

OpenMP device constructs 2

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Contents

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- How kernels execute on a GPU
- Optimisation
 - Data locality
 - Accelerated libraries
 - Kernel performance
 - vectorisation
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 - collapsing loops

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The wheel has been invented already



- There is a large ecosystem of tuned GPU libraries
 - Cray libsci_acc
 - man into_libsci_acc (after module load craype-accel-nvidia60)
 - BLAS 1,2,3
 - LAPACK
 - ScaLAPACK
 - PBLAS
 - Third party: cuBLAS, MAGMA, cuFFT, etc.

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Library Interoperability in OpenMP (v4.5)

```
PROGRAM main
  <stuff>
!$omp target data map(from:a) map(to:b)
  <stuff>
!$omp target data use device ptr(a,b)
 CALL library(a,b)
!$omp end target data
 <stuff>
!$omp end target data
  <stuff>
END PROGRAM main
```

- use_device_ptr exposes accel. memory address
 - Must synchronise before and after
 - CUDA kernel written as usual

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Library Interoperability in OpenACC

```
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```

```
PROGRAM main
  <stuff>
!$acc data pcopyout(a) pcopyin(b)
 <stuff>
!$acc wait
!$acc host data use device(a,b)
 CALL library(a,b)
!$acc end host data
!$acc wait
 <stuff>
!$acc end data
  <stuff>
END PROGRAM main
```

- use_device exposes accel. memory address
 - Must synchronise before and after
 - CUDA kernel written as usual

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Kernel scheduling



- Once data movements have been optimised
 - the next step is to improve the kernel scheduling
 - i.e. how the kernels actually execute on the accelerator
- For this, need to understand how the hardware works
 - we'll concentrate on Nvidia GPUs for this
- A kernel executes as a large number of parallel threads
 - the iterations of the loopnest are divided between these threads
 - This is called "partitioning" of the loops
 - need to understand how these threads are executed on the GPU

How a CUDA kernel is executed on a GPU



The threads are logically divided into sets

- called a grid of threadblocks in CUDA
 - user must specify the size of these sets (number of threads per threadblock)
- each threadblock executes independently on a different piece of hardware
 - Symmetric Multiprocessor (SM), which is (almost) like a single vector processor

Within a threadblock

- The threads are logically divided into sets of 32 threads called warps
 - threads within a warp execute in lockstep (i.e. as SIMD vector instructions)
- so the threadblock executes as a sequence of warps

The CUDA programming model does not make warps explicit

- the user only specifies the number of threads per threadblock
- but they are crucial to understand kernel performance

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OpenMP accelerator threads



OpenMP target region threads follow a similar model

- teams directive generates a league of threadteams
- a threadteam maps exactly onto a CUDA threadblock
 - each threadteam executes on a single SM
 - the league of threadteams is distributed across the SMs
- the threadteam will execute as a set of SIMD instructions
 - each SIMD instruction maps exactly onto a CUDA warp
 - multiple SIMD instructions are needed to execute threadblock
 - warps are not made explicit in OpenMP

OpenACC accelerator threads



OpenACC threads follow one of two models, either:

- parallel directive generates a set of gangs of vectors
- a gang maps exactly onto a CUDA threadblock
- a vector maps exactly onto the CUDA threads within a threadblock

Or, you can expose three levels of parallelism

- parallel directive generates a set of gangs of workers of vectors
- a gang maps exactly onto a CUDA threadblock
- a worker maps exactly onto a CUDA warp
- a vector is a set of exactly 32 threads making up a warp

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Loop partitioning (scheduling)



When a loopnest is partitioned by the compiler

- The loop iterations are divided across a set of threads
- The threads are then logically grouped to match the hardware requirements
- There are many different ways for the compiler to do this
 - How many and which loop(s) in loopnest should be partitioned?
 - How many threads (and how divided into threadblocks and threads per threadblock)?
 - How should the iterations be divided?

If user gives no further instruction, the compiler makes a decision

- You can see what this was from the compiler feedback
- You can then over-ride this decision (at the next compilation)
 - by using further clauses and directives

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Loop partitioning with OpenMP

- teams directive generates league of threadteams
- distribute directive partitions the loop iterations
 - Can use composite directive target teams distribute
- Completing the partitioning
 - The OpenMP standard is vague on how distribute should work
 - could only partition at the threadblock level
 - then need nested parallel, do/for, simd directives to complete the partitioning
 - could partition over all levels of parallelism (CCE behaviour)
 - parallel directive allowed, but only with one thread
 - simd directive can optionally be used to tune the scheduling

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Loop partitioning with OpenACC



- parallel directive generates gangs of workers/vectors
- loop directive partitions the loop iterations
 - Can use composite directive parallel loop
- These allow full partitioning of up to three nested loops
- Can optionally use gang, worker, vector clauses
 - Added to top-level loop directive or on additional ones
 - Allows developer to tune the loop scheduling



Why warps matter (1): vectorisation



SMs execute warps as a stream of vector instructions

- The vectors are 32 slots wide
- Every slot does the same operation at the same time, but with different data
- If all 32 threads in a warp want to do the same thing at the same time, then can execute this as a single vector instruction
- If not, will need multiple (sequential) vector instructions (masking out results from some slots each time)

Kernels should be written to take advantage of this

- Wherever possible, arrange that groups of 32 consecutivelynumbered threads are doing the same thing at the same time
- This is called "vectorising" the code

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Kernel vectorisation



- The first optimisation:
 - using data regions to minimise data movement
- The second optimisation:
 - make sure all the kernels vectorise
 - meaning the compiler is efficiently using vector instructions on GPU
- How can I tell if there is a problem?
 - see if a kernel is "surprisingly slow" on accelerator
 - profile the code executing on the CPU; note the relative ordering (by time) of routines
 - profile the code executing on the accelerator; compare the ordering to that from the CPU
 - look for any anomalously-slow kernels
 - examine the compiler commentary

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Vectorisation and loopmark



- Always generate the compiler commentary
 - CCE: compile with flag -hlist=a to generate *.lst loopmark file
- Should see loop iterations divided both:
 - over threadblocks and over threads within a threadblock
- A single loop:
 - should be partitioned across both levels of parallelism
 - look for this in the CCE loopmark: Gg
- A loopnest:
 - Two (maybe three) loops should be separately partitioned
 - look for G and 2 (or maybe 3) g-s (possibly some numbers in between)

An example of CCE loopmark (OpenMP)



A loop starting at line 172 was partitioned across the thread blocks.

