Adapting to Memory Pressure from within Scientific Applications on Multiprogrammed Environments

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July 20, 2004

Work supported by NSF and a DOE Computational Science Graduate Fellowship administered by Krell Institute. Performed using facilities made possible by Sun Microsystems, NSF, the Commonwealth of Virginia, and the College of William and Mary.

Research goals

Goal: Enable scientific codes to run efficiently in non-dedicated, shared resource environments:

- Loose networks of workstations (may share everything!)
- SMP machines (share memory, even w/ space-shared CPUs)
- Big buzzword: “Grid Computing”

Work has focused on two shared resources (CPU + RAM):

- CPU: Dynamic load balancing via algorithmic modifications
  - Specific class of inner-outer iterative methods
  - Simple *algorithmic* modifications
  - Very low overhead
- RAM: Dynamic adaptation to memory pressure

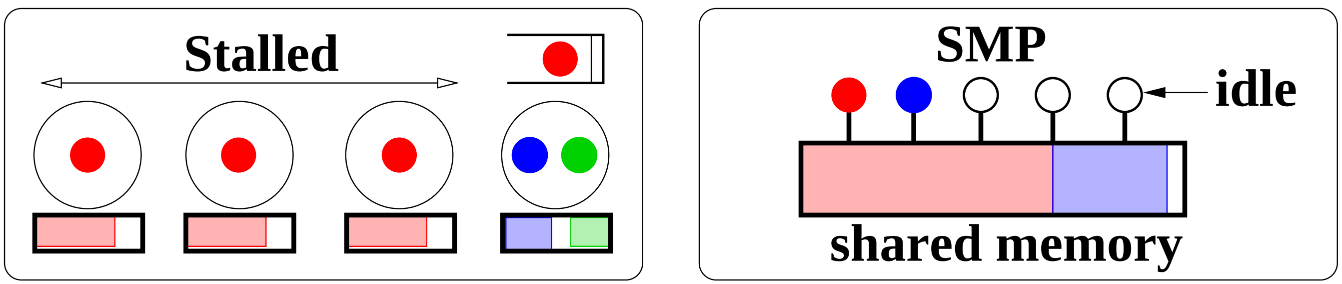
Memory pressure in shared environments

Over-committing memory can cause severe performance penalties! E.g.:

- Multigrid, no memory pressure: 14 seconds per iteration
- With Matlab QR factorization: 472 seconds per iteration

System response to memory shortage:

- The system may move a process to wait queue



Synchronous parallel programs stall, despite load balancing!

Memory pressure in shared environments

Over-committing memory can cause severe performance penalties! E.g.:

- Multigrid, no memory pressure: 14 seconds per iteration
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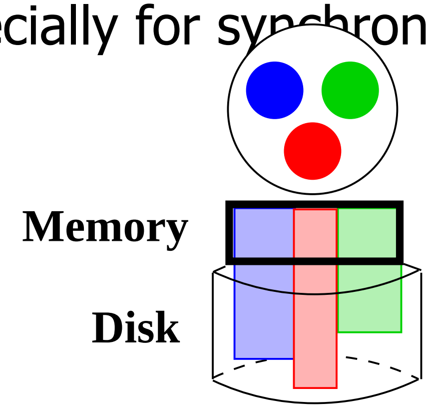
System response to memory shortage:

- The system may move a process to wait queue.
- Or, all jobs run, resulting in thrashing.
- Either case is disastrous,
  especially for synchronous parallel programs!



Many CPU cycles wasted!

Avoiding/coping with memory pressure

Many approaches exist at OS, compiler, middleware levels:

- Adaptive schedulers, VM modifications, compiler support, middleware memory managers, ...

We explore an **application-level** memory adaptation framework.

Why? Application has full knowledge of

- Granularity
- Communication pattern
- Memory access pattern
- Dynamic memory size requirements

Goal: Applications exploit this knowledge to adapt memory requirements to memory availability.

Memory-adaptation framework

Target scientific apps, where large, repetitive data access typical.

