

Parallel Programming SS21 Final Project

02 Gaussian Elimination

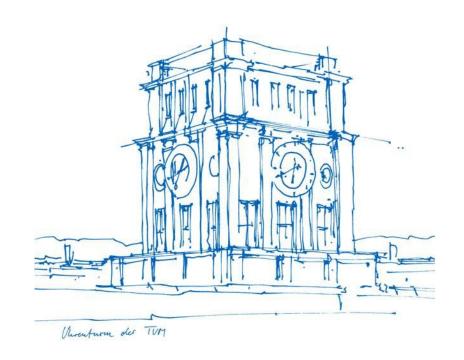
Group 218

13.07.2021

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Outline



- 1. Sequential code analysis
- 2. OpenMP
- 3. MPI
- 4. Hybrid
- 5. Bonus
- 6. Conclusion

Sequential code analysis - Forward Elimination



When calculating the forward elimination, for every row, we take the diagonal element d, calculate an elimination factor f=d/x such that for all lower elements in the column r*x-r=0. This diagonal element stays constant with respect to x. Thus we do not need to calculate it over and over again.

Graphically, that is

$$d_1 = 1$$

 $x_{11} = 6$
 $f_1 = \frac{1}{6}$
 $x_{11} = x_{11} \cdot f_1 - x_{11} = 0$
Repeat for all x_{1j} .

1	2	3	1	а		1
6	-4	5	0	b	_	6
2	3	5	0	С	_	9
5	-10	1	0	d		0

 \Rightarrow We can see that d₁ stays constant for all eliminations. The given algorithm constantly calculates d_i, thus we moved this calculation outside. All further analyses apply to the algorithm with this change.

Sequential code analysis - Theoretical Analysis

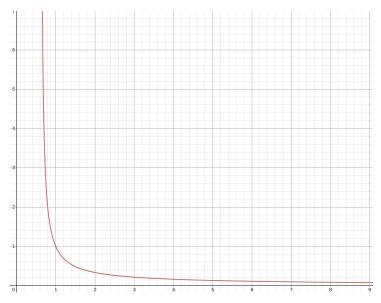


For the Forward Elimination we have n(n+1)/2 division $(2n^3+3n^2-5n)/6$ multiplications $(2n^3+3n^2-5n)/6$ subtractions $= n(n+1)/2 + (2n^3+3n^2-5n)/3 = FE(n)$ operations

For the Backward Elimination we have n(n-1)/4 multiplications n(n-1)/4 additions = n(n-1)/2 = BE(n) operations

Let's look at the ratio for **BE(n)/FE(n)!**

- ⇒ Quickly converges to 0
- ⇒ FO outweighs BO by a lot
- \Rightarrow E.g., for n = 1024, FO causes 99,85% of the computations
- ⇒ Gives rise to only optimizing **FO** due to high overhead



The graph f(n)=BE(n)/FE(n) showing the ratio of BE and FE indicating the importance of BE

Sequential code analysis - Profiling and Backward



- Perf output roughly coincides with the theoretical calculation
- FE percentage slightly lower since other operations cause overhead
- Backward elimination not even visible

The backward algorithm is

- 1. doing a negligible amount of work
- 2. has strong sequential data dependency
- ⇒ Neglect the backward algorithm throughout all our future optimizations and the rest of the presentation

Overhead	Command	Shared Object	', Event count (approx.): 122283612 Symbol
97,42%	serialge	serialge	[.] Serial::ForwardEliminationOptimized
0,36%	serialge	serialge	[.] Serial::SerialSolve
0,35%	serialge	libstdc++.so.6.0.28	[.] std::num_put <char, std::ostreambuf_iterator<="" td=""></char,>
0,19%	serialge	libstdc++.so.6.0.28	[.] std::num_get <char, std::istreambuf_iterator<="" td=""></char,>
0,14%	serialge	libstdc++.so.6.0.28	[.] std::istream::sentry::sentry
0,13%	serialge	libstdc++.so.6.0.28	[.] std::num_get <char, std::istreambuf_iterator<="" td=""></char,>
0,13%	serialge	libc-2.31.so	[.]GIstrtod_l_internal
0,08%	serialge	libstdc++.so.6.0.28	[.] std::string::reserve
0,07%	serialge	libc-2.31.so	[.] malloc
0,06%	serialge	libstdc++.so.6.0.28	[.] std::string::_Rep::_M_clone
0,05%	serialge	libc-2.31.so	[.]strlen_avx2
0,05%	serialge	libstdc++.so.6.0.28	[.] std::convert_to_v <double></double>
0,05%	serialge	[kernel.kallsyms]	[k] clear_page_erms
0,04%	serialge	serialge	[.] ReadLine

Figure: Perf profiling output for serial implementation

Sequential code analysis - Amdahl's law



Q: What portion of the algorithm is parallelizable?