```
171. 1 G----> !$omp target teams distribute

172. 1 g-----> DO k = 2,kmax-1

173. 1 g 3----> DO j = 2,jmax-1

174. 1 g 3 g--> DO i = 2,imax-1

175. 1 g 3 g solution solution
```

Numbers denote serial loops

A loop starting at line 174 was partitioned across the 128 threads within a threadblock.

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An example of CCE loopmark (OpenACC)



A loop starting at line 172 was partitioned across the thread blocks.

```
171. 1 G-----> !$acc parallel loop ...

172. 1 g------> DO k = 2,kmax-1

173. 1 g 3----> DO j = 2,jmax-1

174. 1 g 3 g--> DO i = 2,imax-1

175. 1 g 3 g solution solu
```

Numbers denote serial loops

A loop starting at line 174 was partitioned across the 128 threads within a threadblock.

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Why warps matter (2): coalescing



Data is loaded from (and stored to) memory in chunks

- 32 contiguous addresses in memory
- A warp is 32 threads executing the same instruction on different data
- If a warp processes a contiguous block of 32 elements from memory,
 - then can service this with a single vector memory operation
- If not, need multiple operations (with some data "wasted", i.e. unprocessed)

Kernels should be written to take advantage of this

- Wherever possible, arrange that warps process contiguous blocks of memory.
- Vectorised should index the fastest-moving dimension of the data arrays
 - left-most in Fortran, right-most in C
- This ensures the minimum number of (expensive) memory operations
- This is called "coalescing" the memory accesses

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Helping vectorisation (1)



Every kernel should have a vectorised loop

- "partitioned across threads within a threadblock"
- generally want to vectorise the innermost loop
- usually labels fastest-moving array index
 - to enable coalescing

• If not vectorised, can we make it vectorise?

- Can loop iterations be computed in any order?
- No? Then can we rewrite code?
 - avoid loop-carried dependencies
 - e.g. buffer packing: calculate rather than increment
 - these rewrites will probably perform better on CPU

