Toward robust numerical linear solvers for large scale simulations

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Sparse linear systems



Sparse linear systems



Application consumers of linear solvers

Scientific and engieneering application areas

- ★ Accelerator physics
- * Chemical process simulations
- * Earth and environmental sciences including climate
- ★ Fluid flow
- ★ Fusion energy
- * Structural analysis
- * Structural biology

Iterative methods

Principle

Iterative methods for solving linear system Ax = b, begin with initial guess for solution and successively improve it until solution is as accurate as desired.

Two main classes

- Stationary methods (fixed point schemes: e.g., Jacobi, Gauss-Seidel, ...).
- Krylov subspace methods (CG [Hestenes, Stiefel, NIST, 52], GMRES
 [Saad, Schultz, SISC, 86], Bi-CGStab [Vorst, SISC, 92], ...)

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General framework

Faults in the literature

- ★ Soft errors.
- ★ Hard faults.

In this presentation

- ★ Hard fault: invalid core (memory, caches, network connections, ...).
- Assumption: when a fault occurs we can start a new process on another core.

- 1. Fixed point schemes and resilience
- 2. Recovery strategies in Krylov subspace methods
- 3. Preliminary experimental results
- 4. Concluding remarks and perspectives

Mathematical models: fixed point iteration

$$x^* = F(x^*) \Rightarrow x^{k+1} = F(x^k)$$

Governing ideas to express parallelism

Split the problem in sub-problems, solve the subproblems in parallel with updates along the interfaces using available data (no-synchronization).

Chaotic/Asynchronous scheme definition

Let $x^0 \in E$ we consider the series of iterates defined by:

$$\forall k \in \mathbb{N}, \ \forall p \in \{1, ..., m\}, \ x_k^{k+1} = \begin{cases} x_p^k & \text{if } p \notin s(k) \\ F_p(w) & \text{if } p \in s(k) \end{cases}$$

where $w = (x_{\ell}^{c_{\ell}(k)})_{\ell=1,m}$, $w \in E$; $c_{\ell}(k) = k - d_{\ell}(k)$ accounts for delays and s(p) defines the relaxation strategy (e.g. $s(k) \equiv \{1, ..., m\}$ and $d_{\ell} \equiv 0$ reduces to block Jacobi).

Theorem [J.C. Miellou, 75; F. Robert, 75]

Let assume that

F is a *J*-contraction with respect to the fixed point x^* , that is there exists a nonnegative matrix $J \in \mathbb{R}^{m \times m}$ with $\rho(J) < 1$ such that

$$\begin{pmatrix} \|F(x_1) - F(x_1^*)\|_1\\ \vdots\\ \|F(x_m) - F(x_m^*)\|_m \end{pmatrix} < J. \begin{pmatrix} \|x_1 - x_1^*\|_1\\ \vdots\\ \|x_m - x_m^*\|_m \end{pmatrix}$$

Then chaotic relaxation scheme defines the iterates x^k converge to x^* the fixed point of *F*.

Brief overview on chaotic relaxation schemes

- ★ Brief history (non-exhaustive):
 - Pioneer paper [D. Chazan and W. Miranker, LAA, 69].
 - Convergence analysis: contraction properties [D. Chazan and W. Miranker, LAA, 69], [F. Robert, LAA, 75], [L. Giraud, P. Spiteri, RAIRO, 91], order interval [J.C. Miellou, RAIRO, 75], [J.C. Miellou, D. El Baz, P. Spiteri, MathComp, 98].
 Recent book [J. Bahi, S. Contassot-Vivier, R. Couturier, Chapman & Hall,

2007].

- Application areas: PDE [D. Amitai, A. Averbuch, M. Israeli, S. Itzikowitz, SISC, 98], DDM [A. Frommer, D. Szyld, JCAM, 97] inverse problems [V. Pereyra, ANM, 99], convex optimization [P. Tseng, SIOPT, 91], network flow [P. Tseng, D. P. Bertsekas, J. N. Tsitsiklis, SICON, 90], etc ...
- Renewed interest with Grid computing (latency/bandwith network).

Asynchronous relaxation v.s. resilience

- ★ By construction, the chaotic relaxation schemes are resilient to message loss.
- * To comply with fault tolerance, the $c_k(p)$ non decreasing function of p implies uncoordinated local checkpointing of each core running on E_i (no synchronization).
- * <u>Good candidates for fault tolerance:</u> classical fixed point iterations where convergence analysis is based on contraction properties

$$Ax = b$$

the scheme $x^{k+1} = x^k + B(b - Ax^k)$, will converge for any x^0 if $\rho(I - BA) < 1$; e.g. classical Schwarz alternating method (1870). Fixed point schemes and resilience

Schwarz Alternating method [H.A. Schwarz, 1870]

$$\begin{cases} -\Delta u = f & \text{in } \Omega, \\ u = 0 & \text{on } \partial \Omega. \end{cases}$$



Fixed point iteration scheme

$$\begin{cases} -\Delta u_1^{n+1} = f & \text{in } \Omega_1, \\ u_1^{n+1} = u_2^n|_{\Gamma_1} & \text{on } \Gamma_1, \end{cases} \text{ and } \begin{cases} -\Delta u_2^{n+1} = f & \text{in } \Omega_2, \\ u_2^{n+1} = u_1^{n+1}|_{\Gamma_2} & \text{on } \Gamma_1. \end{cases}$$

Convergence analysis based on contraction property of a product of projectors (also referred to as multiplicative Schwarz) [P.L. Lions, 88].