Many scientific apps use blocked access pattern:

```
for i = 1:P
    Get panel p_i from lower memory level
    Work on p_i
    Write results and evict p_i to lower level
```

Suggests an adaptation framework:

- Use named mmap() to access data set
- Cache (mmap) as many panels as possible in-core
- Control RSS by varying number of panels cached
- User-defined replacement policy
- Encapsulate caching decisions within **`get_panel()`**

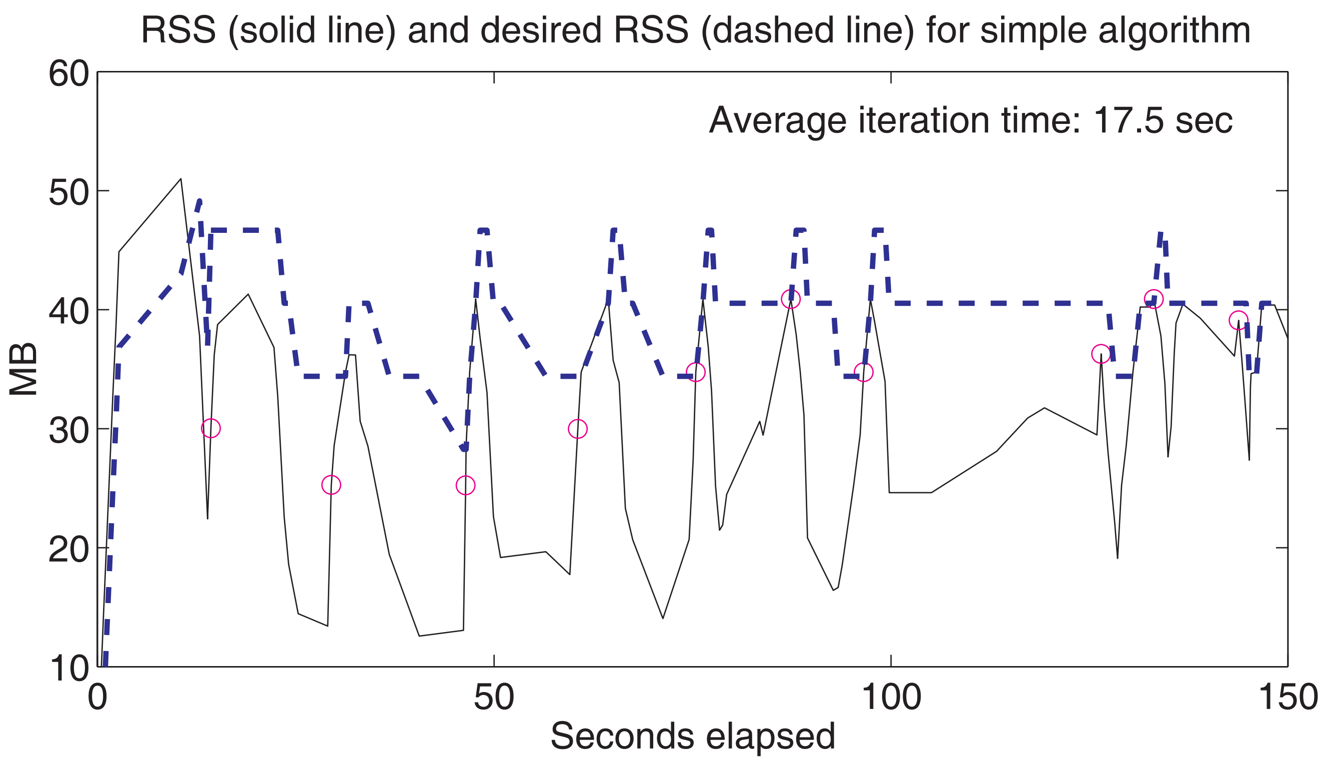
Detecting memory shortage/surplus

OS provides no accurate estimate of available memory!

