Robust 3-D Motion Correction for Spiral Projection Imaging

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Introduction Motion during MR acquisitions significantly degrades image quality. Spiral Projection Imaging [1] is a relatively fast 3-D imaging sequence that presents self-navigation for motion correction [2]. Data are collected on 2-D planes that fill a sphere in k-space (*Fig. 1 left*). The planes intersect on lines which can be found by comparing the data from every pair of planes. Rotational motion can be deduced by solving for a geometry that is the most consistent with the measured intersections (*Fig. 1: right*), by minimizing a system of nonlinear equations. Translational motion can be deduced via a direct linear system.

Typical solvers for the nonlinear system of equations are highly dependent on the initial condition, since they can fall into local minima that limits accuracy [3]. In this study a new, physically based solver was developed, that provides global minimization, and an analysis is performed with respect to the challenges of off-resonance, under-sampling, coil sensitivities, non-rigid motion and warping from non-linear gradients.

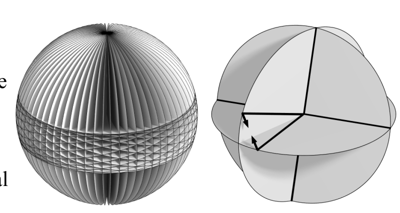

Figure 1: Spiral planes are collected to fill a sphere (left). The data from each pair of planes are compared to calculate where planes intersect (right: dark lines on planes). Springs pull the measured intersections together (right: force vectors).

Methods For *N* number of planes there are *N(N-1)* intersections and only *3N* degrees of freedom. Simultaneous minimization of this type of nonlinear system is both tedious and volatile. Instead of minimizing an objective function that characterizes the consistency between the matched intersections and the motion estimates, a new solver was created that applies a torque to a plane from every intersection. This is analogous to having springs that pull the measured intersections together (visualized as the force vectors in *Fig. 1 right*). Multiple torque forces applied to a single plane can merely be summed, providing a fast and accurate iterative method. Convergence is reached when the net force acting on all planes is negligible (also minimizes the total potential energy of all springs).

Data were collected on a GE HDX 3 T scanner at 1 mm resolution. Data were collected using with variations in the ADC time (to affect off-resonance), acquisition coil and gradient system ('whole' body gradients have a larger linear range versus 'zoom' gradients that present greater warping). To compare the accuracy when some non-rigid motion is present versus the accuracy of isolated rigid body motion, a volunteer and a pineapple were scanned. To quantify the expected accuracy of the motion estimates, five static scans were collected for each of the different parameter sets. Motion between scans was deduced via FMRIB Software Library's (FSL) linear registration algorithm. A new dataset was created where data for each individual plane was taken from one of the five static scans. This new dataset contained known motion, while maintaining high resolution in-vivo data, and nearly all of the abnormalities of typical data. For a typical experiment, FSL reported the average motion between scans as 10.8 degrees and 8.6 mm (max of 22.2 degrees and 22.8 mm). Two additional scans were also acquired with and without in-vivo motion for comparison. A simulation was also performed to test the ideal accuracy of the motion algorithm.

Results & Discussion The algorithm was tuned and applied to a list of experiments as listed in *Table 1*, along with the estimated error. The simulation provides ideal accuracy, where no system imperfections were modeled other than noise and coil sensitivity. The algorithm performed better on the pineapple due primarily to the lack of any non-rigid parts (such as a neck). Despite varying the scan parameters to affect off-resonance, warping, and RF sensitivity, there was a relatively insignificant variation of accuracy, indicating general robustness of the algorithm to these scan parameters. To test the effect of undersampling the number of planes, subsets of planes were selected randomly from the same dataset. The error with respect to undersampling is plotted in *Fig. 2*. The average rotational estimates are unreliable with fewer than 30 planes, but beyond, the average accuracy does not improve significantly. The average translational estimates are unreliable with fewer than 50 planes, and accuracy improves slightly with the number of planes. An example of performance on in-vivo data is presented in *Fig. 3*. While image quality is nearly restored to the motion set, the motion corrected reconstruction applied to the non-motion dataset provides a small enhancement in image quality due to small movements.

