University of Stuttgart
Department of Mathematics

Using Lossy Compression for Linear Solver Resilience

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Project
Effective Use of Lossy Compression for Numerical Linear Algebra Resilience and Performance

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Using Lossy Compression for Linear Solver Resilience

Key objectives

- Efficient recovery from a data-loss, i.e. node-loss
- Minimal overhead in a fault-free scenario

Classical techniques

- Classical checkpoint-restart too memory-intensive (and too slow)
- Triple modular redundancy too power-hungry

Our approach

- In-memory checkpointing
- Local recovery instead of global roll-back
- Lossy compression to reduce memory overhead

Using Lossy Compression for Linear Solver Resilience

Assumptions

- Problem is bandwidth-limited
- Matrices are stored in persistent memory or can be recomputed
- After a process failure a new process can be spawned and is able to
  - Replace the old process in the communicator with a new one (ULFM[1])
  - Work up to the iterative solver using message logging or similar techniques[2]
  - Receive the compressed backup from another processor

[1] G. Bosilca et al., **An Evaluation of User-Level Failure Mitigation Support in MPI**, Computing, Springer, 2013

[2] C. Cantwell and A. Nielsen, **A Minimally Intrusive Low-Memory Approach to Resilience for Existing Transient Solvers**, Journal of Scientific Computing, 2019

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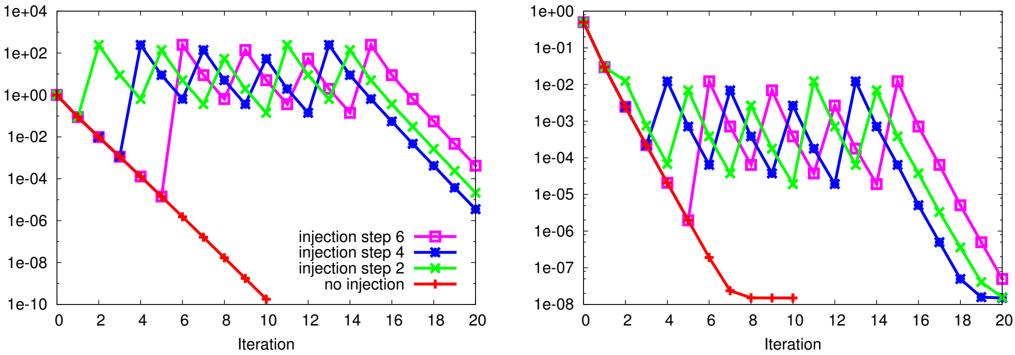
Question

What happens if a part of the iterative data is lost?

Multigrid and faults

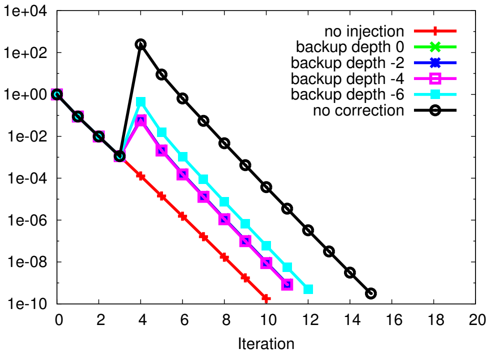


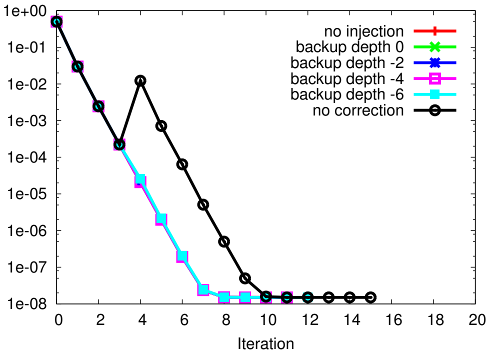
Observations

- A fault is comparable to a restart of the multigrid solver
- Multigrid converges always if the fault-rate is not to high
- Node-losses and Silent Data Corruptions show a similar behavior

Multigrid compression

- Use multigrid transfer operators to compress checkpoint
- Data reduction in d dimensions: $\sim 2^d$ per backup depth (regular coarsening)
- Restore lost data with prolongated (decompressed) checkpoint





