

Deterministic and stochastic acceleration techniques for Richardson-type iterations

Massimiliano Lupo Pasini¹, Michele Benzi¹, Thomas M. Evans², Steven P. Hamilton², Stuart R. Slattery², Phanish Suryanarayana³

¹Emory College, Department of Mathematics and Computer Science, 400 Dowman Drive, Atlanta, GA 30322

²Oak Ridge National Laboratory, 1 Bethel Valley Rd, Oak Ridge, TN 37830

³Georgia Institute of Technology, School of Civil and Environmental Engineering, 790 Atlantic Drive NW, Atlanta, GA 30332

Introduction

- Scientific computing is moving to exascale
- Applications require high level of concurrency
- Next generation computers will exhibit more hardware failures – applications must be resilient
- Standard Krylov subspace methods struggle to simultaneously obtain efficiency and concurrency
- Standard Krylov methods struggle to achieve resilience
- Richardson's schemes benefit computational and data locality

Mathematical framework

- Reformulate the sparse linear system of interest

$$A\mathbf{x} = \mathbf{b}$$

as a fixed point scheme

$$\mathbf{x} = H\mathbf{x} + \mathbf{f}$$

such that the Neumann series recasts the solution as

$$\mathbf{x} = \sum_{i=0}^{\infty} H^i \mathbf{f} \quad (1)$$

- One level fixed point schemes are renowned for their deteriorated asymptotic convergence rate
- Multilevel schemes can accelerate convergence
- Purely deterministic algorithms struggle to deal with inherently random faulty phenomena

One level relaxation scheme

Deterministic accelerations improve convergence

Stochastic accelerations enhance resilience

Alternating Anderson-Richardson (AAR)

AAR uses approximate solutions computed by successive Richardson's steps to build the matrix

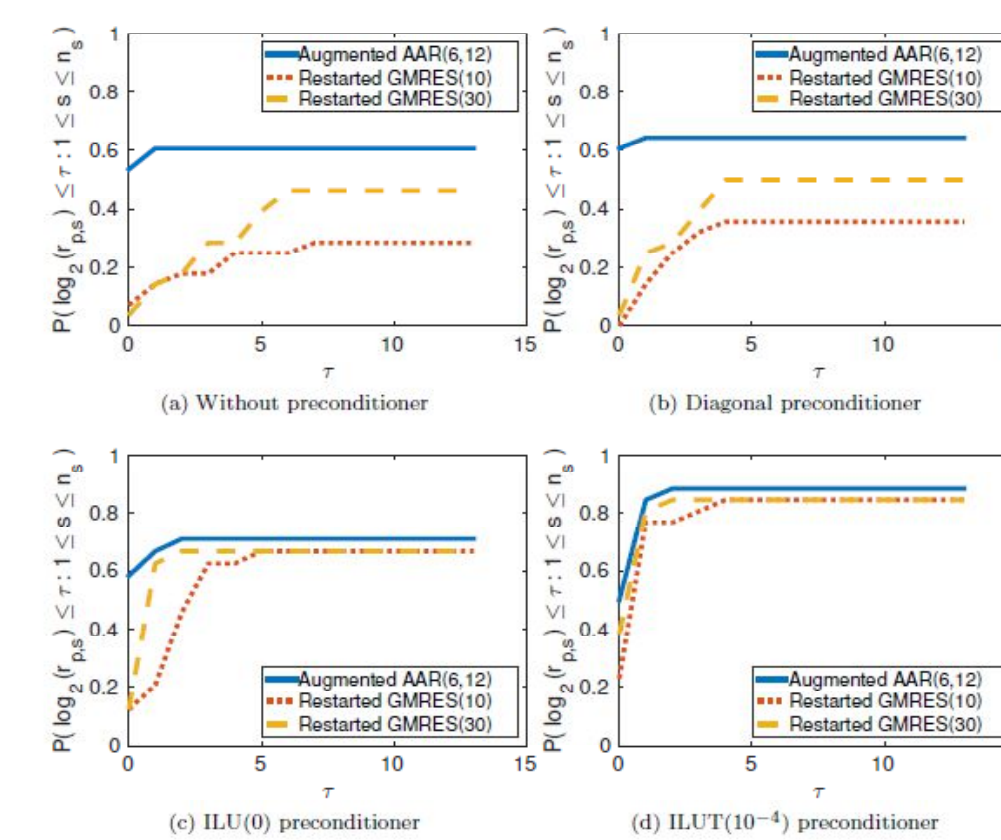
$$U_k = [-(\mathbf{x}^{k-p+1} - \mathbf{x}^{k-p}), \dots, -(\mathbf{x}^k - \mathbf{x}^{k-1})].$$

The **Anderson mixing** is defined as

$$\bar{\mathbf{x}}^k = \mathbf{x}^k + U_k \mathbf{g}_k.$$

The vector \mathbf{g}_k is chosen so as to minimize the residual norm.