- We infer shortage if RSS decreases w/o unmapping by us.
- Detecting surplus is more complicated:
  - Periodically probe for more memory
    - Map new panel w/o unmapping another (increase panels_in)
  - If memory available, RSS grows by one panel
  - Otherwise, RSS stays constant or decreases
  - Note: Don't probe if RSS < dRSS = panels_in * panel_size
- Simplest policy: Probe when RSS = dRSS = panels_in * panel_size

Simplest policy too aggressive

- Safe RSS/dRSS is 30-35 MB; regularly exceeded!
- Unsuccessful probes drop RSS dramatically.



70 MB adaptive job vs. 70MB dummy job; 128 MB system RAM.

Use dynamic delay to reduce aggressiveness

We must reduce frequency of probes for surplus memory:
After a detected shortage, delay probing for some time.

Choice of delay must consider two penalties:

- Probe too often → VM system takes memory ("incursion penalty")
  penalty: (maxRSS / B_w)
- Probe too infrequently → Wasteful reads from disk ("inaction penalty")
  penalty: ((maxRSS – RSS) / B_w)

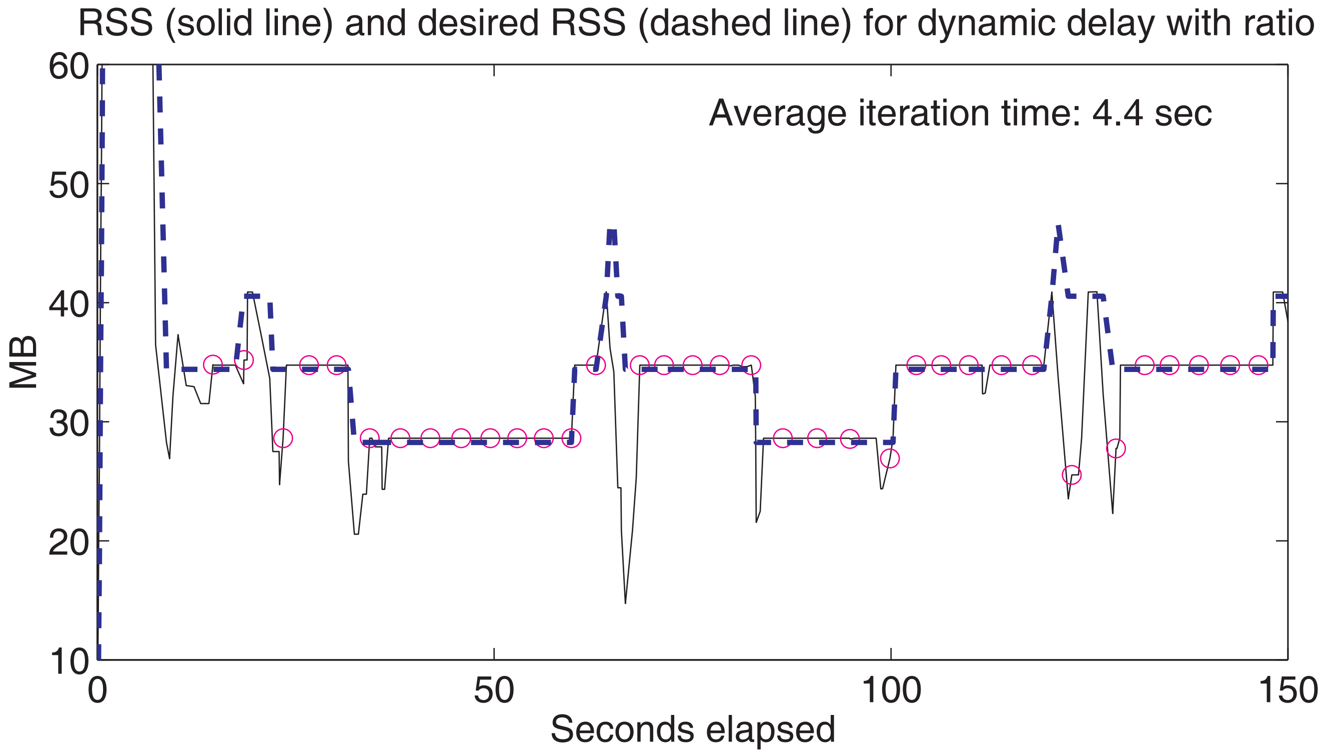
Can balance two penalties by scaling some base delay by their ratio.

