

OpenCL Vectorising Features

Andreas Beckmann

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Levels of Vectorisation

- vector units, SIMD devices
 - width, instructions
 - SMX, SP cores
 - Cus, PEs
- vector operations within kernels



Intel Legacy Vector Features

MMX (1997) Pentium MMX

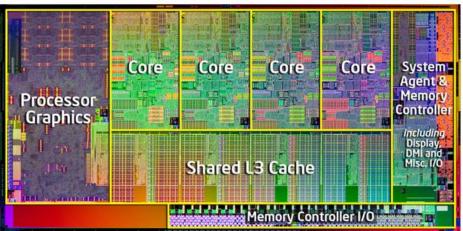
+ 64-bit registers: 2x32/4x16/8x8 integer operations only

Streaming SIMD Extensions (SSE) introduced in 1999 with Pentium III

- + Maximum vector size = 128 bits
- + Maximum number of registers = 2 (e.g. A = A + B)
- + Support for only one data type: 4 32-bit FP numbers

SSE2 - SSE4

- + More data types and instructions
- + Still only 128-bit, two register

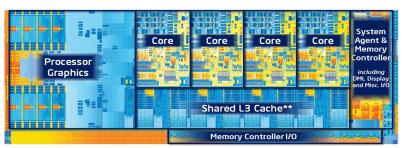




Intel Sandy Bridge / Ivy Bridge Vector Features

Sandy Bridge introduction

- + Doubled size to 256-bit vectors
- + New instruction encoding, also for 128-bit vector operations
- + Support for 3 registers per instruction
- + e.g. C = A + B
- + Allows non-destructive operations
- + legacy SSE supported with switching penalties
- + 1 Addition + 1 Multiplication per cycle



Improved in Ivy Bridge

- + Conversion between compressed 16-bit FP format and 32-bit single precision format
- + Latter is used for AVX, SSE
- + Enables higher precision calculations
- + Future support for up to 1024 FP vector support
- + More operations per instruction -> less power usage



Intel Haswell/Broadwell Vector Features

FMA – fused multiply-add
$$A = A * B + C \qquad B = A * B + C \qquad C = A * B + C \quad (Intel)$$

$$D = A * B + C \quad (AMD)$$

Two FMA instructions per cycle!

More instructions incl. Cross-lane shuffling

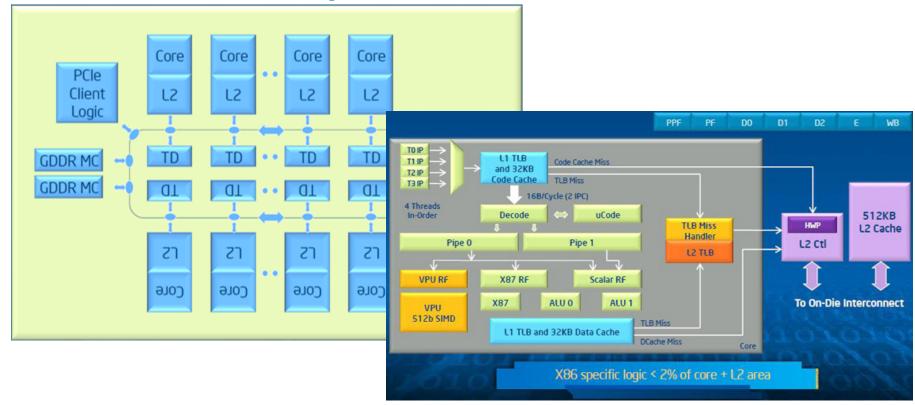
Additional special purpose feature sets (crypto etc.)

Intel Skylake Vector Features

Skylake-SP Xeon with AVX512 (a subset of the AVX512 in KNL)



Intel Xeon Phi Coprocessor



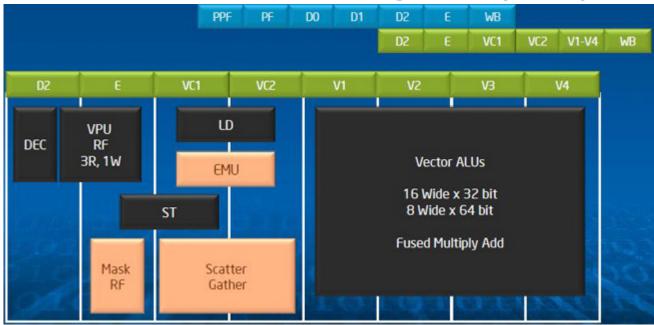
General purpose programming environment

- runs Linux (full service, open Source OS)
- runs applications written in Fortran, C, C++, OpenMP, OpenCL, ...
- runs x86 ISA + SIMD extension, supports x86 coherent memory model

x86 collateral (libraries, compilers, debuggers, ...)



Intel Xeon Phi Coprocessor Vector Processing Unit (VPU)



- 512-bit SIMD instruction set
- can execute 16 single-precision (SP) or 8 double-precision (DP) operations per cycle and supports Fused-Multiply-ADD (FMA)
- mask register allows per lane predicated execution
- supports gather / scatter instructions (non-unit stride vectorisation)
- Extended Math Unit can execute vector operations as square root, log, ...