1	2	3	1	а		1
6	-4	5	0	b	_	6
2	3	5	0	С	_	9
5	-10	1	0	d		0

- Low data dependency
- Each of i+1th rows is only dependent on the element A_{ii}
- Therefore, propagating down the diagonal element can be nicely parallelized
- As this is all the algorithm is doing (besides a few other operation),
 we expect roughly 97% (according to Perf) to be parallelizable

Sequential code analysis - Amdahl's law



Q: What portion of the algorithm is parallelizable?

So let's evaluate this, given our OMP speed up of L = 14.

Amdahl's Law is given by

$$L_p(s) = 1 / (1 - p + p/s)$$

where L is the latency (i.e., the speed up), p is the portion to be parallelizable and s the amount of workers.

Plugging in all the values yields

$$14 = 1 / (1 - p + p/s)$$

$$\Leftrightarrow p \approx 0.96$$

⇒ According to a speed up of factor 14, approximately 96% of the program is parallelizable

Similarly, we can ask ...

Sequential code analysis - Amdahl's law



Q: Given the portion of the algorithm to parallelizable (p=0.97), what's the theoretical speed up maximum?

Plotting the $L_p(s)$ yields

- ⇒ Assuming 97% parallelizability using 32 CPUs theoretical speed up of factor 16.5
- ⇒ Clearly sublinear but still very nice curve.
- ⇒ Theoretical max speed up: $L_p(s)$ converges towards 33.3 for $s \rightarrow \infty$.

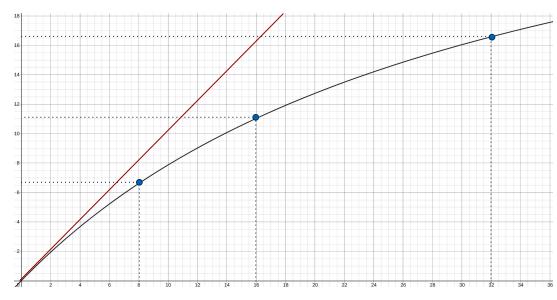


Figure: Amdahl's law with p=0.97.

OpenMP - Parallelized implementation and approach



Initial approach

- Used **OMP task** to parallelize program
- Resulted in no speed up at all
- Taking a closer look we recognized not the correct approach
- OMP Tasks are (loosely speaking) a way to dynamically distribute workload
- Use case would be recursion with no interdependence between tree branches
- GE has low data dependence in forward algorithm, however,
- Dynamically distributing matrix rows very inefficient

Current approach

- For every pivot row from step i=1, we have to modify the following n-i rows
- All following n-i rows are only dependent on i-th row's pivot element
- Statically spread the workload across all workers minimizing overhead

OpenMP - Parallelized implementation and approach



We found that

- 1. Out of the explicit scheduling schemes (static, dynamic, guided) static is the fastest
- 2. Runtime system using schedule(auto) picks static too →static seems like a good strategy

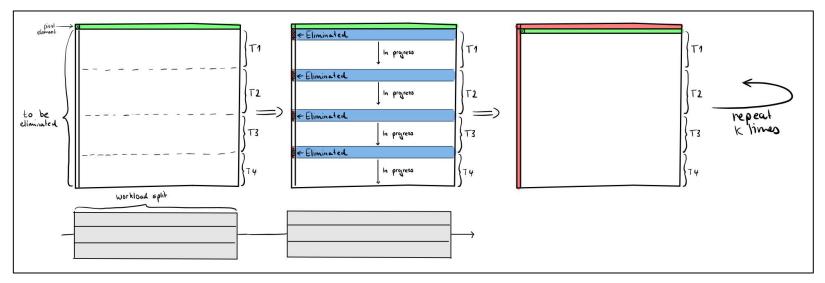


Figure: Schematic workload spread for k × k in forward algorithm with n=4 and static scheduling.

OpenMP - Overhead and when to parallelize



Q: At what problem size does parallelization make sense?

- Ran every problem size 10 times and averaged over computation vs. overhead
- For small problems overhead takes almost 100% of computing time ⇒ parallelization makes no sense
- For the sample problems given, starting from size 512 overhead starts to decrease (but still, 91% overhead)
- Size 2024 fist point very computation time > overhead

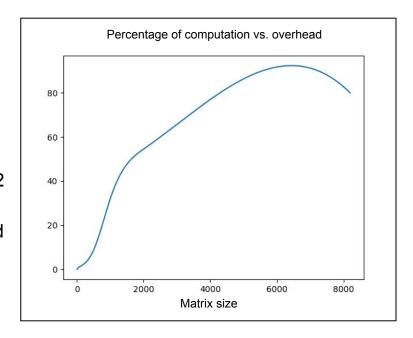


Figure: Spline (with k=3) displaying ratio computation vs. overhead.