- After shortage, must touch panels to re-load lost pages.
  → Use time for sweep through all panels as base delay.

Delay = (Time for last full sweep) * (maxRSS / (maxRSS – RSS))

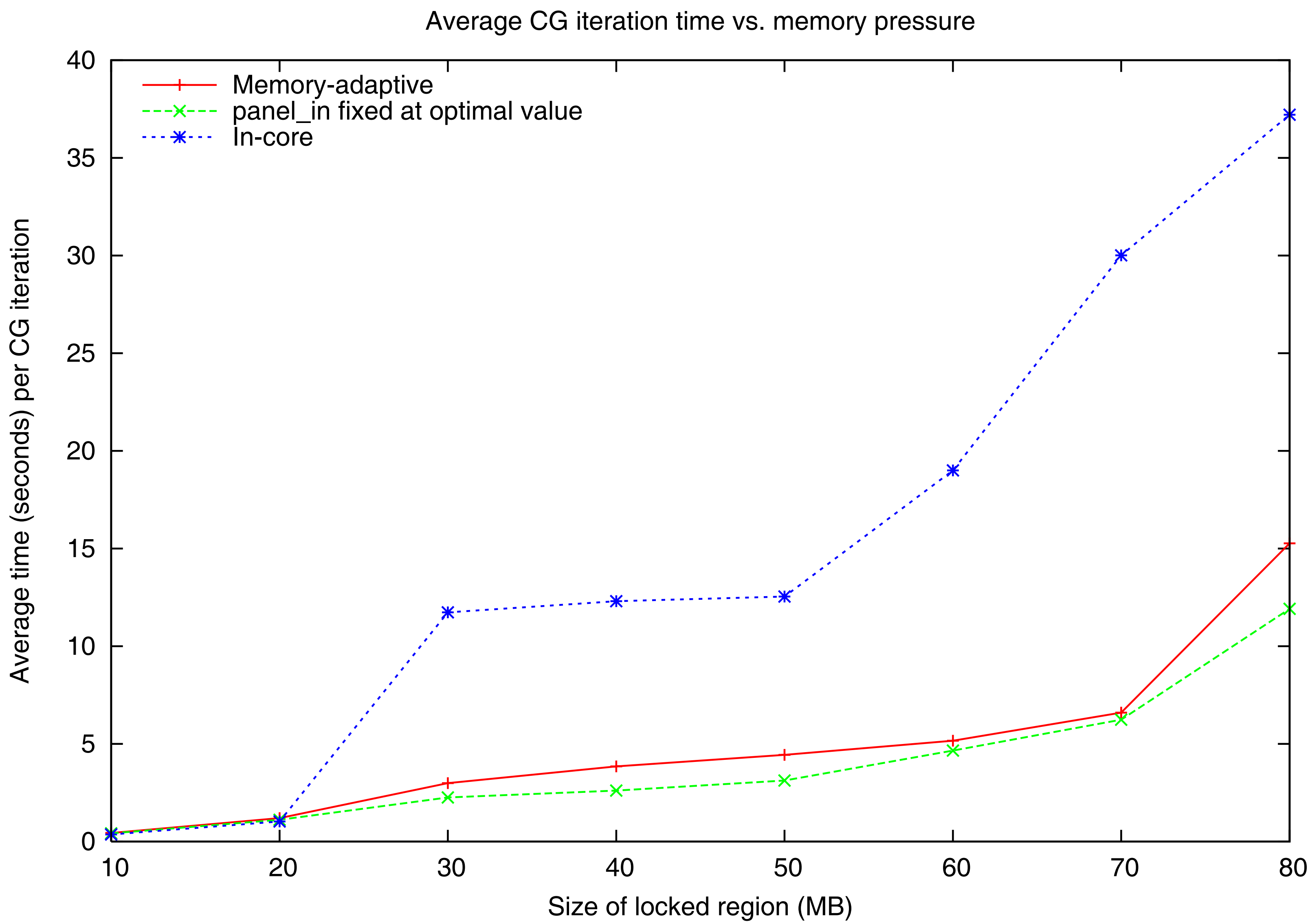
Dynamic delay improves performance

- dRSS quickly finds safe value.
- Fluctuations in RSS greatly reduced.
- Time per matvec reduced from 17.5 sec to 4.4 sec.