- Multiple Richardson's steps without optimization benefit computational and data locality
- Convergence on **positive definite matrices** guaranteed



Conclusions and future developments

- Identified classes of matrices for which convergence is guaranteed
- Competitive performance compared to restarted GMRES for different choices of preconditioner
 - Convergence analysis on specific classes of problems
 - Performance assessment at extreme scale
 - Use of GPU accelerations

References

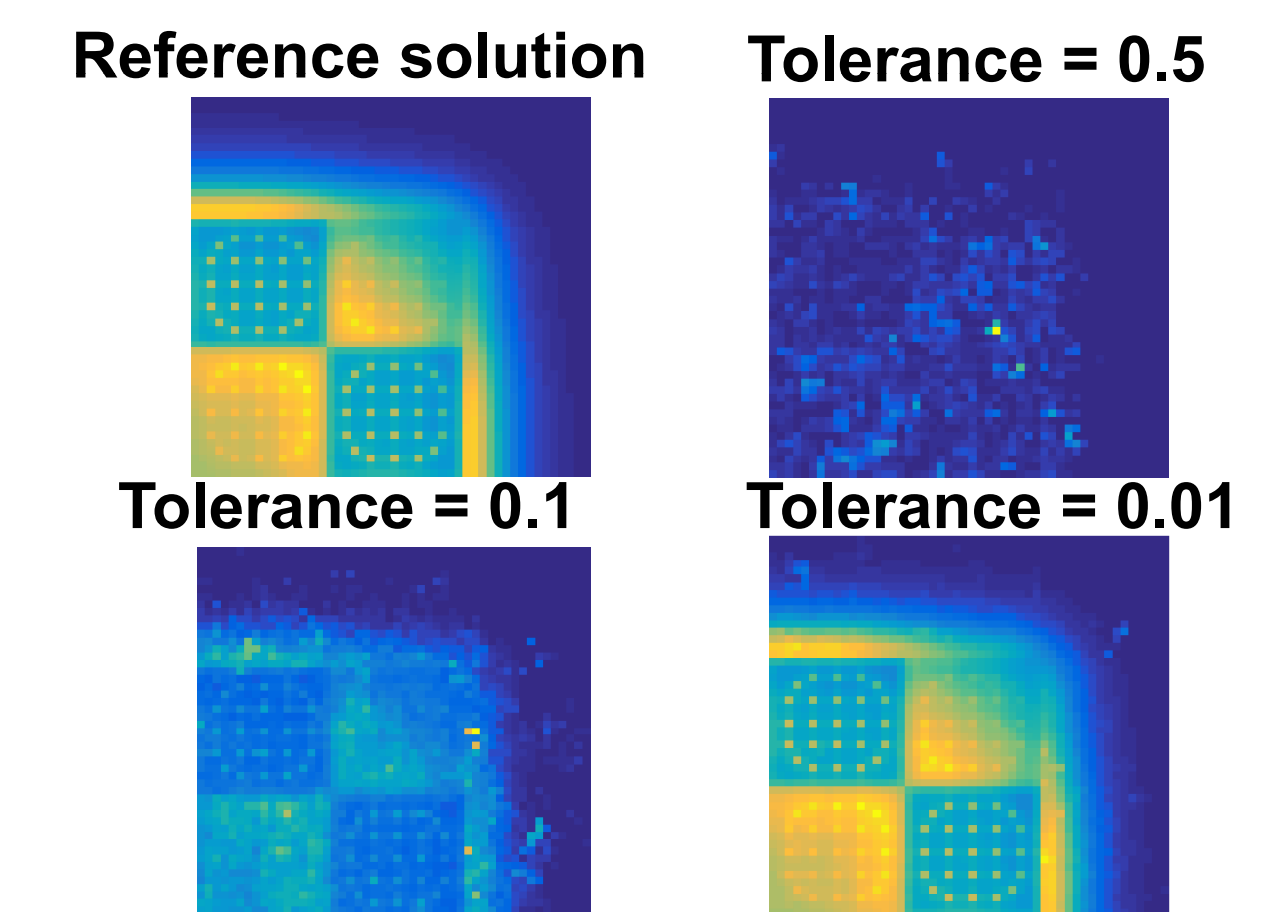
- "Anderson acceleration of the Jacobi iterative method: an efficient alternative to Krylov methods for large, sparse linear systems", P. P. Pratapa, P. Suryanarayana, and J. E. Pask – J. Comput. Phys., 306, pp. 4354, 2016.
- "Convergence analysis of Anderson-type acceleration for Richardson's iteration", M. Lupo Pasini – In preparation.

Monte Carlo Linear Solvers (MCLS)

MCLS use random walks defined on a transition matrix \mathbf{P} and a sequence of weights $\mathbf{w}_{ij} = \mathbf{H}_{ij} / \mathbf{P}_{ij}$, the statistical estimator redefines (1) as

$$\theta = x_i = f_i + \sum_{l=1}^{\infty} \sum_{k_1=1}^n \dots \sum_{k_\ell=1}^n P_{i,k_1} \dots P_{k_{\ell-1},k_\ell} w_{i,k_1} \dots w_{k_{\ell-1},k_\ell} f_{k_\ell}.$$

- Convergence guaranteed for **strictly diagonally dominant, M matrices, generalized diagonally dominant matrices**
- Choice of preconditioners affects convergence
- We use adaptive methods to select the number of histories



Conclusions and future developments

- Identified classes of matrices and preconditioners for which MCLS are guaranteed to converge a priori
- Difficulty in ensuring a priori convergence of MCLS for a general problem
 - Algorithm scalability has not yet been analyzed
 - Testing MCLS on large parallel architectures and evaluating their resilience in presence of faults still to be addressed

References

- "A Monte Carlo synthetic-acceleration method for solving the thermal radiation diffusion equation". T. M. Evans, S. W. Mosher, S. R. Slattery, S. P. Hamilton – J. Comp. Phys., Vol. 258, 2014, pp. 338-358.
- "Analysis of Monte Carlo Accelerated Iterative Methods for Sparse Linear Systems". M. Benzi, T. M. Evans, S. P. Hamilton, M. Lupo Pasini, S. R. Slattery – Numer. Linear Algebra Appl. Vol. 24, Issue 3, 2017.