

An Error Correction Solver for Linear Systems

Evaluation of Mixed Precision Implementations

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Engineering Mathematics and Computing Lab (EMCL) $\frac{P}{P}(\vec{\mathbf{v}}_h^{k+1} = \mathbf{v}_h^k, \mathbf{u}_h) + a(\mathbf{v}_h^{k}, \mathbf{u}_h) + a(\mathbf{v}_h^{k}, \mathbf{v}_h^k, \mathbf{u}_h) = (F^k, \mathbf{u}_h)$ $\frac{(\mathbf{v}_h^{k+1}, \mathbf{w}_h) = (\bar{\mathbf{v}}_h^{k+1}, \mathbf{w}_h)}{P}(\vec{\mathbf{v}}_h^{k+1}, \mathbf{w}_h)$

Numerical Simulation, Optimization and HPC









Numerical Simulation, Optimization and HPC









Topics

- Meteorology and Environment
- Medicine and Biotechnology
- Energy

Tools

- Mathematical Modeling
- FEM-Software
- Scientific Computing

Numerical Simulation, Optimization and HPC





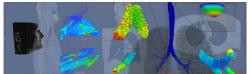




Topics

- Meteorology and Environment
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Simulation of the Human Respiratory System

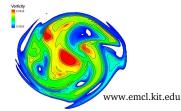


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Tools

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- Scientific Computing

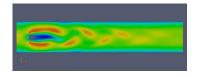
Simulation of Tropical Cyclones



Computational Fluid Dynamics



Linear Systems in Fluid Dynamics



- Partial differential equations model Fluid Flow Problems
- Discretization methods lead to nonlinear equations systems
- **Linearization methods** lead to linear system Ax = b

Solving the linear system is often the most time-consuming step in the simulation process.

Computational Effort

- Characteristics of the linear problem
- Characteristics of the applied solver
- Used floating point format

Acceleration Concepts

- Use of different precision formats
- Use of Coprocessor Technology
- Parallelization of the linear solvers

Fundamental Idea of Mixed Precision Solvers:

- Acceleration without loss of accuracy
- High precision only in relevant parts
- Low precision for most of the algorithm
- Outsource low precision computations on parallel low precision Coprocessor
- Use different precision formats within the Iterative Refinement Method

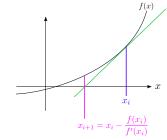


Iterative Refinement Method



Newton's Method:

$$x_{i+1} = x_i - (\nabla f(x_i))^{-1} f(x_i)$$



Idea: Apply Newton's Method to the function f(x) = b - Ax

$$x_{i+1} = x_i - (\nabla f(x_i))^{-1} f(x_i)$$

$$= x_i - (-A^{-1})(b - Ax_i)$$

$$= x_i + A^{-1}(b - Ax_i)$$

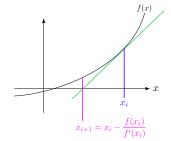
$$= x_i + \underbrace{A^{-1}r_i}_{=:c_i}$$

Iterative Refinement Method



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$$= x_i + \underbrace{A^{-1}r_i}_{=:c_i}$$

1: initial guess as starting vector: x_0

2: compute initial residual: $r_0 = b - Ax_0$

3: while ($||Ax_i - b||_2 > \varepsilon || r_0 ||$) do

4: $r_i = b - Ax_i$

5: solve: $Ac_i = r_i$

6: update solution: $x_{i+1} = x_i + c_i$

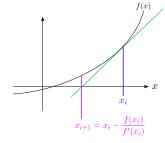
7: end while

Iterative Refinement Method



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In-Exact Newton Method

- \blacksquare Apply iterative method to solve $Ac_i = r_i$
- Residual stopping criterion $\varepsilon_{inner} >> \varepsilon$
- E.g. Krylov Subspace Solver

Mixed Precision Iterative Refinement



1: initial guess as starting vector: x_0

2: compute initial residual: $r_0 = b - Ax_0$

3: while ($||Ax_i - b||_2 > \varepsilon || r_0 ||$) do

 $r_i = b - Ax_i$

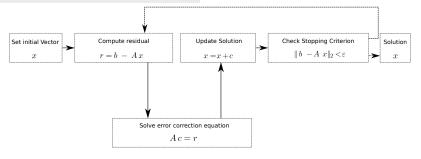
solve: $Ac_i = r_i$

update solution: $x_{i+1} = x_i + c_i$

7: end while

Any error correction solver can be used

i.e. Krylov Subspace Methods (CG, GMRES ...)



Mixed Precision Iterative Refinement



1: initial guess as starting vector: x_0

2: compute initial residual: $r_0 = b - Ax_0$

3: while ($||Ax_i - b||_2 > \varepsilon || r_0 ||$) do

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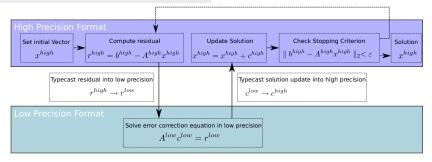
5: solve: $Ac_i = r_i$

6: update solution: $x_{i+1} = x_i + c_i$

7: end while

Any error correction solver can be used

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Numerical Experiments





Implementation Issues

- Double precision GMRES-(10) on 1 core
- Mixed precision GMRES-(10) on 1 core
- Double precision GMRES-(10) on 4 cores
- Mixed precision GMRES-(10) on 4 cores
- Mixed precision GMRES-(10) on NVIDIA TESLA S1070

