PIRT- Parallel Iterative Reconstruction Tomography, with correction for center of rotation errors

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Outline

Tomography
Algorithm & Implementation
3D solver

Outline

Basics

- Radon transform : Real $\rightleftarrows$ Sinogram space.
- $Rf(\tau,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\delta(\tau - x\cos(\theta) - y\sin(\theta))dxdy$

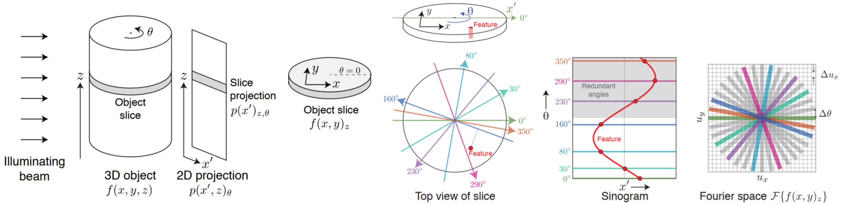

Figure: Spinning the object to obatin "sinograms", reconstruct each slice independently. Figure taken from Jacobsen [2019]

Center of rotation drifts

- $P_\theta = x^*_\theta(1 - cos(\theta) + y^*_\theta sin(\theta))$
- $Rf(\tau, \theta, 0, 0) =$
  $Rf(\tau - P_\theta, \theta, x^*_\theta, y^*_\theta)$
- Translation of sinogram by P_θ achieved by convolution with Gaussian.
- Recover P_θ to obtain accurate reconstruction[1].

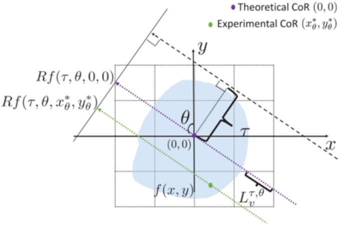

Figure: Center of rotation drift causes us to measure the shifted sinograms, figure from Austin et al. [2019]

[1] Austin et al. [2019]

Tomography software

- Efficient distributed memory parallel tomography software available for CPU and GPU [2]
- Error correcting capabilities available in popular tomography packages like TomoPy [3]
- Need a software package that has error correction capabilities and is distributed memory parallel

[2] Bicer et al. [2017]; Chen et al. [2019]; Hidayetoğlu et al. [2019]; Marchesini et al. [2020]; Palenstijn et al. [2016]

[3] Gürsoy et al. [2017]

Outline

Optimization formulation

Discretize & Vectorize

- $\mathcal{W}$: object vector
- $\mathcal{L}$: discretized Radon transform
- $\mathcal{D}$: measured sinogram

Least squares cost function

- Assuming no shifts, we need $\min\limits_{\mathcal{W} \geq 0} \frac{1}{2} ||\mathcal{L}\mathcal{W} - \mathcal{D}||$
- To recover both shifts and object :
  $\min\limits_{\mathcal{W} \geq 0, P_\theta} \phi(\mathcal{W}, P_\theta) = \frac{1}{2} ||\mathcal{L}\mathcal{W} - g(\mathcal{D}, P_\theta)||$
- First order derivatives analytically computable :
  $\nabla \phi(\mathcal{W}, P_\theta) = [\mathcal{L}^T, \nabla_{P_\theta} \phi(\mathcal{W}, P_\theta)]^T (\mathcal{L}\mathcal{W} - g(\mathcal{D}, P_\theta))$

Implementation

- Implemented in C++ using :
  - PETSc/TAO (optimization routines, data management and parallel I/O)
  - Boost (geometry routines)
  - FFTW (fourier space convolution)

Joint

- Combine shifts and sample into one vector and optimize for both together

Alternating

- Alternate between optimizing with respect to sample and with respect to shifts

Demonstration

- Quality of reconstructed image and corrected sinograms, with and without error correction.

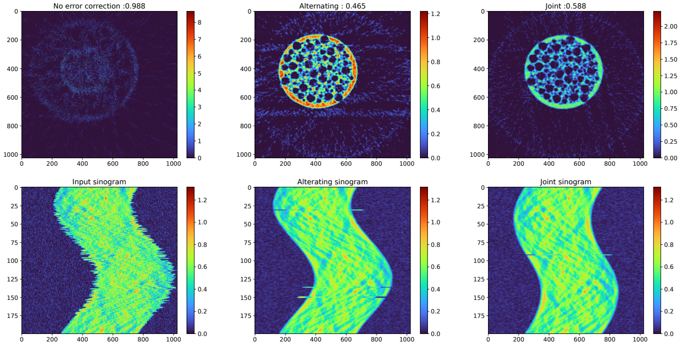

Figure: Demonstration of PIRT solvers : (Left to Right) with no error correction, alternating solver, joint solver. Test object is 1024^2 with 200 projections, with 10% center of rotation drifts and 10 % added noise.