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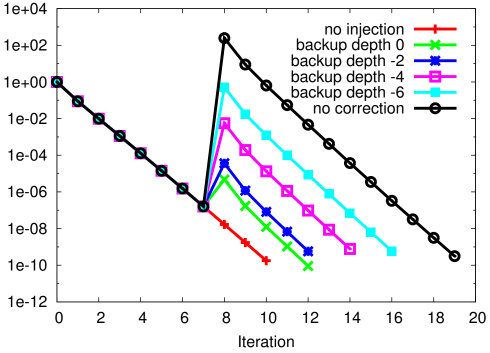

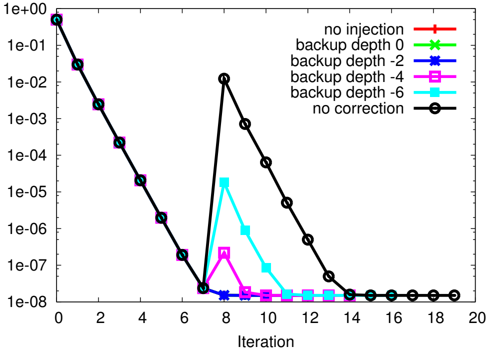

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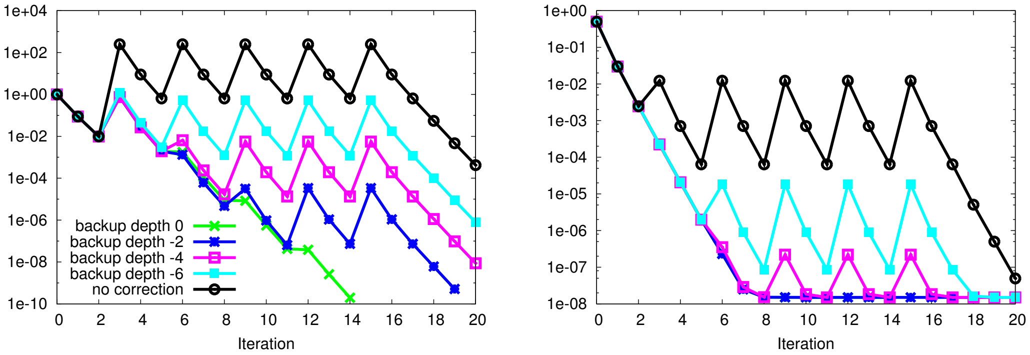

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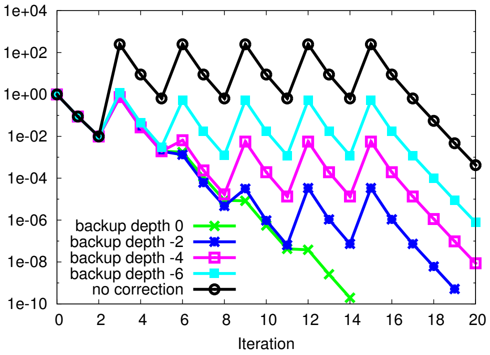
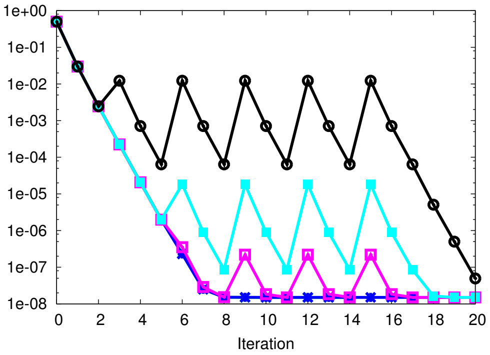




Discretisation error on coarser grids limits quality of repair

Improved restoration

Auxiliary problem (compare Huber et al.[3])

Extend faulty/lost indices $\mathcal{F} \subset \mathbb{N}$ which are owned by the processor, e.g. by using the connectivity pattern of operator $\mathbf{A}$ or an overlap, to $\mathcal{J}$ and solve

$$\begin{aligned} \mathbf{A}(\mathcal{J},\mathcal{J})\tilde{x}(\mathcal{J}) &= b(\mathcal{J}) && \text{in } \mathcal{F} \\ \tilde{x} &= x && \text{on } \mathcal{J}\setminus\mathcal{F} \end{aligned}$$

iteratively with initial guess $\tilde{x} = x_{cp}$ in $\mathcal{F}$.