```
Replace:
  D0 y = 2, N-1
     i = i+1
     buffer(i)=a(2,y)
  ENDDO
  buffsize = i
By:
  DO y = 2, N-1
     buffer(y-1)=a(2,y)
  ENDDO
  buffsize = N-2
```

Helping vectorisation (OpenMP)



- Can loop iterations be computed in any order?
- Yes? Then we should guide the compiler
 - put simd directive above this loop
 - check the code is still correct (as well as running faster)
 - the compiler might not be vectorising the loop for a good reason

Advice:

Remember to repeat any reduction clauses on simd directives

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Helping vectorisation (OpenACC)



- Can loop iterations be computed in any order?
- Yes? Then we should guide the compiler
 - put "acc loop vector" directive above this loop
 - check the code is still correct (as well as running faster)
 - the compiler might not be vectorising the loop for a good reason

Advice:

Remember to repeat any reduction clauses on new loop directives

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Changing the vectorisation (OpenMP)



- If the inner loop is vectorising but performance is still bad
- Is the inner loop really the one to vectorise in this case?
 - in this kernel, perhaps we know mmax is small
 - or perhaps CrayPAT loop-level profiling told us this
 - so we should vectorise the i-loop

Put simd directive above i-loop

- m-loop now not partitioned
- executed "redundantly" by every thread
- this may also help performance
 - t is now an i-loop private scalar
 - rather than a reduction variable

```
DO i = 1,N

t = 0

DO m = 1,mmax

t = t + c(m,i)

ENDDO

a(i) = t

ENDDO
```

Changing the vectorisation (OpenACC)



- If the inner loop is vectorising but performance is still bad
- Is the inner loop really the one to vectorise in this case?
 - in this kernel, perhaps we know mmax is small
 - or perhaps CrayPAT loop-level profiling told us this
 - so we should vectorise the i-loop

Put vector clause above i-loop

- m-loop now not partitioned
- executed "redundantly" by every thread
- this may also help performance
 - t is now an i-loop private scalar
 - rather than a reduction variable

```
DO i = 1,N

t = 0

DO m = 1,mmax

t = t + c(m,i)

ENDDO

a(i) = t

ENDDO
```

An aside on this example



- because mmax was too small
 - small loops will not give the GPU enough work

Performance is still likely to be bad

- Memory accesses to c are no longer coalesced
- The vectorised loop does not index the fastest-moving array dimension
 - 32 threads execute together as a warp (vector), each with different i-values
 - each warp needs 32 elements of data, e.g. c(m,1:32)
 - this is not a contiguous chunk of memory, so need multiple vector loads per warp
- loads/stores from global memory are slow, so performance will suffer
 - this is a hardware feature, not a limitation of the programming model

```
DO i = 1,N

t = 0

DO m = 1,mmax

t = t + c(m,i)

ENDDO

a(i) = t

ENDDO
```

Improving coalescing

Consider re-ordering arrays

- Keep vectorising i-loop
 - as mmax small
- Make i fastest index of new array ct
- ct(1:32,m) is a contiguous chunk
- Now get coalesced loads

Requires refactoring code

- may be much work (but maybe not)
- may also get better CPU performance
 - e.g. with AVX instructions

```
DO i = 1,N

t = 0

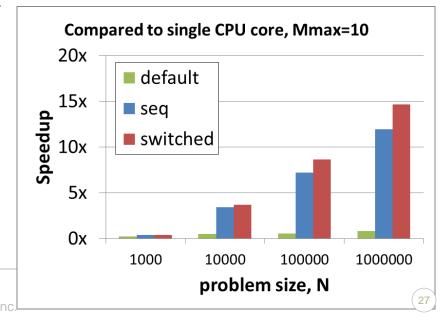
DO m = 1,mmax

t = t + ct(i,m)

