybrid-space.

Experiments: Volunteer studies were performed in a GE 1.5T Signa scanner for in vivo studies of the head and knee. The algorithm was first tested on the head study with simulated motion.

Scan Parameters: *Head study:* axial T1-weighted fluid-attenuated-inversion-recovery 2D sequence, echo train length = 6, TE/TI/TR = 26.9/750/822 ms, resolution = 0.82×1.01 mm^2, 5 mm slice, FOV = 26×23.4 cm^2, bandwidth = ±31.25 kHz, 8-ch head coil. *Leg study:* axial gradient-recalled-echo 2D sequence, TE/TR = 3.1/51 ms, resolution = 0.94×0.96 mm^2, 5 mm slice, FOV = 24×24 cm^2, bandwidth = ±31.25 kHz, 4-ch knee coil.

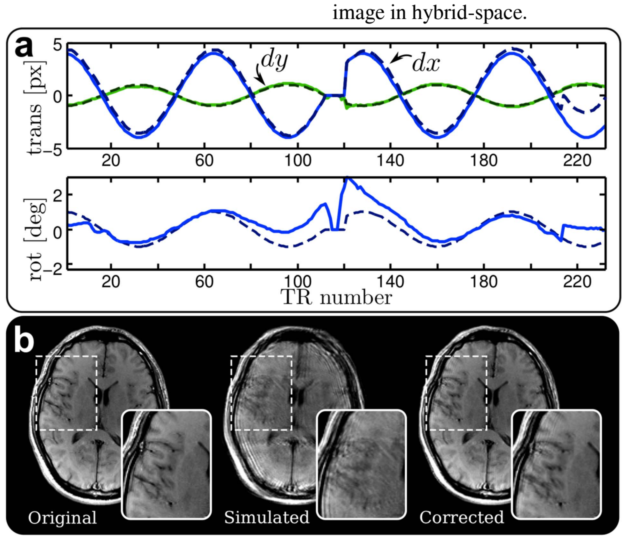

FIG. 2: *Simulation results.* **a:** Applied translational & rotational motion (dotted lines), and the estimated motion from applying the algorithm (solid lines). **b:** From left to right, original brain scan, image after motion simulation, and the final corrected image. With the k-space shearing approx., the rotational motion is more difficult to characterize (esp. near the center of k-space) and some residual artifacts remain. Fortunately, the algorithm was able to characterize the motion and correct the image. The final image demonstrates a reduction in motion-artifacts and a recovery of the white/grey matter contrast.

RESULTS & DISCUSSION: By applying this method to conventional scans, a reduction of motion-artifacts can be seen (Fig. 3). The approach explores the area of phase-retrieval – first proposed in Ref. 5. Our approach expands on that idea and uses advancements of accelerated imaging to improve the reconstruction. Note that the k-space magnitude constraint is not a convex set. By limiting the severity of the motion (such as through gating/triggering or prospective correction), we can ensure convergence. Also, through-plane motion can be limited by monitoring the motion with self-navigation or external devices. Lastly, rotating and gridding the data can further improve the automatic correction for rotations.

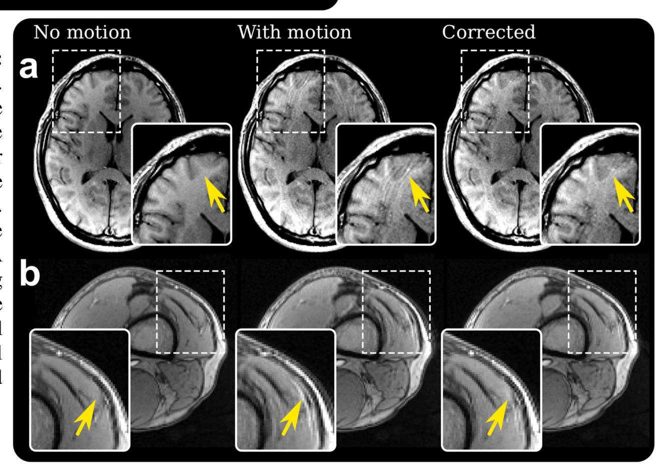

FIG. 3: *In vivo results.* **a:** Head scan. **b:** Upper leg scan. The first column shows the scans with no motion. For the second column, the volunteer was asked to perform in-plane movements during the scan. The corrected images are shown in the last column. A reduction in motion ghosting and some noise can be appreciated. Some residual artifacts remain due to a small degree of non-rigid motion and through-plane motion.

CONCLUSION: We demonstrate and present a novel method for automatic rigid motion correction by leveraging parallel imaging and sparsity. This method can be easily extended to support 3DFT imaging and to support accelerated acquisitions.

REFERENCES: **[1]** TD Nguyen et al, MRM 46:1037-1040, 2001. **[2]** RL Ehman and J Felmlee, MRI 173:255-263, 1989. **[3]** M Lustig and JM Pauly, MRM 64:457-471, 2010. **[4]** M Lustig, D Donoho, and JM Pauly, MRM 58:1182-1195, 2007. **[5]** M Hedley and H Yan, JVCIR 3:325-337, 1992.