Advantages

- Convergence behavior can be restored
- Speed-up when using better checkpoints as initial guess
- Local problem: Possible to use a ‘superman’ strategy for further speed-up

[3] M. Huber, B. Gmeiner, U. Rüde, B. Wohlmuth, **Resilience for Massively Parallel Multigrid Solvers**, SIAM Journal on Scientific Computing, 2016

Summary: Multigrid compression

- Multigrid compressed checkpoints can be used to recover from faults
- Early fault: Highly compressed data is sufficient
- Late fault: Compression rate has to be decreased
- Eventually an auxiliary problem has to be solved to ensure convergence
- The decompressed data is a good initial guess for this auxiliary problem
- Same idea could be used with other hierarchic methods

But

Multigrid is good preconditioner, but rarely a standalone solver

D. Göddeke, M.A., D. Ribbrock, **Fault-tolerant finite-element multigrid algorithms with hierarchically compressed asynchronous checkpointing**, Parallel Computing, 2015

Next steps

Application-oriented solvers

- BiCGStab, CG, GMRES, ...
- Nested solvers, Inner-outer approaches, Newton-like methods, ...
- ...

Evaluating impact of

- Various (lossy) compression techniques
  - Multigrid compression
  - SZ compression
- Variable checkpoint frequencies
- Different restoration methods
  - Local restoration based on compressed checkpoint
  - Global roll-back to compressed checkpoint
  - Improved restoration by solving auxiliary problem

SZ compression

How it works

- Save initial point value (with reduced accuracy): Unpredictable data
- Predict next point based on previous processed points via an interpolation based on n layers
- Compare predicted value with real value and improve it through a *Huffman*-like coding
- If still not ‘close enough’ data is stored as unpredictable and compressed via binary-representation analysis

Advantages and disadvantages

- Adaptive controllable compression rate (via parameter)
- More computational overhead than multigrid compression
- Lower compression rate $\rightarrow$ higher computation time

D. Tao, S. Di, Z. Chen and F. Cappello, **Significantly Improving Lossy Compression for Scientific Data Sets Based on Multidimensional Prediction and Error-Controlled Quantization**, Computing Research Repository, 2017

Numerical tests

- Anisotropic diffusion in 2D with dirichlet-boundary condition:

$$-\nabla \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0.01 \end{pmatrix} \nabla u = b$$

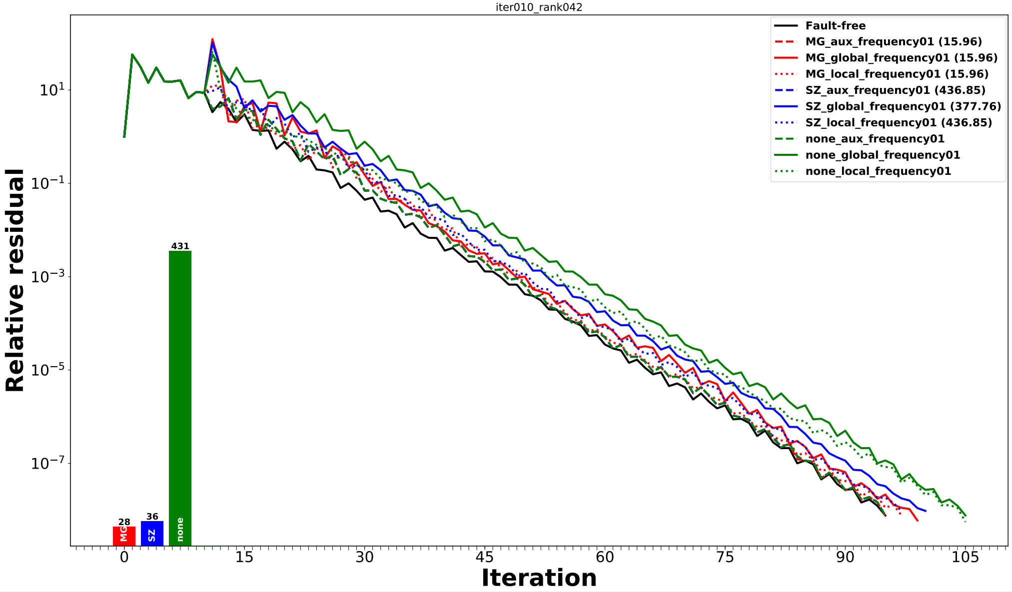
- Linear finite elements on partitioned grid (64 ranks, overlapping Schwarz)
- $146\,531$ degrees of freedom per rank
- Solver: Conjugated gradient
- Preconditioner: Algebraic multigrid (9 levels, one V-cycle)
- MG compression of 2 levels; adaptive SZ compression (2.0.2.0; PW_REL):

$$\texttt{locale\_def\_norm\_at\_backup\_time} \;/\; \sqrt{\texttt{def.size()}} * 10^{-3}$$