Test Matrices

Artificially created Test Matrices

- Increasing dimension
- Fixed Condition Number
- sparse/dense

Real Application Test Matrices

 Discretization of Fluid Flow in Venturi Nozzle

Numerical Experiments

 different dimension, condition number, sparsity

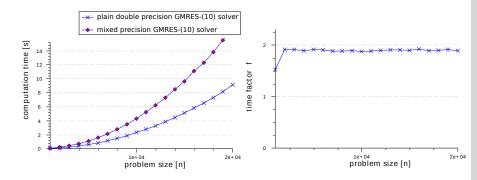
Test-Case: Artificial Test Matrices



M1	M2	M3
\begin{pmatrix} 10 \cdot n & * & \cdot \cdot & * \\ * & 10 \cdot n & \cdot \cdot & \cdot \cdot \cdot \cdot & \cdot	\begin{pmatrix} & & & & & & & & & & & & & & & & & & &	H -1 0 ··· -1 0 ··· 0
problem: artificial matrix problem size: variable sparsity: $nnz = n^2$ cond. number: $\kappa < 3$ storage format: MAS	problem: artificial matrix problem size: variable sparsity: $nnz = n^2$ cond. number: $\kappa \approx 8 \cdot 10^3$ storage format: MAS	problem: artificial matrix problem size: variable sparsity: $nnz=5n$ cond. number: $\kappa\approx 8\cdot 10^3$ storage format: CRS

Mixed Precision Iterative Refinement GMRES



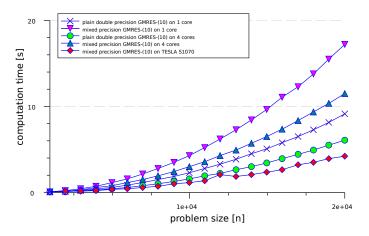


Artificial Test-Matrix M1: κ < 3, $nnz = n^2$

- Constant factor f
- Plain GMRES performs faster due to low condition number

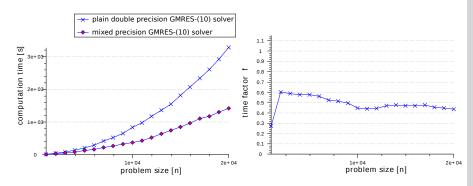
Mixed Precision Iterative Refinement GMRES





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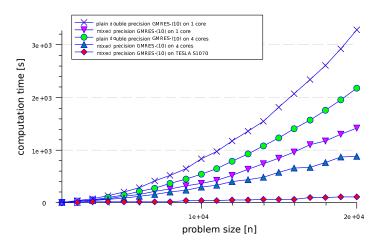


Artificial Test-Matrix M2: $\kappa \approx 8000$, $nnz = n^2$

- Constant factor f
- Mixed Precision Iterative Refinement GMRES performs faster due to high condition number

Numerical Experiments

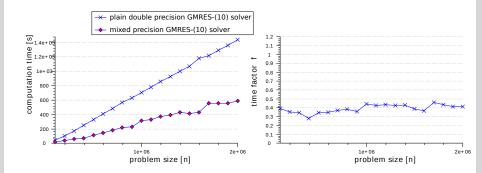




Artificial Test-Matrix M2: $\kappa \approx 8000$, $nnz = n^2$

Mixed Precision Iterative Refinement GMRES



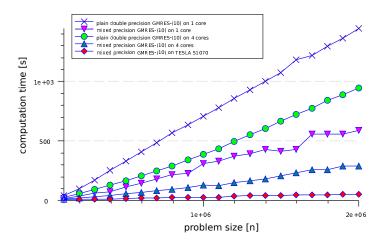


Artificial Test-Matrix M3: $\kappa \approx 8000$, nnz = 5n

- Constant factor f
- Mixed Precision Iterative Refinement GMRES performs faster due to high condition number

Mixed Precision Iterative Refinement GMRES



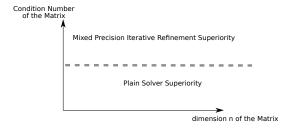


Artificial Test-Matrix M3: $\kappa \approx 8000$, nnz = 3n



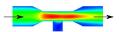
Numerical Experiments

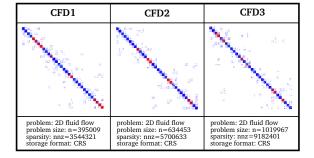
- Plain solver is superior for low condition numbers
- Mixed precision mode superior for high condition numbers
- Quotient between plain- and mixed-precision- mode independent of problem size
- Acceleration by Coprocessor Technology



Test-Case: Fluid Flow in Venturi Nozzle

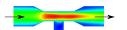


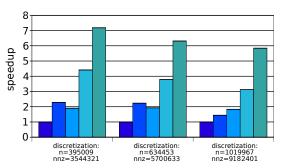




Test-Case: Fluid Flow in Venturi Nozzle







- plain double precision GMRES-(10) on 1 core mixed precision GMRES-(10) on 1 core plain double precision GMRES-(10) on 4 cores mixed precision GMRES-(10) on 4 cores mixed precision GMRES-(10) on NVIDIA TESLA S1070

Mixed Precision Solvers

- Exploiting the excellent low precision performance of Accelerator Technology (e.g. GPU)
- High potential in case of computationally expensive problems (e.g. our CFD-Problems)
- FPGA-Technology offers free choice of Floating Point Formats



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