ENDDO

a(i) = t

ENDDO
```



It's all vectorising, but still performing badly



- Profile the code and start where it takes most time
 - check the slowest thing really is compute kernels
 - if it really is GPU compute kernels...
- GPUs need lots of parallel tasks to work well
 - check that there really are enough loop iterations (beware of test cases)
- Then look at loop scheduling using clauses
- Then might need to consider more extreme measures
 - source code changes
 - handcoding CUDA kernels

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Tuning the OpenMP partitioning

- Before we alter the schedule, there are two easy tuning choices
 - number of threads per threadblock; total number of threadblocks
- Do this on a per-kernel basis using clauses on team directive
 - This is optional, unlike in CUDA
- thread_limit(<value>)
 - changes the number of threads per threadblock
 - CCE-specific details:
 - value needs to be fixed at compile time
 - allowed values are: 1, 32, 64, 128, 256, 512, 1024 (default value is 128)
- num_teams(<value>)
 - changes the number of threadblocks
 - the compiler will make a default choice of sufficient blocks

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Tuning the OpenACC partitioning

- Before we alter the schedule, there are two easy tuning choices
 - number of threads per threadblock; total number of threadblocks
- Do this on a per-kernel basis using clauses on parallel directive
 - This is optional, unlike in CUDA
- vector_length(<value>)
 - changes the number of threads per threadblock
 - CCE-specific details:
 - value needs to be fixed at compile time
 - allowed values are: 1, 32, 64, 128, 256, 512, 1024 (default value is 128)
- num_gangs(<value>)
 - changes the number of threadblocks
 - the compiler will make a default choice of sufficient blocks

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Advanced loop scheduling



- Loop schedules (usually) are limited by the loop bounds
 - one loop's iterations are divided over threadblocks
 - another loop's iterations are divided over threads in threadblock
- This has limitations, for instance
 - "tall, skinny" loopnests (j=1:big; i=1:small) won't schedule well
 - inner loop is too small
 - if less than 32 iterations won't even fill a warp, so wasted SIMT
 - "short, fat" loopnests (j=1:small; i=1:big) also not good
 - outer loop is too small
 - want lots of threadblocks to swap amongst SMs