- Auxiliary solver reduction to absolute residuum norm of

$$\texttt{locale\_def\_norm\_at\_backup\_time} \; * 10^{-(\texttt{age\_of\_backup}+1)}$$

Early fault



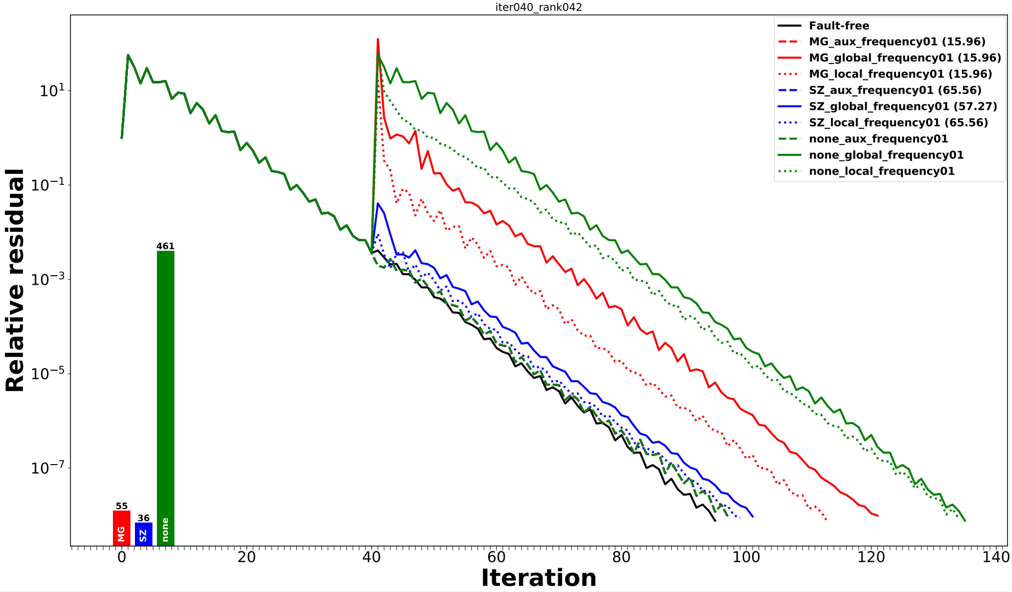
iter010_rank042
Relative residual
Iteration
Fault-free
MG_aux_frequency01 (15.96)
MG_global_frequency01 (15.96)
MG_local_frequency01 (15.96)
SZ_aux_frequency01 (436.85)
SZ_global_frequency01 (377.76)
SZ_local_frequency01 (436.85)
none_aux_frequency01
none_global_frequency01
none_local_frequency01
28
36
431
MG
SZ
none

