Parallelization of C programs through dependency analysis

Jos van Eijndhoven jos@vectorfabrics.com

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Discovering potential concurrency



Slow application and Silicon goes unused

Fast application Silicon put to work



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Presentation index

- Multi-processors will further expand
- Partitioning workload across multiple cores:
 - Data partitioning
 - Functional partitioning
- Tooling for dependency analysis
- Example: LAMMPS
- Conclusion



Programming parallel computers



nVidia TEGRA 3



Intel Aubrey Isle (MIC)

- Multi-processor machines are all around us, ranging from mobile to super-computers.
- Multi-processor architectures are driven by technology factors: increased integration densities and power efficiency requirements.
- Parallel (multi-threaded) programs are required to exploit their capability.
- However, parallel programming is difficult and error-prone. Unfortunately, software productivity already is a major bottleneck.
- Distributed-memory architectures and heterogeneous processors (GP-GPUs) add further complications.

Application programmers need more help!



Creating multi-threaded concurrency

Basic fork-join pattern, created through different higher-level programming constructs





Parallelization – two partitioning options

Source code:

```
for (i=0; i<4; i++) {
    A(i);
    B(i);
    C(i);
}</pre>
```

Sequential execution order:



Data partitioning:



Functional partitioning:





Functional versus data partitioning

Data partitioning:

- Allows a high degree of parallelization for loops with high iteration count.
- Allows good distribution of workload across (homogeneous) processors.
- Loop-carried data dependencies can severely impact performance.

Functional partitioning:

- Best for separation of workload across heterogeneous processors.
- Inter-function data dependencies typically converted into buffered streams.

Choice is directed by data dependency patterns.



Example functional partitioning

```
int A[N][M];
while (..)
{ produce_img();
   consume_img();
}
produce_img()
{ for (i ...)
   for (j ...)
        A[i][j] = ...
}
```

```
consume_img()
{ for (i ...)
    for (j ...)
    ... = A[i][j];
}
```

```
Thread1: while (..)
    produce_img();
```

```
Thread2: while (...)
    consume_img();
```

Synchronize thread progress:

- True dependency: consumer must wait for valid data
- Anti dependency: producer must wait with over-writing until after consumption



Function pipelining: synchronization

int A[N][M];



Channel ch;

Pipeline dependency analysis



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Function pipelining: Channel APIs

Too many choices for channel-based communication:

- Standard Java util.concurrent queue classes
- Intel's TBB (C++) queues
- Linux 'pipes' and 'sockets'
- OpenCL channels
- OpenMAX IL for streaming media processing
- MPI message-passing channels

...

Very different queue implementations:

- Inter-thread, inside process memory context
- Inter-process, inside shared-memory system
- Inter-system, through device interfaces

NOTE: C++ STL queues are **NOT** thread-safe!

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Example data partitioning

```
int sum = 0;
for (i=0; i<N; i++) {
    int value = some_work(i);
    sum += value;
}
```

- Distribute the workload over multiple cores.
- Each core handles part of the loop index space.

```
int sum = 0;
#pragma omp parallel for reduction (+:sum)
for (i=0; i<N; i++) {
    int value = some_work(i);
    sum += value;
}
```

- Workload scales nicely across multiple cores
- Easy to write down ③, but hard to grasp all consequences!
- Highly dangerous, might cause extremely hard-to-track bugs! 8

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Application Analysis



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Finding data dependencies

Vector Fabrics' approach:

- Compile program source code, compiler is adapted for instrumentation.
- Execute the instrumented program:
 - Traps all memory load/store operations: match ld/st operations that address the same memory location
 - Relates Id/st operations with nested loop structure: separate loop-carried dependencies from loop in-bound and loop out-bound dependencies
 - Builds an execution profile (call tree), across file boundaries
- Analyze loops with their data dependencies for parallelization patterns



Recognize parallelization patterns

Analyze loops with data dependencies for parallelization patterns:

- Reduction expressions
- Induction expressions
- Streaming dependencies, allowing data duplication and localization

Avoid considering 'false' memory dependencies:

- Local variables on stack, duplicated through thread local storage
- Re-use of memory locations through malloc() and free().

Relate data dependencies and patterns to locations in C(++) source code for required code transformations.



Example: LAMMPS molecular simulator

Source code configured for sequential version.
About 187Klines of C++ source code in 636 files.

Coverage	Delay
	100.00
100	100.00
80	100.00
78	100.00
99	100.00
32	99.78
79	0.50
86	99.26
84	99.26
100	8.72
67	2.78
40	1.56
100	78.95
100	78.91
100	77.07
100	0.99
100	6.15
	Coverage 0 100 80 78 99 32 79 32 79 85 84 100 67 40 100 100 100 100 100

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Example: LAMMPS data dependencies

- Parallelization opportunity detected in loop over particles, inside loop over time steps
- Different dependency patterns shown in different colors

1/ Modify::initial / 1/ PairL/Cut:compute	
🖻 Loop_10535	
□ Loop_10536	
Modify::initial N N L Loop_10536	Modify::fi
🗹 💳 Compute dependency 📝 🗮 Memory dependency 🗹 💳 Streaming pattern 🔲 💳 Anti-dependency	Ø
Loop_10535 total loop carried transfer rate: 462 Mi transfers/s 2 streams (32.9 Ki transfers/s); 3 data dependency clusters (70.5 Mi transfers/s); 2 compute dependencies (392 Mi transfers/s); 3 anti- and output dependency clusters	

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Parallel performance prediction

Estimate overhead from thread fork/join and synchronization
Estimate execution schedule with loop-carried dependencies
Speedup of this loop: 3.9x, overall speedup: 2.4x





- Today's gap: multi-processor machines are everywhere, yet multithreaded programming is difficult and error-prone.
- Proper tooling is required to avoid (data race-) errors and obtain insight in performance issues. Obtain such insight before spending time on re-coding for parallelization.
- Various tools are available today. They do support real-world application analysis.



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Thank you

Check www.vectorfabrics.com for a free trial of concurrency analysis