Fixed point schemes and resilience

Schwarz Alternating method: 1D illustration



- ★ Contraction based analysis, $\forall u_0 \| u u^k \| \le \rho^k \| u u^0 \|$.
- Matlab demo: visual evidence.

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Krylov subspace methods

General concept of Krylov subspace methods

Search for the slolution of a linear system of dimension *n* in a specific subspace of dimension *k* smaller than *n*. Basically, $x^k = F(x^0, ..., x^{k-1})$.

Krylov subspace

Let $A \in \mathbb{R}^{n \times n}$ and $b \in \mathbb{R}^n$, let $k \le n$, the space denoted by $\kappa(b, A, k)$ with $\kappa(b, A, k) = Span\{b, Ab, ..., A^{k-1}b\}$ is referred to as the Krylov space of dimension k associated with A and b.

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Parallelization of the iterative methods

Distribution of a sparse matrix



Two categories of lost data

★ Static data:

Matrix A, right-hand side b and possibly preconditioner M.

⋆ Dynamic data:

all the vectors and small matrices generated by Krylov solvers during the iterations.













Linear System (LS) [J. Langou et al., SISC, 2007]

Linear system

$\left(\right)$	· : ··.	$A_{I-1,I}$	· ·) : :		(·) :			
	$A_{I,I-1}$	$A_{I,I}$	$A_{I,I+1}$	\times	x_I	=	b_I	
	· · : :	$A_{I+1,I}$	· :)		:			

Linear System (LS) [J. Langou et al., SISC, 2007]

Linear system



Recovery

- * $A_{I,I}x_I = (b_I A_{I,I-1}x_{I-1} A_{I,I+1}x_{I+1}).$
- * Exact strategy for single fault, if the solver had converged.

Linear System (LS) [J. Langou et al., SISC, 2007]

Linear system



Recovery

*
$$A_{I,I}x_I = (b_I - A_{I,I-1}x_{I-1} - A_{I,I+1}x_{I+1}).$$

* Exact strategy for single fault, if the solver had converged.

Linear least square problem



Recovery of x_I

*
$$A_{:,I-1}x_{I-1} + A_{:,I}x_I + A_{:,I+1}x_{I+1} = b.$$

*
$$b_{new} = b - A_{:,I-1}x_{I-1} + A_{:,I+1}x_{I+1}$$
.

Linear least square problem



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Linear least square problem



Recovery of *x*_{*I*}

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.

Linear least square problem

$$\begin{pmatrix} \vdots & \cdots & A_{I-1,I} & \vdots & \vdots \\ \hline A_{I,I-1} & A_{I,I} & A_{I,I+1} \\ \hline & \ddots & & \\ \vdots & \vdots & A_{I+1,I} & \ddots & \vdots \\ \vdots & \vdots & & & \end{pmatrix} \times \begin{pmatrix} \vdots \\ \vdots \\ x_I \\ \vdots \\ \vdots \end{pmatrix} = \begin{pmatrix} \vdots \\ b_I \\ \vdots \\ \vdots \end{pmatrix}$$

Recovery of x_I

$$x_{I} = \operatorname{argmin} \|b_{new} - \begin{pmatrix} A_{I-1,I} \\ A_{I,I} \\ A_{I+1,I} \end{pmatrix} x\|.$$

Multiple Faults

More than one fault at the same iteration

Processors I and J failed

$\left(\right)$	· : ·.			· · : :	$\left \begin{array}{ccc} \cdot & \cdots \\ \vdots & \ddots \end{array}\right\rangle$		$\left(\begin{array}{c} \cdot \\ \cdot \\ \cdot \end{array}\right)$		$\left(\begin{array}{c} \cdot \\ \cdot \\ \cdot \end{array}\right)$	
	$A_{I,I-1}$	$A_{I,I}$	$A_{I,I+1}$	$A_{I,I+2}$	· · : :		<i>x</i> _I		b_I	
	· : ·.	· · : :	· · : :	· · :::	· ··· : ··.	×	:	=	:	
	$A_{J,J-2}$	A_{J-1}	$A_{J,J}$	$A_{J,J+1}$	· ·		<i>x</i> _J		b_J	
	· : ·.	· · : :	· · : :	· · : :	· ··· : ···)				$\left(\begin{array}{c} \cdot \\ \vdots \end{array}\right)$	

