Parallel CS-Wave

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Target Audience: Users looking to improve Wave-CAIPI reconstruction with compressed sensing, i.e, CS-Wave.

Purpose: Using uniform undersampling in Wave-CAIPI acquisitions allows for parallelizing the 3D reconstruction into 2D subproblems. Each subproblem unaliases a set of slices, and the number of aliased slices in each subproblem is given by the acceleration factor in the partition direction, R_z. Although wave encoding induces incoherence within the encoding model to facilitate CS reconstruction, how to determine the regularization weighting for each subproblem remains an open question. In this work, we explore a novel way to perform "multi-slice" CS-Wave. By using a concatenation operator, Ω, in the regularization term, we can perform CS-Wave with automatic parameter selection to reconstruct all R_z slices within a subproblem at once (Figure 1). Thus, 3D imaging is reconstructed using CS-Wave reconstructions that run in parallel across different aliased slice groups.

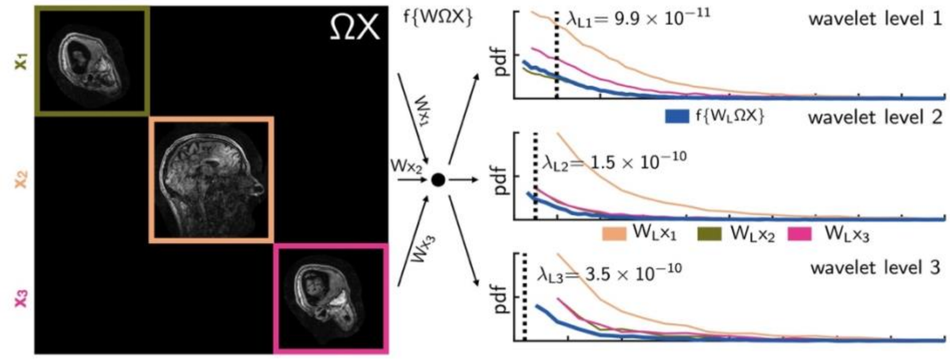

Figure 1- Approach for parallel CS-Wave. Concatenation of zero-filled reconstructions and applying the wavelet transform, $W\Omega X$, is equivalent to combining wavelet coefficients across slices within the reconstruction problem, $f\{W\Omega X\}$, and from the combination we determine the regularization weighting for each level of the wavelet transform. This process is applied to each 2D CS-Wave subproblem.

Methods: Cartesian MPRAGE data were acquired using a 3T system (MAGNETOM Prisma, Siemens Healthcare, Erlangen Germany) with 32 receiver coils. Sequence parameters were 1mm isotropic resolution, FOV of 256x256x192 mm, TE/TI/TR = 3.49/1100/2500 ms, and FA 7°. Wave gradients were with $G_{y,z}$ of 10 mT/m, G_{slew} of 166 mT/m/ms, and 13 cycles. 3D imaging with 3x3 acceleration rate led to a 1:26 min scan. A reference scan was used to estimate sensitivity coil maps with ESPIRiT after coil-compression to 21 virtual coils, and the wave's point-spread-function was estimated using autoPSF.

We compared Wave-CAIPI (Least-squares, 10 iterations) to parallel CS-Wave (ISTA, 50 iterations) in their 2D-reconstruction format, which splits the 3D reconstruction problem into partitions/R_z=192/3=64 subproblems. In each subproblem, absolute-valued wavelet coefficients from zero-filled reconstructed slices were averaged, and the determination of the regularization weighting in 3 wavelet levels was defined by k-means algorithm. We included 3D CS-Wave reconstruction to benchmark the three reconstructions styles. Reconstructions were performed on a MAC with M1 Pro chip and 32 GB of memory RAM, which allows it to work with 10 workers in MATLAB. We analyzed image quality along and perpendicular to 2D reconstructions, and reconstruction times are relative to Wave-CAIPI.

Results: 10-fold difference maps show that parallel CS-Wave removes mostly noise from Wave-CAIPI at the expense of minor blurring in all directions. Furthermore, reformatting slices perpendicular to reconstructions does not show any structural inconsistencies due to our approach (Figure 2). There were no significant differences in terms of reconstruction quality between parallel CS-Wave and 3D CS-Wave; however, reconstruction times were 2.4x and 13.87x slower than wave-CAIPI.

Discussion: Our approach enables parallelization of CS-Wave in 2D given the acceleration factor in the partition direction. Although reconstruction time reduction might scale with higher acceleration factors, reconstruction quality could be SNR-limited.

Conclusion: Our theoretical concatenation trick, and its practical implementation based on the combination of wavelet coefficients across slices enables fast, efficient, and automatic determination of level-based regularization weightings to reconstruct multiple 2D CS-Wave subproblems in parallel for wave-encoded 3D imaging. Preliminary results indicate that parallel CS-Wave is one order of magnitude faster than the original 3D CS-Wave, which could facilitate its translation to online reconstruction.

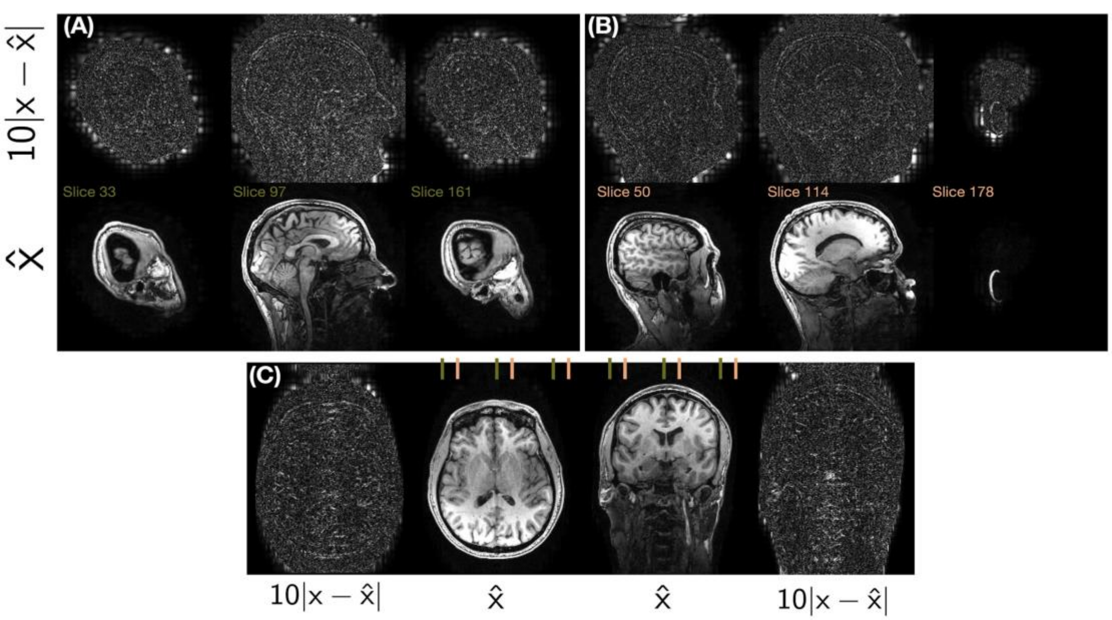

Figure 2- Image quality assessment of parallel CS-Wave. Two sets of reconstructions (olive and peach, respectively) are presented on panels (A-B), and panel (C) shows reformatted slices perpendicular to the original reconstruction direction. The 10-fold difference maps against wave-CAIPI show that our approach removes mostly noise at the cost of slight blurring in all directions.