OpenMP - Perf and possible bottlenecks



- No change between actual work across the programs
- Makes sense as the program **semantics** do not change at all - only the way work is being executed
- 65% of program are arithmetics
- Straightforward element-wise operations
- Theoretically suitable SIMD use case
- Compiler is already taking care of it
- **30% of program are reading**, writing and moving of elements

 Use matrix instead of element-wise operations delements
- Again, compiler is already taking care of it

```
/home/marcelbraasch/CLionProjects/openmp/serialge [Percent: local period]
```

```
Samples: 13K of event 'cycles', 4000 Hz, Event count (approx.): 11385415991
OMP::ForwardElimination /home/marcelbraasch/CLionProjects/openmp/ompge [Percent: local period]
```

```
'cycles', 4000 Hz, Event count (approx.): 25442538013
                        /home/marcelbraasch/CLionProjects/openmp/ompge [Percent: local period]
0,05
              bauvomv
                           (%rax, %r13, 1), %xmm6
```

Figure: Perf output for the respective OMP vs. serial programmes

MPI - Parallelized Implementation and Approach

loop



- Initial parallelization approach
 - Calculate distribution based on current status
 - Send rows from root to other ranks
 - Get calculated rows back
- Motivation of implementation
 - Easy to implement / intuitive solution
 - Organization only done in rank 0
- Bottleneck due to high amount of communication

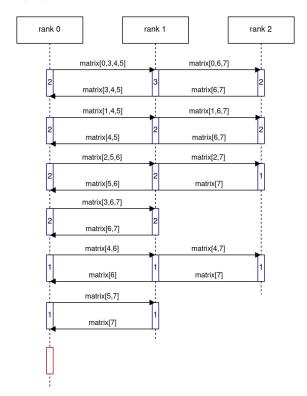


Figure: Schematic sketch of our first approach.

MPI - Parallelized Implementation and Approach



- Bottleneck is removed by:
 - Distribute in the beginning
 - Only share current master row
- Improvements
 - Less communication overhead
 - Worse distribution of calculation load
 - More complex implementation

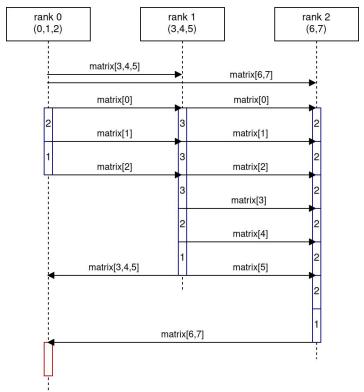
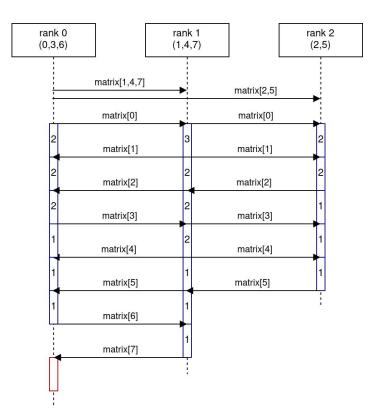


Figure: Schematic sketch of the improved approach.

MPI - Final Implementation improvements and new speed-up



- When starting with hybrid, we developed an even better approach
 - Distribute in the beginning in round robin sequence
 - Matrix is worked off evenly by all processes



MPI - Speed up comparison



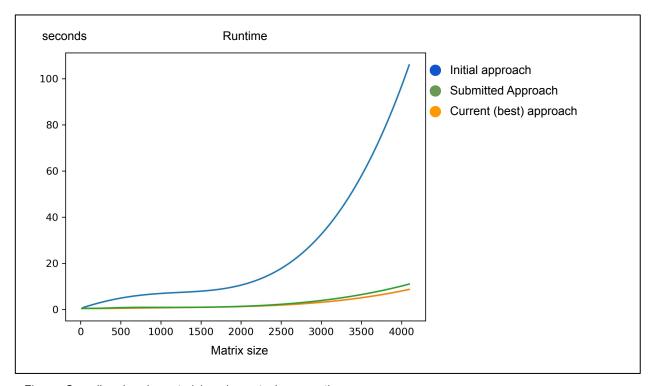


Figure: Compiler already vectorizing element-wise operations.