GPU Computing

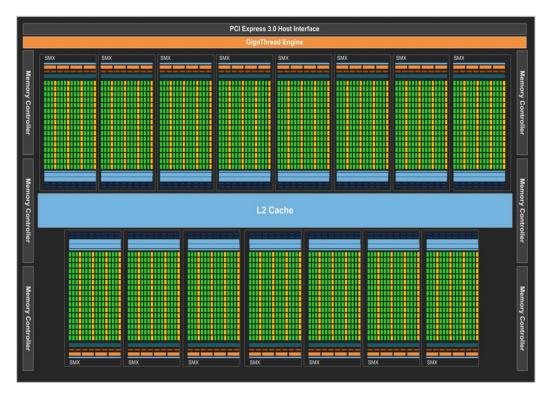


Fig.: Nvidia

Kepler GPU (GK110):

- Each green square = single FPU
- Each FPU (about 2700) available for a different thread
- Overall, GK110 can handle more than 30000 threads simultaneously...

...and even better, in our program we can send billions of threads to the GPU!



Vector Operations

- modern microprocessors include vector units:
 - functional units that carry out operations on blocks of numbers
- for example, x86 CPUs have over the years introduced MMX, SSE, AVX, AVX2, AVX512 instruction sets ...
 - characterized in part by their widths (e.g. SSE operates on 128 bits at a time, AVX 256 bits etc)
- to gain full performance from these processors it is important to exploit these vector units
- compilers can sometimes automatically exploit vector units.
 - experience over the years has shown, however, that you all too often have to code vector operations by hand.



Vector intrinsic challenges

example using 128 bit wise SSE:

- requires an assembly code style of programming:
 - Load into registers
 - Operate with register operands to produce values in another vector register
- Non portable: Change vector instruction set (even from the same vendor) and code must be re-written
- Consequences:
 - very few programmers are willing to code with intrinsics,
 Most programs only exploit vector instructions that the compiler can automatically generate
 - most programs grossly under exploit available performance.



Vector types

OpenCL provides a high-level portable vector instruction set

- a set of vector instructions in C kernel programming language
- portable between different vector instruction sets
- instructions support vector lengths of 2, 4, 8, and 16 ... for example:
 - char2, ushort4, int8, float16, double2, ...
- properties of these types include:
 - endian safe
 - aligned at vector length
 - vector operations (elementwise) and built-in functions



Vector operations

Vector literal int4 vi0 = (int4) -7; -7 -7 -7 -7

int4 vi1 = (int4) (0, 1, 2, 3) $\frac{1}{1}$ $\frac{1}{2}$ $\frac{1}{3}$

Vector components

vi0.lo = vi1.hi; 2 3 -7

2

3

int8 v8 = (int8) (vi0, vi1.s01, vi1.odd);

2 3 -7 -7 0 1 1 3

-7

Vector ops

vi0 += vi1;

vi0 = abs(vi0);

 0
 1
 2
 3

 2
 4
 -5
 -4

 2
 4
 5
 4

-7

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Using vector operations

You can convert a scalar loop into a vector loop using the following steps:

- based on the width of your vector instruction set and your problem, choose the number of values you can pack into a vector register (the width):
 - e.g. for a 128 bit wide SSE instruction set and float data (32 bit), you can pack four values (128 bits = 4*32 bits) into a vector register
- unroll the loop to match your width (in our example, 4)
- set up the loop preamble and postscript, e.g. if the number of loop iterations doesn't evenly divide the width, you'll need to cover the extra iterations in a loop postscript or pad your vectors in a preamble
- replace instructions in the body of the loop with their vector instruction counter parts



Vector instructions example

scalar loop:

```
for (i = 0; i < 34; i++) x[i] = y[i] * y[i];
```

- width for a 128-bit SSE is 128/32=4
- unroll the loop, then add postscript and premable as needed:

```
NLP = 34+2; x[34]=x[35]=y[34]=y[35]=0.0f // preamble to zero pad for (i = 0; i < NLP; i = i + 4) {
    x[i] = y[i] * y[i]; x[i+1] = y[i+1] * y[i*1];
    x[i+2] = y[i+2] * y[i*2]; x[i+3] = y[i+3] * y[i*3];
}
```

replace unrolled loop with associated vector instruction

```
float4 x4[DIM], y4[DIM];

// DIM set to hold 34 values extended to multiple of 4 (36)

float4 zero = {0.0f, 0.0f, 0.0f, 0.0f};

NLP = 34 % 4 + 1; // 9 values (as 34 isn't a multiple of 4)

x4[NLP-1] = 0.0f; y4[NLP-1] = 0.0f; // zero pad arrays

for (i = 0; i < NLP; i++)

x4[i] = y4[i] * y4[i]; // actual vector operations
```



Exercise OpenCL_Vectorising_Features/dot

- inspect the provided dot programs
 - dot_product.cc (host part)
 - DotProduct1.cl (device part)
- and execute it on one of the course test platforms
 - make
 - ./dotproduct cpu | gpu | acc [<kernel.cl>]
- complete the TODO section in the vectorised-kernel
 - DotProduct2.cl
- by using vector instructions (cf. slide 12 or reference card)

activate the new kernel in the host program and execute



Auto-vectorisation

- the OpenCL device compilers are good at auto-vectorising your code
- adjacent work-items may be packed to produce vectorized code
- by using vector operations the compiler may not optimize as successfully
- so <u>think twice</u> before you explicitly vectorize your OpenCL kernels, you might end up hurting performance!