```
DO j = 1,Nj
DO i = 1,Ni
:
ENDDO
ENDDO
```

- In both cases there are enough total iterations to keep the GPU busy
 - but division of iterations between the two loops is non-optimal for the GPU

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collapse clause

- A way of increasing loop scheduling flexibility
- Merges iterations of two or more loops together
 - Then applies scheduling to composite loop (automatic or explicit scheduling)
- Both "tall, skinny", "short, fat" examples will benefit from collapse(2)
 - collapse the j and i loops into a single iteration space, effectively: DO ij=1, small*big
 - then divide the total iterations over all levels of parallelism on the GPU
- Things to look for
 - the compiler may use this automatically (look for C in CCE loopmark feedback)
 - no guarantee that it is faster [index rediscovery uses expensive integer divisions]
 - e.g. j = INT(ij/big); i = ij j*big
 - you can only collapse perfectly nested loops
- Advice: generally best to fully collapse loopnest

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Tuning performance with the loop schedule



Tuning the loop schedule is main performance tuning

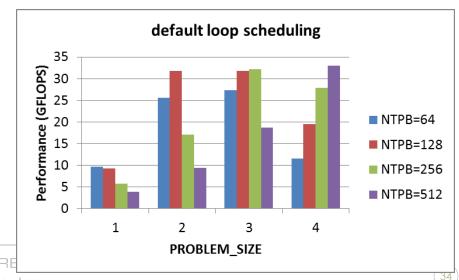
- first make sure you've minimised data transfers
- then make sure the default schedule is sensible
 - loop(s) partitioned both ACROSS and WITHIN threadblocks
- then think about using tuning clauses to improve performance

The next few slides give a tuning Case Study

- The scalar Himeno code that we discussed earlier
- Applying tuning clauses to the jacobi stencil kernel

Scalar Himeno performance

- PROBLEM_SIZE=1,2,3,4
 - For a parallel problem, this simulates strong scaling choices
 - Here we look at all 4 options (all double precision)
- threads per threadblock choices: NTPB=64,128,256,512
 - Easy tuning choice, but needs a recompile with CCE
 - easiest to compile with -DNTPB=<value>
 - CCE defaults to 128
- This has a BIG effect
 - best NTPB relative to default:
 - PROBLEM_SIZE=1: + 4%
 - PROBLEM_SIZE=2: no change
 - PROBLEM_SIZE=3: + 1%
 - PROBLEM_SIZE=4: +69%

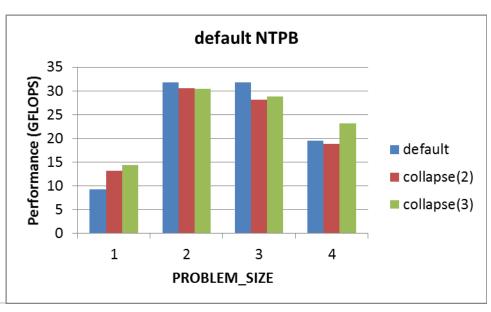


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Scalar Himeno performance

- PROBLEM_SIZE=1,2,3,4
- 3 scheduling choices for jacobi stencil kernel
 - default scheduling
 - collapse(2) inner i,j-loops
 - collapse(3) all loops
- NTPB is default
- Effect also quite big
 - PROBLEM_SIZE=1: +55%
 - PROBLEM_SIZE=2: no change
 - PROBLEM_SIZE=3: no change
 - PROBLEM_SIZE=4: +19%



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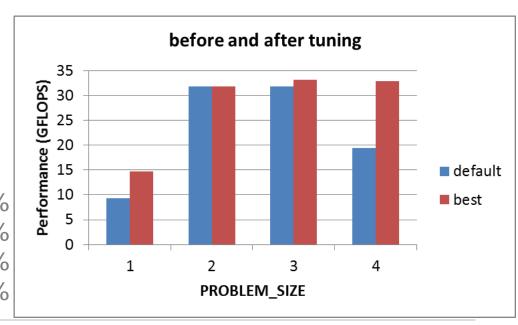
Scalar Himeno performance

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- PROBLEM_SIZE=1,2,3,4
- 3 scheduling choices for jacobi stencil kernel
 - default scheduling
 - collapse(2) inner i,j-loops
 - collapse(3) all loops
- optimal NTPB

Final improvements

- PROBLEM_SIZE=1: +60%
- PROBLEM_SIZE=2: + 1%
- PROBLEM_SIZE=3: + 4%
- PROBLEM_SIZE=4: +69%



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Scalar Himeno tuning conclusions



Tuning can have a big effect, relative to default

- It is worth doing, but only after you optimise the data locality
 - data region gave 44x speedup; kernel tuning gave less than 2x
- We gained something at almost every problem size
- Only explored NTPB and basic scheduling (collapse)
 - only change was directive clauses; CPU version same

General conclusions for scalar Himeno:

- Larger NTPB suited larger problem sizes
 - 64 best for PS1; 128 best for PS2; 256 best for PS3; 512 best for PS4
- collapse(3) was best for small problems (PS1,4)

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Aside: Will my code accelerate well?



- Computation should be based around loopnests processing arrays
- Loops should have defined tripcounts
 - either at compile- or run-time
 - while loops will not be easy to port
 - they are hard to execute on a GPU
- Data structures should ideally be simple arrays
 - derived types, pointer arrays, linked lists etc. may stretch compiler capabilities
- Loopnests should have a large total number of iterations
 - at least measured in the thousands
 - even more is better
 - less will execute, but inefficiently

- The loops should span as much code as possible
 - maybe with some loops very high up the callchain
- Loopnest kernels should not be too branched
 - one or two nested IF-statements is fine
 - too many will lead to slow execution on many accelerators
- The code can be task-based
 - but each task should contain a suitable loopnest

Conclusions



Optimisation path:

- minimise data movements
- use libraries if possible
- ensure vectorisation of correct loop
- consider data reordering
- look at collapsing perfectly nested loops

Only then consider the more advanced optimisations

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e.g. hand-coded CUDA

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Tuning code performance



- Remember the Golden Rules of performance tuning:
 - always profile the code yourself
 - always verify claims like "this is always the slow routine" as codes and computers change
 - optimise the real problem running on the production system
 - a small testcase running on a laptop will have a very different profile
 - optimise the right parts of the code
 - the bits that take the most time, even if these are not the exciting bits of the code
 - e.g. it might not be GPU compute; it might be comms (MPI), I/O...
 - keep on profiling
 - the balance of CPU/GPU/comms/IO will change as you go
 - refocus your efforts appropriately
 - Keep on checking for correctness
 - Know when to stop (and when to start again)

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