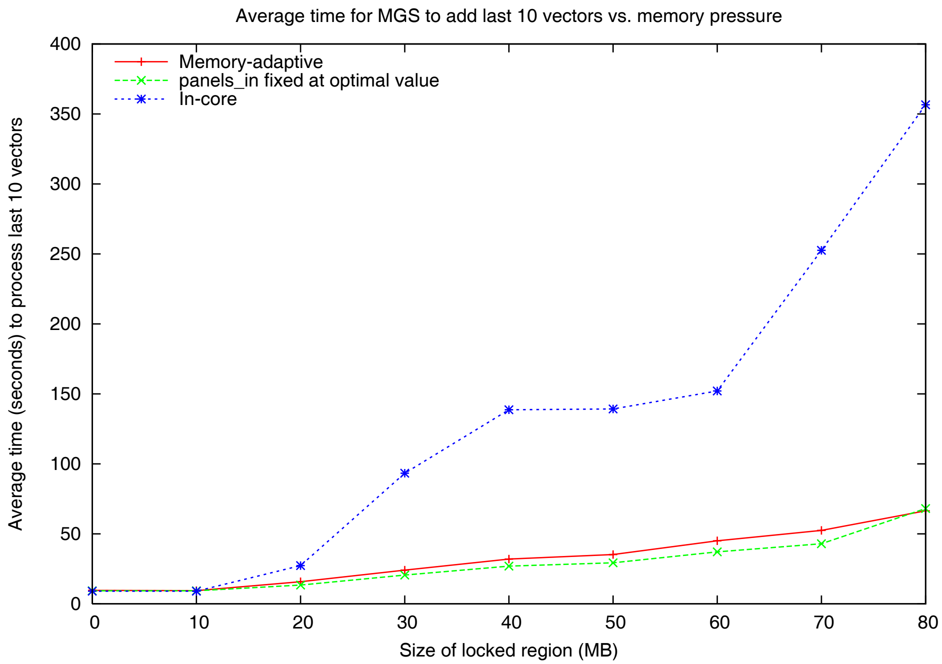


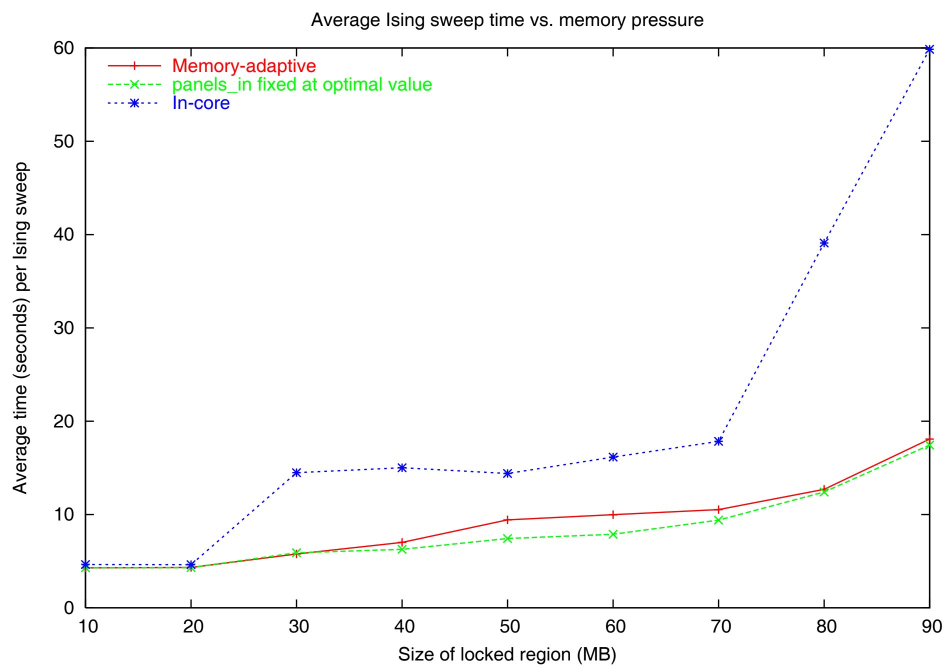
70 MB adaptive job vs. 70MB dummy job; 128 MB system RAM.