Early fault

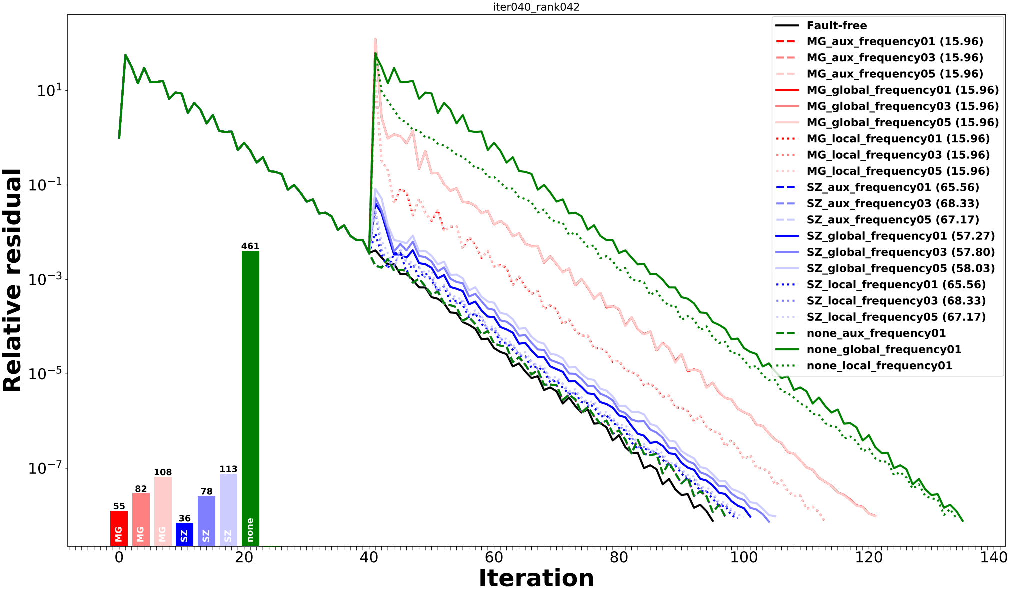
Observations

- No backup: Similar to a restart; nearly 10 additional iterations
- With backup: Local restoration better than global roll-back
- Multigrid compression has lower iteration number but worse compression rate
- Auxiliary problem can restore convergence behavior:
  - With zero initial guess a lot of iterations are necessary
  - MG or SZ compressed backup reduces iteration count significantly

Intermediate fault



Intermediate fault

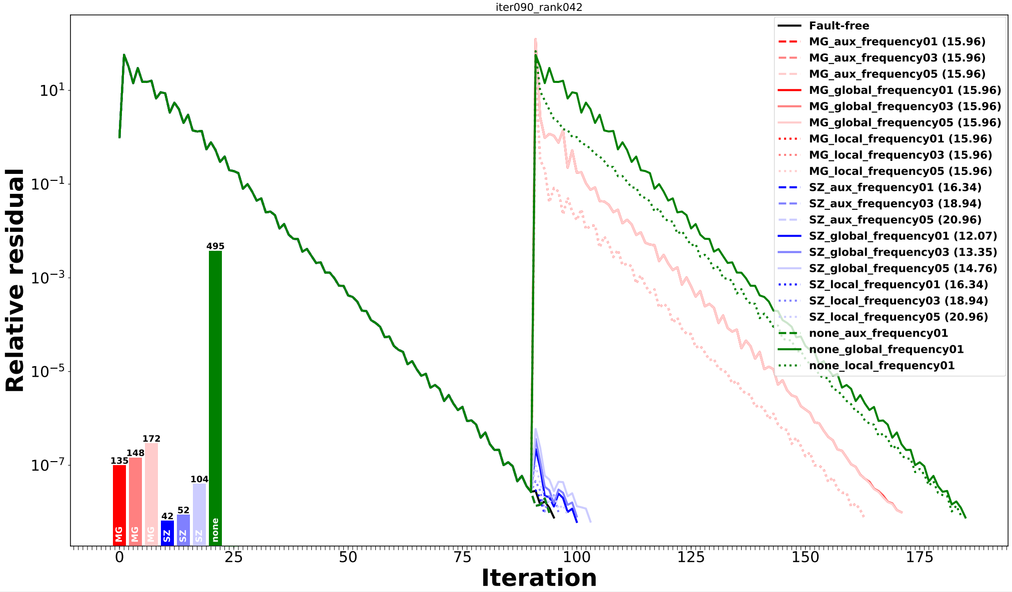


Intermediate fault

Observations

- Local restoration always superior than global
- Multigrid compression not competitive anymore
- SZ compression works good and still has a compression factor of 60
- A delay deteriorates the quality of repair global-rollback
  But: Local recovery is only marginal deteriorated
- Auxiliary solver improves quality significantly but increases overhead
- Delayed backups increase iteration count of auxiliary solver