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	$A_{I,I-1}$	$A_{I,I}$	$A_{I,I+1}$	$A_{I,I+2}$	· · · · · · · · · · · · · · · · · · ·		<i>x</i> _I		b_I	
	· ···	· · : :	· · : :	· ·	· ··· : ··.	×		=	:	
	$A_{J,J-2}$	A_{J-1}	$A_{J,J}$	$A_{J,J+1}$	· · : :		xJ		b_J	
	·	· · : :	· · : :	· · : :	· ··· : ···)		·) (:)		·)	

Parallel recovery

Parallel recovery: handle each block independently

Recovery of x_I

$\left(\right)$	· ··· : ··.		· · · · · · · · · · · · · · · · · · ·	· · : :	· ···) : ··.				$\begin{pmatrix} \cdot \\ \vdots \end{pmatrix}$
	$A_{I,I-1}$	$A_{I,I}$	$A_{I,I+1}$	$A_{I,I+2}$	· · : :		·		b_I
	· : ·.	· · : :	· · : :	· · : :	· ··· : ··.	×	÷	=	:
	$A_{J,J-2}$	A_{J-1}	$A_{J,J}$	$A_{J,J+1}$	· · : :		0 _J		b_J
	· ··· : ··.	· · : :	· · : :	· · : :	· ··· : ···)				

Parallel recovery

Parallel recovery: handle each block independently

Recovery of x_J

$\left(\right)$	· : ·.		· · ·	· · : :	· ···) : ··.		$\begin{pmatrix} \cdot \\ \vdots \end{pmatrix}$	$\begin{pmatrix} \cdot \\ \vdots \end{pmatrix}$
	$A_{I,I-1}$	$A_{I,I}$	$A_{I,I+1}$	$A_{I,I+2}$	· · : :		01	b_I
	· : ·.	· · : :	· · :::	· · : :	· ··· : ··.	×	: =	:
	$A_{J,J-2}$	A_{J-1}	$A_{J,J}$	$A_{J,J+1}$	· · : :		XJ	b_J
	· ··· : ··.	· · : :	· · : :	· · : :	· ··· : ···)			

Assembled recovery

Assembled recovery: assemble blocks that failed

Assembled recovery

			 : :	$\left \begin{array}{cccc} \cdot & \cdots & \cdot \\ \vdots & \ddots & \end{array}\right $	$\begin{pmatrix} \cdot \\ \cdot \end{pmatrix} \begin{pmatrix} \cdot \\ \cdot \end{pmatrix}$
$A_{I,I-1}$	A _{I,I}	$A_{I,I+1}$	$A_{I,I+2}$	· · : :	x_I b_I
$A_{J,J-2}$	A_{J-1}	$A_{J,J}$	$A_{J,J+1}$	· · : :	\times x_J = b_J
· ··· : ··.	· · : :	· · : :	· · : :	· ···· : ··.	
· ···· (: ···	· · : :	· · : :	· · : :	· · · · · · · · · · · · · · · · · · ·	$\left(\begin{array}{c} \cdot \\ \vdots \end{array}\right) \left(\begin{array}{c} \cdot \\ \vdots \end{array}\right) \left(\begin{array}{c} \cdot \\ \vdots \end{array}\right)$

Experimental set up

Experimental environment

- * Matlab prototype.
- * Simulation of a parallel environment.
- Weibull distribution.
- * Set Mean Time Between Fault (MTBF) of cores.
- Assumption "instantaneous recovery" : study numerical behaviour only.

Single fault

GMRES- Matrix Nasa_nasa290 - P= 34 - (32 faults)



Single fault

BICGSTAB- Matrix Nasa_nasa290 - P= 34 - (9 faults)



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Multiple faults

GMRES- Matrix Nasa_nasa290 - P= 34 - (18 MF)



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Toward robust numerical linear solvers for large scale simulations

Multiple faults

BICGSTAB- Matrix Nasa_nasa290 - P= 34 - (29 MF)



Preliminary experimental results

Impact of the MTBF on the convergence rate

GMRES - LLS-A - Matrix Nasa_nasa290 - P= 34



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Toward robust numerical linear solvers for large scale simulations

Concluding remarks

- * Overhead free when no fault.
- * Reset strategy does not work.
- ★ The parallel recovery might be poor.
- ★ The assembled recovery is more robust, but more costly.
- * Convergence speed increases when fault rate decreases.

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Perspectives

- ★ Estimation of the recovery costs.
- * Inexact recovery strategies (iterative based).
- * ABFT variant, and possible hybrid.
- ★ Soft error recovery ?

ANR blanche RESCUE project (GRAND-LARGE, ROMA); G8 ECS project.

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Thank you pour votre attention. Questions ?

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