References [1] Irrazabal P, Nishimura DG. MRM 33:656, [2] Johnson KO, Pipe JG. ISMRM 2008 #1470, [3] *Numerical Recipies in C 2nd Edition*, Press et al, 1992.

				Rotational (degrees)			Translational (mm)		
Subject	Gradients	Coil	ADC	Mean	RMS	Max	Mean	RMS	Max
Simulation	-	8-Channel	-	0.004	0.005	0.041	0.004	0.005	0.017
Pineapple	Whole	Quadrature	3.9	0.15	0.16	0.31	0.14	0.16	0.33
Pineapple	Zoom	8-Channel	3.4	0.15	0.16	0.33	0.20	0.23	0.48
Head	Whole	Quadrature	3.9	0.47	0.54	1.30	0.34	0.38	0.91
Head	Zoom	Quadrature	3.4	0.35	0.39	1.01	0.28	0.32	0.79
Head	Zoom	8-Channel	4.4	0.45	0.51	1.52	0.27	0.31	0.86
Head	Zoom	8-Channel	8.9	0.40	0.45	1.53	0.24	0.27	0.72
Head	Zoom	8-Channel	2.3	0.37	0.43	0.99	0.27	0.31	0.92

Table 1: Estimated error for the motion estimates of the experiments with known motion as calculated via FSL.

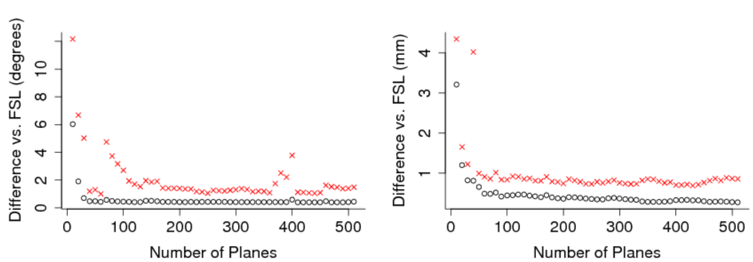

Figure 2: Mean (black O) and maximum (red X) estimated error versus the number of planes in the dataset for both rotation (left) and translation (right) motion estimates.

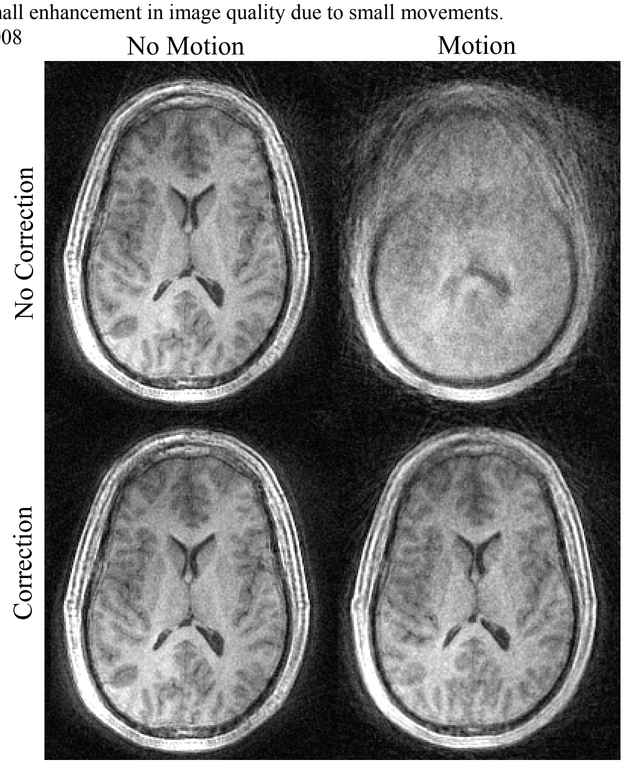

Figure 3: 3-D reconstructions of in-vivo motion data with and without motion correction applied.