Late fault



iter090_rank042
Relative residual
Iteration
10^{1}
10^{-1}
10^{-3}
10^{-5}
10^{-7}
0
25
50
75
100
125
150
175
Fault-free
MG_aux_frequency01 (15.96)
MG_aux_frequency03 (15.96)
MG_aux_frequency05 (15.96)
MG_global_frequency01 (15.96)
MG_global_frequency03 (15.96)
MG_global_frequency05 (15.96)
MG_local_frequency01 (15.96)
MG_local_frequency03 (15.96)
MG_local_frequency05 (15.96)
SZ_aux_frequency01 (16.34)
SZ_aux_frequency03 (18.94)
SZ_aux_frequency05 (20.96)
SZ_global_frequency01 (12.07)
SZ_global_frequency03 (13.35)
SZ_global_frequency05 (14.76)
SZ_local_frequency01 (16.34)
SZ_local_frequency03 (18.94)
SZ_local_frequency05 (20.96)
none_aux_frequency01
none_global_frequency01
none_local_frequency01
135
148
172
42
52
104
495
MG
MG
MG
SZ
SZ
SZ
none

Late fault

Observations

- Previous observations still valid
  - Local restoration superior to global-rollback
  - Higher delay deteriorates quality
  - Auxiliary problem restores convergence behavior
  - Multigrid compression is not competitive
- SZ maintains a compression rate of approximately 20

Late fault

Observations

- Previous observations still valid
  - Local restoration superior to global-rollback
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Question

What about performance and overhead?

Performance analysis

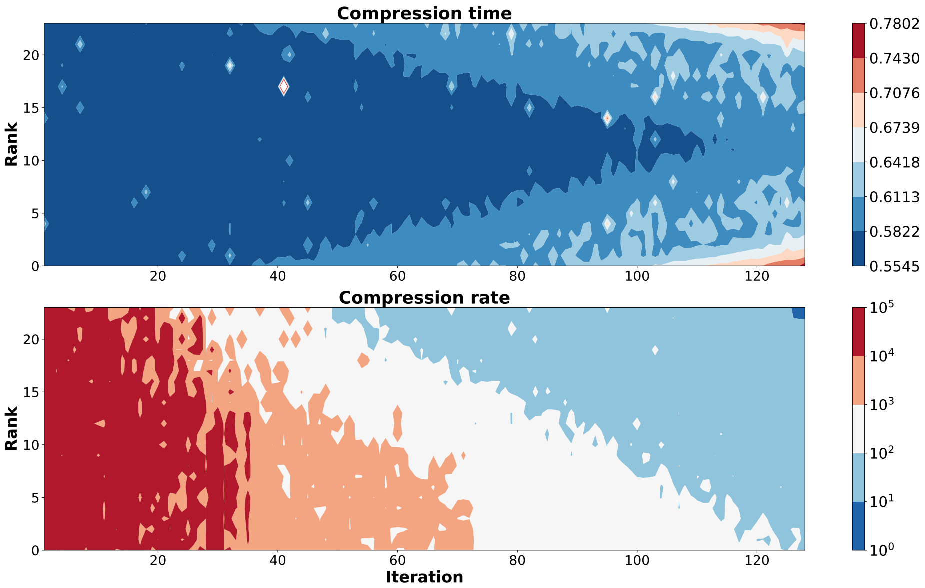
Settings

- Same problem as described before but fault-free
- 210 917 529 degrees of freedom $\Rightarrow$ ca. 8 800 000 per core
- Two nodes with Intel(R) Xeon(R) Silver 4116 CPU (2×12 cores):
  - Base frequency: 2.10 GHz
  - Turbo frequency: 3.00 GHz
  - L3 Cache: 16.5 MB
- 2×96 GB RAM
- No hyper-threading