Graceful performance degradation in CG



Modified Gram-Schmidt; Ising via Metropolis





In summary...

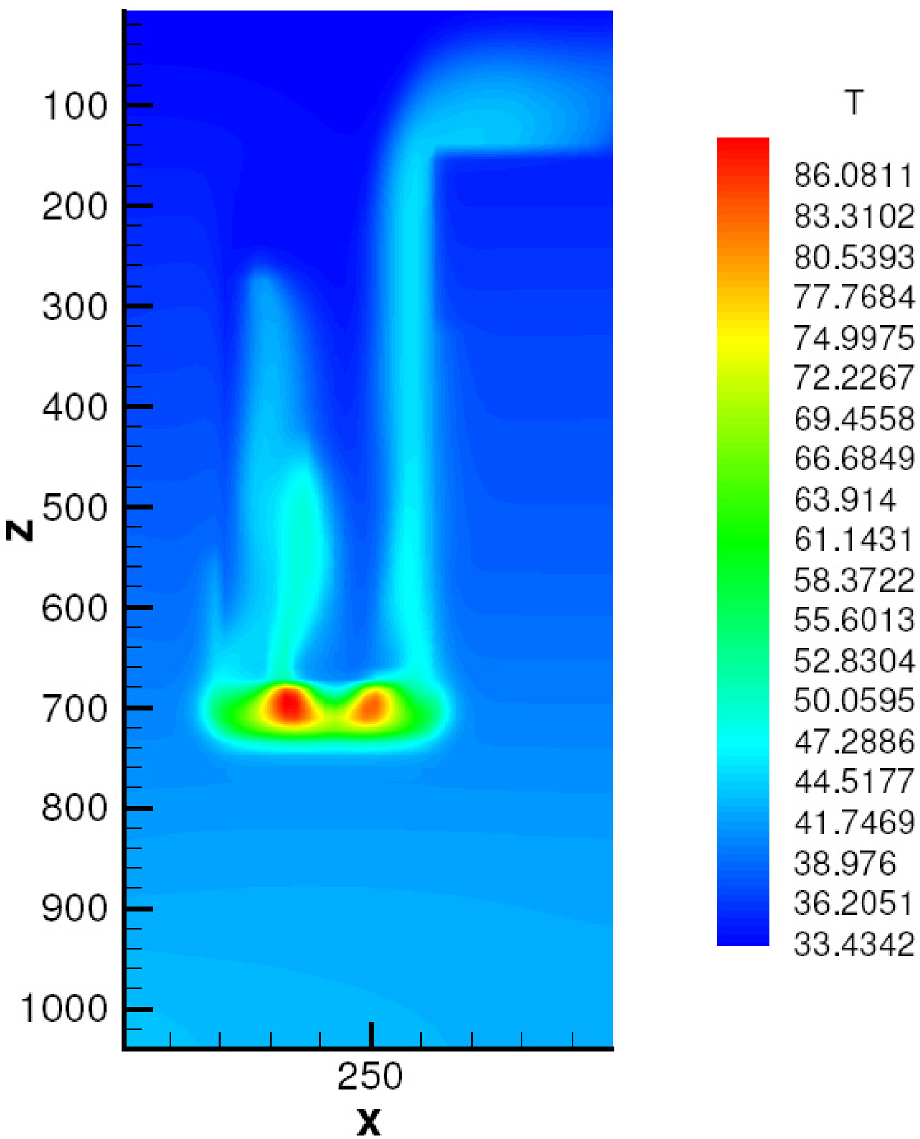
Application-level memory-adaptation framework:

- Enables graceful performance degradation under memory pressure (order of magnitude speedups not atypical)
- Minimal reliance on OS-provided information
- Requires minimal code changes to many scientific kernels
- Suited to non-centrally administered, open systems

Key contributions:

- Algorithm judges memory availability with single metric
- Demonstrated in three application kernels
- Modular, flexible supporting library

PFLOW: Multiphase subsurface flow

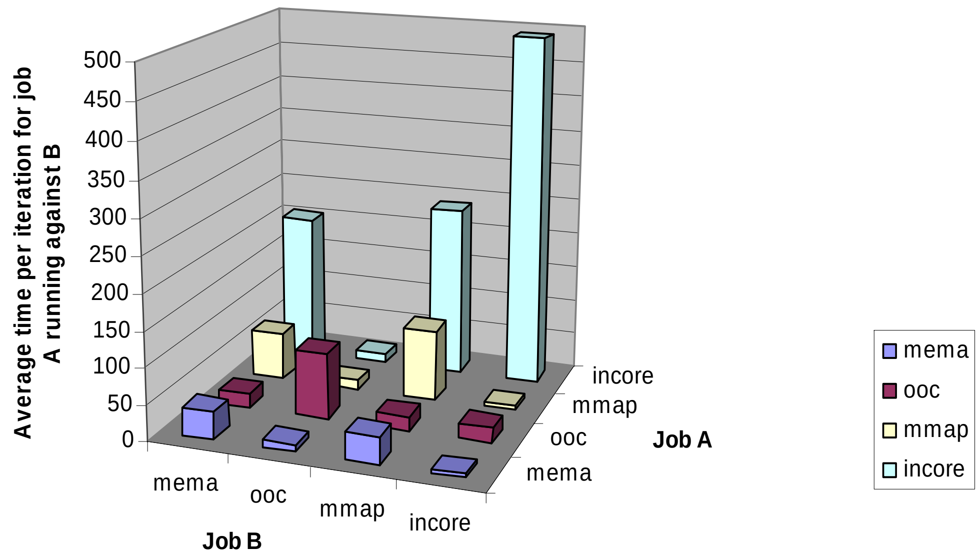


- Parallel, multiphase, fully-implicit subsurface flow
- Object-oriented Fortran 90 code: uses derived types, modules to provide encapsulation
- Uses PETSc iterative solvers, communication constructs

Comparison of different CG implementations

Compared memory adaptive CG (mema) with other CG codes:

- Conventional in-core (incore)
- Conventional out-of-core (ooc)
- Memory-mapped I/O (mmap)



	mema	ooc	mmap	incore
mema	38.66	9.89	37.8	5.32
ooc	19.87	92.1	19.76	20.25
mmap	66.34	12.18	99.72	7.59
incore	203.4	11.74	239.8	493

