Distributed and Parallel Computing

Lecture 06

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- Round-off errors

Coalesced Global Memory Access

Global memory accesses occur in *memory transactions* or *bursts* of size 32, 64 or 128 bytes.

- Each memory transaction takes nearly the same amount of time
- Thus reading or writing 8, 16 or 32 words, assuming those reads or writes are appropriately aligned, take approximately the same amount of time as reading a single word.
- So long as the consecutive threads in a warp read consecutive words, only 1 memory transaction is required.
- If consecutive threads read non-consecutive words, then each read requires a separate memory transaction $\Rightarrow$ strided access is much worse than consecutive access
- Array of Structs (AoS) vs Struct of Arrays (SoA)
- Specially important for 2- or 3- dimensional arrays

```
struct {int a; int b} X[LEN] ;        // X[0].a = X[0].b
struct {int a[LEN]; int b[LEN]} X ; // X.a[0] = X.b[0]
```

Shared Memory Banks

Shared memory accesses are approximately 2 orders of magnitude faster than global memory accesses

- Shared Memory in GPUs of compute capability 2.0 or better is divided into 32 equally sized banks
- Shared memory is organised so that 32 consecutive memory word accesses are spread over all 32 banks, one word from each
- On devices of compute capability 3.0 or higher, the banks can be configured to be organised by double, instead of single word.
- Simultaneous access (by different threads in the same warp) to different banks can be serviced simultaneously (4 cycles for a read or write)
- Simultaneous access to the same bank must be serialised
- **Exception:** simultaneous read of the same *address* by all threads in the warp can be serviced simultaneously (broadcast)
- **Exception:** simultaneous read of the same address by some number of threads in the warp can be serviced simultaneously (compute capability 2.0+ multicast)

Atomic operations

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A[index] += 1 ;
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If multiple threads might be trying to do such an operation on the same memory location, then we have to avoid read/write races. There are a number of options:

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- `http://docs.nvidia.com/cuda/cuda-c-programming-guide/#atomic-functions`