Initial Results

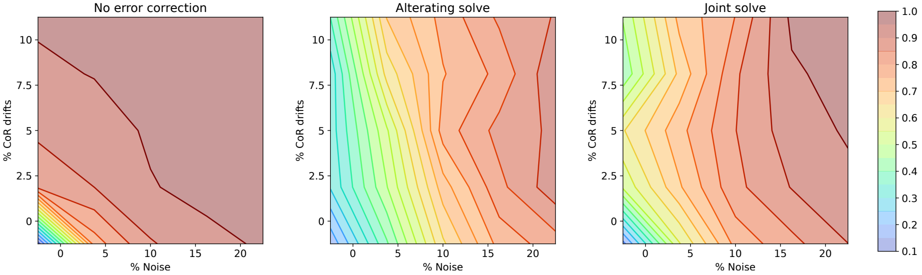

Figure: Quality of reconstruction as a function of center of rotation drifts and added noise for an object with dimensions 1024^2 and 200 projections, metric $\rightarrow$ translation invariant normalized root mean square error, no regularization.

Data decomposition

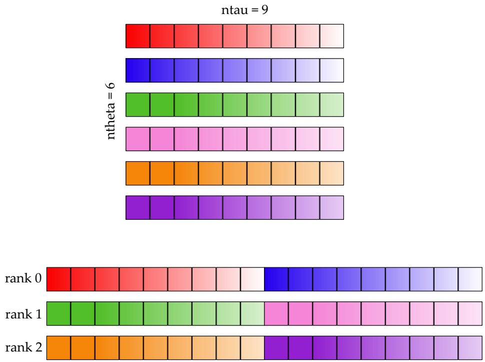

Figure: Naive data distribution over MPI ranks using PETSc heuristics, with the only constraint being that we don't distribute a single projection over multiple MPI ranks. *ntheta* → number of projections, *ntau* → size of each projection.

2D solve scaling

- Tests conducted on LCRC-bebop, dual-socket Xeon Broadwell, Intel Omni Patch interconnect.

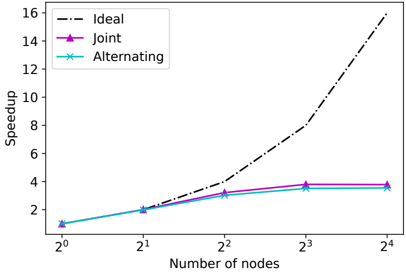

Figure: Strong scaling → object size 2896^2, 800 projections.

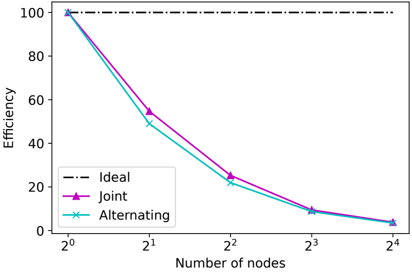

Figure: Weak scaling object size → 1024^2, projections per node 100

Outline

Research choices

- Strong and weak scaling efficieny falls off beyond 4 nodes for a single 2D slice solve.
- Reason being the naive data distribution leading to load balancing issues, ≈ 80 of time being spent in matrix-vector and transposed matrix-vector multiplications.
- However, experimental data is always a 3D data-set! Focus on throughput instead of scalability of a single 2D slice solve.
- Introduced MPI-subcommunicator based 2-level MPI parallelism, with multiple concurrent instances of the solver.

2 level MPI parallelism

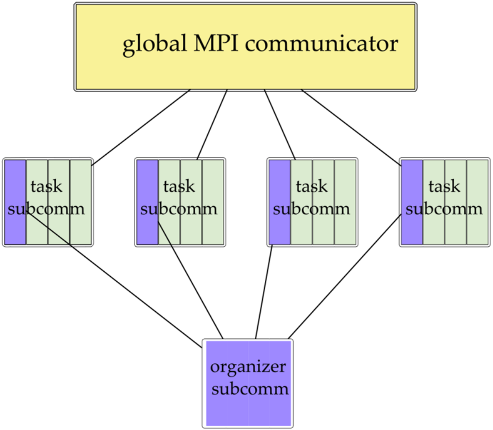

Figure: Architecture of the 2-level parallelism. Each solver instance solves for a "batch" of 2D slices

Throughput Results

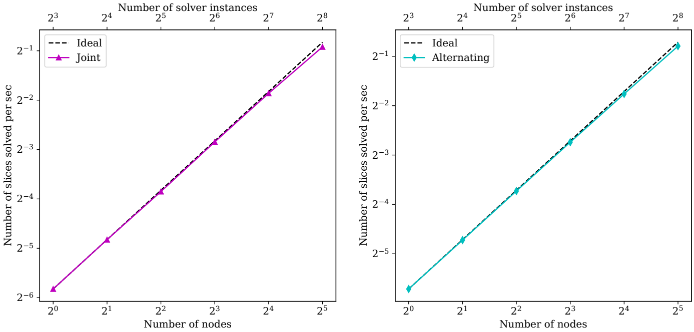

Figure: Number of slices solved per unit time, 256 slices of size 1024^2 and 200 projection angles. Tests conducted on LCRC-bebop, dual-socket Xeon Broadwell, Intel Omni Patch interconnect.

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