MPI - Communication vs. Calculation



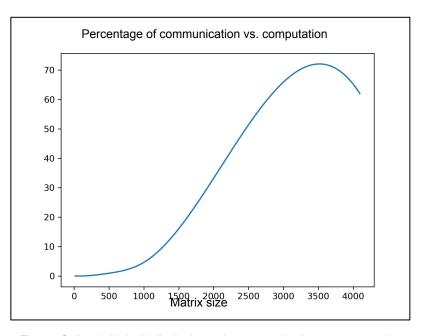
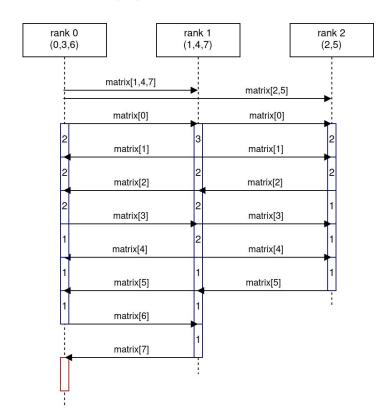


Figure: Spline (with k=3) displaying ratio communication vs. computation using the same procedure as in the OMP part.

Hybrid - Parallelized implementation and approach



- Built on our current best approach
- Addition of OMP similar to OMP part



Hybrid - Final Performance Results



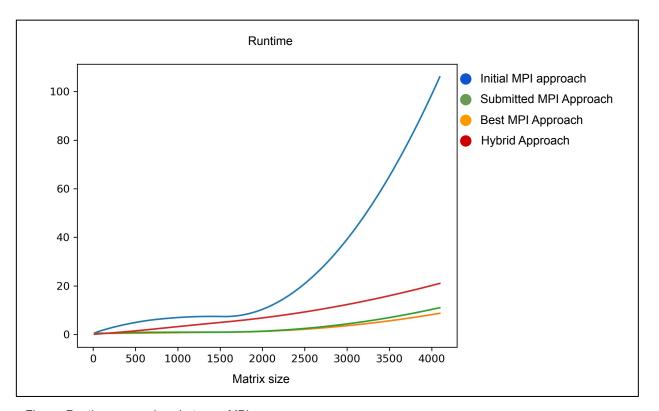


Figure: Runtime comparison between MPI

Hybrid - Communication vs. Calculation



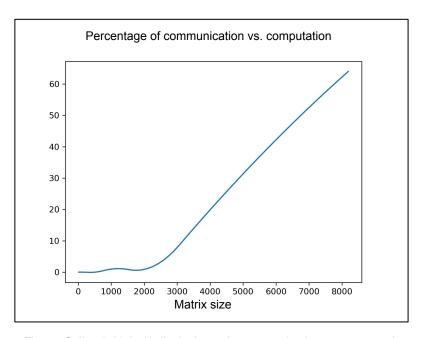


Figure: Spline (with k=3) displaying ratio communication vs. computation using the same procedure as in the OMP part.

Bonus - Parallelized implementation and approach



- Parallelized the inner loop using SIMD intrinsics
- Using double, we can calculate 4 values at once
- Achieved no speed-up
- Using -O3 flag compiler already figures out what to vectorize

Figure: Compiler already vectorizing element-wise operations.

- Using 32 threads, vectorizing rows by a factor of 4
- Theoretically, should yield a work split of 4 × 32 = 128
- By Amdahl's law, theoretical max speed up is then
 - 0 1 / (1 0.97 + 0.97/(4 × 32)) = 26.61

Conclusion



- OMP outperforms all other up to 2048
- MPI is faster for matrices with n ≥ 4092
- Hybrid did not work very well compared to MPI
- The best we got was a speed up of 14
- Amdahl's law indicates a theoretical max of 17
- The compiler is already vectorizing matrix operations

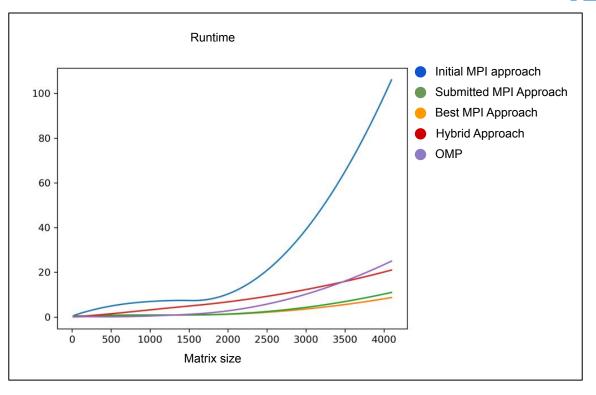


Figure: Runtime comparison between MPI

Additional



System specifications we performed the tests on:

• OS: Ubuntu 20.04.2 LTS

RAM: 32 GB

• CPU: AMD Ryzen 9 5950X

GPU: Nvidia GeForce RTX 3090