Modified Gram-Schmidt

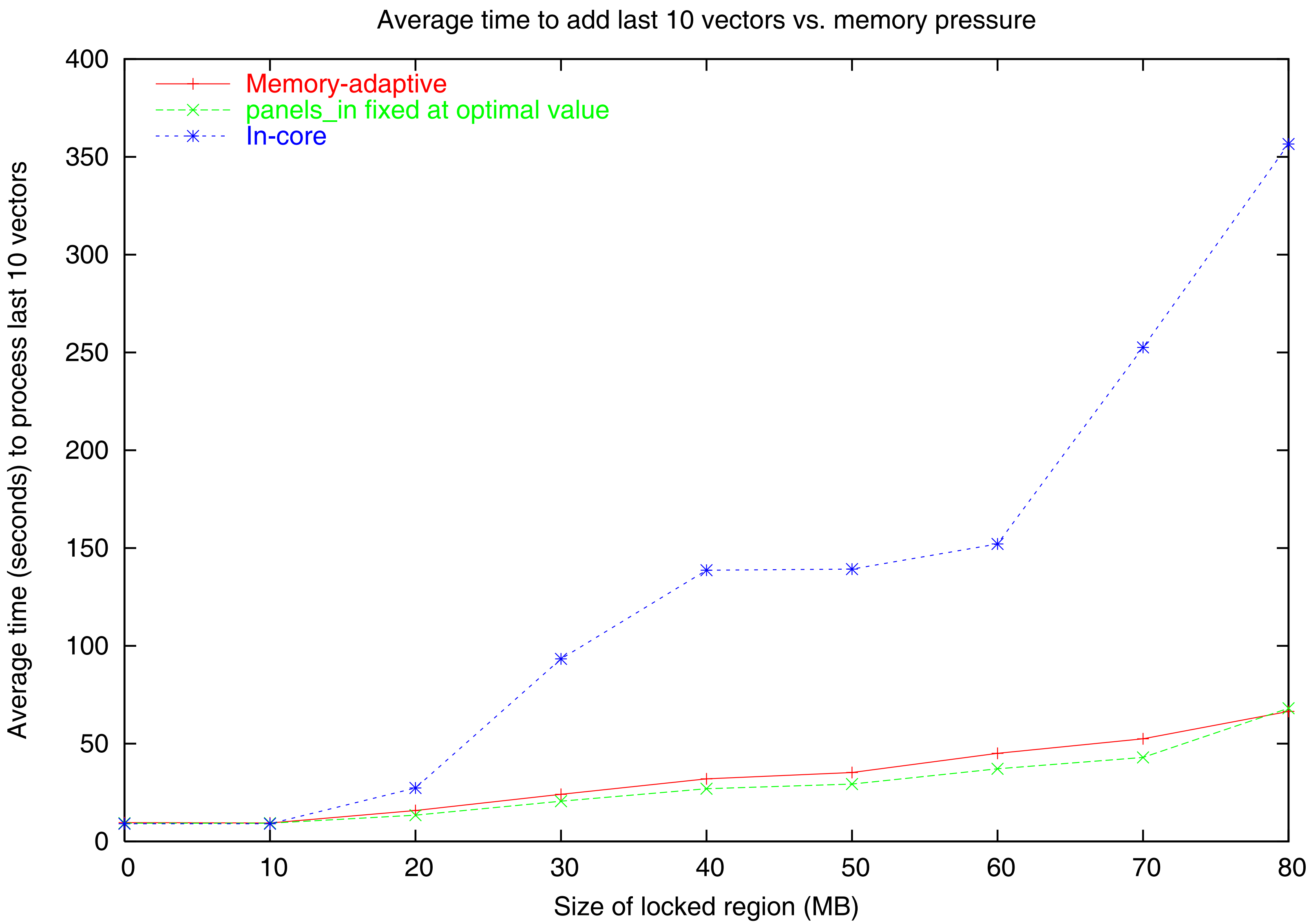
From vectors W, generate orthonormal vector basis V:

- Orthogonalize w_2 against v_1: $v_2 = w_2 - (v_1 * w_2)v_1$
- Orthogonalize w_3 against v_1 and v_2
- Orthogonalize w_i against $v_1, v_2, \ldots, v_{i-1}$

- Working set increases as vectors added to basis.
- Once added to basis, vector not written again.

- Our test code:
  - Generates random vector, orthonormalizes, adds to basis.
  - Restarts (discards vectors) when max basis size reached.
  - Note: Like GMRES, but doesn't build Krylov space.
  - Can specify min basis size to guarantee memory pressure.

Modified Gram-Schmidt



Ising Model via Metropolis

- Ferromagnet modeled as rectangular lattice.
- Sites possess only spin up (+1) or down (-1).
- Interaction with four nearest-neighbors only.
- Similar to a wide range of physics models.

- Monte-Carlo simulation:
- Generate configurations that represent equilibrium.
- Sweep through the lattice, making trial spin flips.
  - Accept new spin if $\Delta E < 0$ OR
  - Accept with probability $\exp(-\Delta E/kT)$ otherwise.

- Partition lattice row-wise into panels.
- At panel boundaries, need both panels for ΔE calc.

Metropolis Ising model simulation