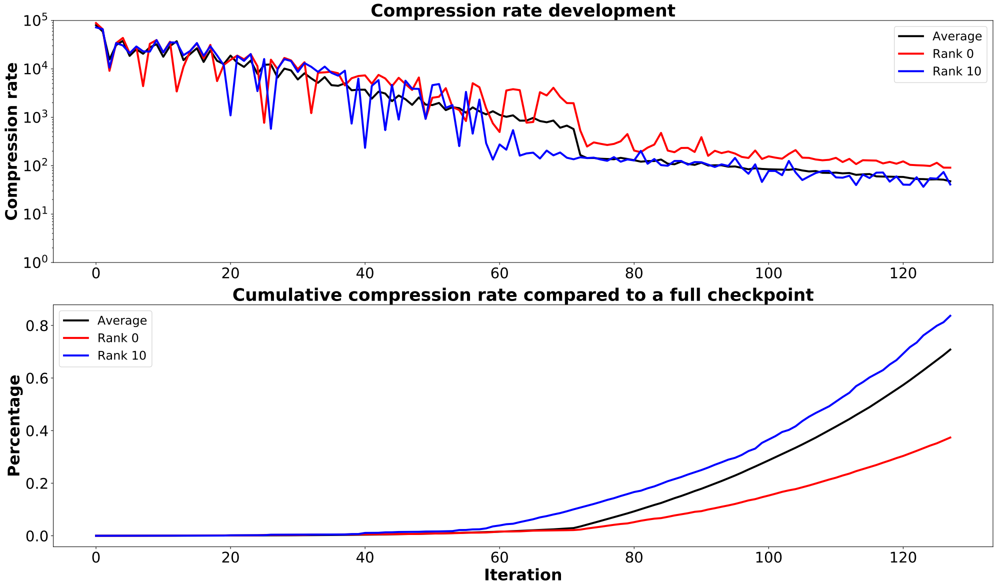
Notable

- 97 iterations until convergence
- One iteration takes on average 98 seconds

Performance analysis



Performance analysis



Summary

- We have combined local recovery with lossy compression
- The obtained method is able to recover in most fault-scenarios with . . .
  - . . . a simple local restoration and some additional global iterations.
  - . . . a local auxiliary problem which can be speed-up by a ‘superman’ strategy.
- Compression target is coupled to local defect norm:
  - Early on a high compression rate can be achieved
  - Backup quality is increased towards the end
- Communication overhead is significantly reduced
- Overhead can be further reduced by using lower checkpoint frequencies
- Asynchronous checkpointing can dispense the communication overhead further over the iterative process

Acknowledgements

Project: Effective Use of Lossy Compression for Numerical Linear Algebra Resilience and Performance

- Jon C. Calhoun (Clemson University, South Carolina, USA)
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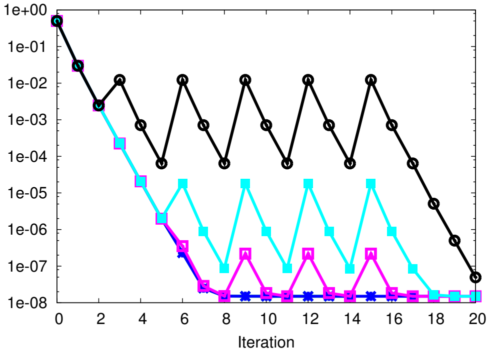
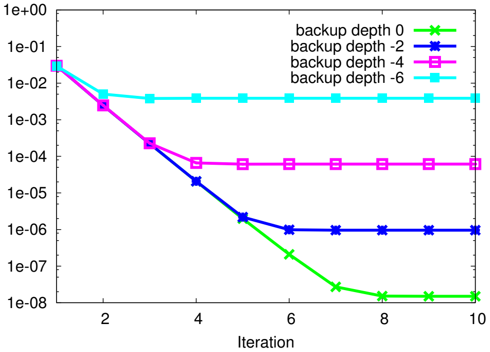
SPPEXA

Multigrid compression

Limits of multigrid compression



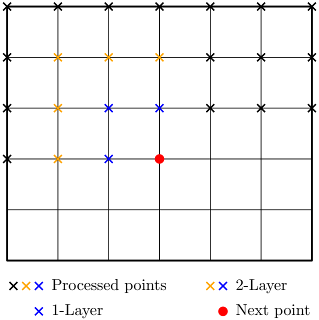


- Discretisation error dominates at some point
- Dominates earlier for highly compressed data
- Factor between L^2-quality and L^2-error depends on amount of repaired data

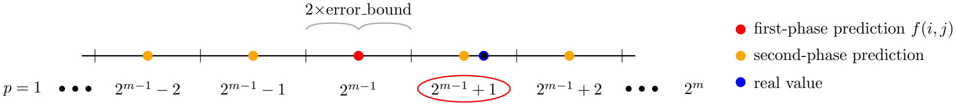
SZ compression (version 1.4.2, 2D)

- Predict values row by row (top to bottom, left to right)
- $\mathcal{V} = \{V(i,j)\}$: set of already compressed point values
- Interpolation based first-phase prediction $f(i,j)$

1-Layer	$V(i,j-1)+V(i-1,j)-V(i-1,j-1)$
2-Layer	$2V(i,j-1)+2V(i-1,j)-4V(i-1,j-1)$ $-V(i,j-2)-V(i-2,j)+2V(i-2,j-1)$ $+2V(i-1,j-2)-V(i-2,j-2)$
…	…

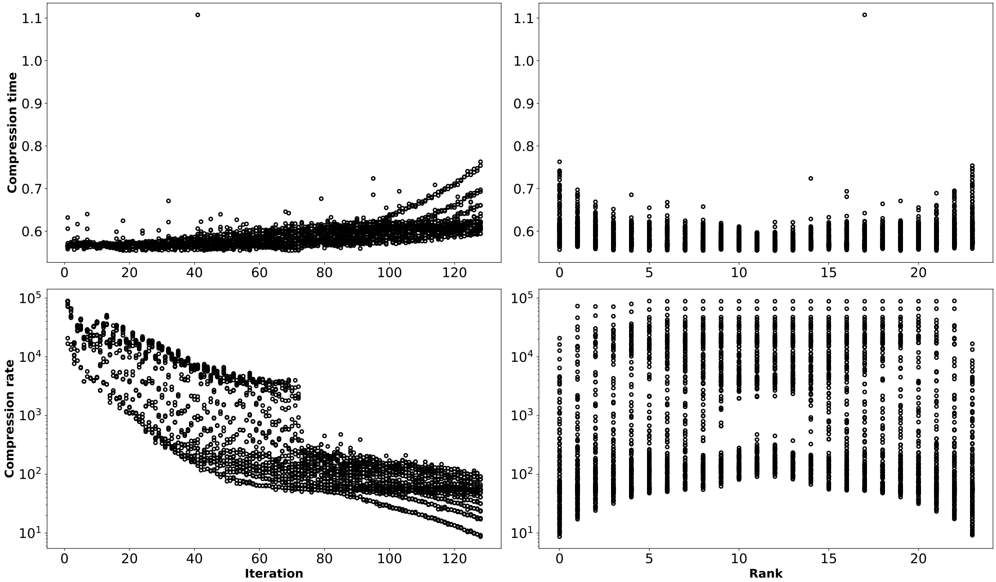


- 2^m intervals with size of $2\times$`error_bound` around $f(i,j)$

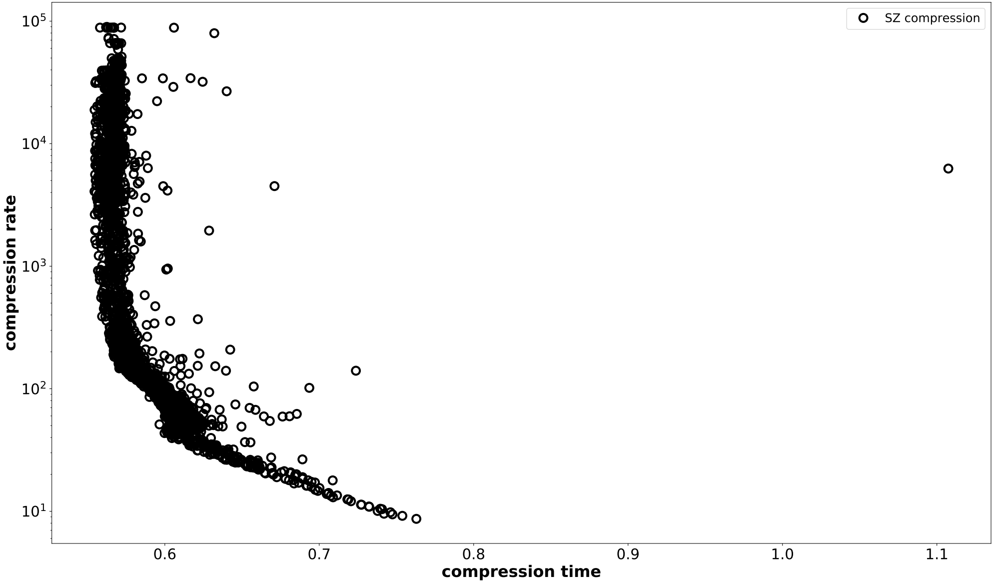


- Store index p or and $p=0$ and compressed binary-representation if the real value is not in any second-phase prediction interval
- Data is decompressed via interpolation and shifted by the Huffman-code

Performance analysis



Compute time vs. compression rate



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