Vector Processing
(aka, Single Instruction Multiple Data, or SIMD)

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Computer Graphics
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What is Vectorization/SIMD and Why do We Care?

Performance!

Many hardware architectures today, both CPU and GPU, allow you to perform arithmetic operations on multiple array elements simultaneously. (Thus the label, "Single Instruction Multiple Data").

We care about this because many problems, especially scientific and engineering, can be cast this way. Examples include convolution, Fourier transform, power spectrum, autocorrelation, etc.

- Signal
- Sine and Cosine values
- Fourier products

SIMD in Intel Chips

<table>
<thead>
<tr>
<th>Year Released</th>
<th>Name</th>
<th>Width (bits)</th>
<th>Width (FP words)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>MMX</td>
<td>64</td>
<td>2</td>
</tr>
<tr>
<td>1999</td>
<td>SSE</td>
<td>128</td>
<td>4</td>
</tr>
<tr>
<td>2011</td>
<td>AVX</td>
<td>256</td>
<td>8</td>
</tr>
<tr>
<td>2013</td>
<td>AVX-512</td>
<td>512</td>
<td>16</td>
</tr>
</tbody>
</table>

Xeon Phi
Note: one complete cache line!
Note: also a 4x4 transformation matrix!

If you care:
- MMX stands for "MultiMedia Extensions"
- SSE stands for "Streaming SIMD Extensions"
- AVX stands for "Advanced Vector Extensions"

Intel SSE

The SSE version of the multiplication instruction happens like this:

```
void SimdMul( float *a, float *b, float *c, int len )
{
    for( int i=0; i < len; i++ )
        c[i] = a[i] * b[i];
}
```

Note that the construct:
```
    a[ 0 : ArraySize ]
```

is meant to be read as:
"The set of elements in the array a starting at index 0 and going for ArraySize elements".

```
    a[ 0 : ]
```

"The set of elements in the array a starting at index 0 and going through index ArraySize".

SIMD Multiplication

```
void SimdMul( float *a, float *b, float *c, int len )
{
    #pragma omp simd
    for( int i=0; i < len; ++i )
        c[i] = a[i] * b[i];
}
```

```
Array * Array
```
### SIMD Multiplication

```c
void SimdMul(float *a, float b, float *c, int len)
{
    c[0:len] = a[0:len] * b;
}
```

### Array * Scalar

```c
void SimdMul(float *a, float b, float *c, int len)
{
    #pragma omp simd
    for (int i = 0; i < len; i++)
    c[i] = a[i] * b;
}
```

### Array * Array Multiplication Speed

![Graph showing the speedup of SIMD over Non-SIMD multiplication.]

**You would think it would always be 4.0 ± noise effects, but it’s not. Why?**

### SIMD in OpenMP 4.0

```c
#pragma omp simd
for (int i = 0; i < ArraySize; i++)
{
    c[i] = a[i] * b[i];
}
```

### Requirements for a For-Loop to be Vectorized

- If there are nested loops, the one to vectorize must be the inner one.
- There can be no jumps or branches. "Masked assignments" (an if-statement-controlled assignment) are OK, e.g.,
  ```c
  B[i] = 1.;
  return A[i] > 0.;
  ```
- The total number of iterations must be known at runtime when the loop starts.
- There can be no inter-loop data dependencies such as:
  ```c
  a[i] = b[i-1] + 1;
  ```
- It helps performance if the elements have contiguous memory addresses.

### Prefetching

Prefetching is used to place a cache line in memory before it is to be used, thus hiding the latency of fetching from off-chip memory.

There are two key issues here:

1. Issuing the prefetch at the right time
2. Issuing the prefetch at the right distance

**The right time:**

If the prefetch is issued too late, then the memory values won’t be back when the program wants to use them, and the processor has to wait anyway.

If the prefetch is issued too early, then there is a chance that the prefetched values could be evicted from cache by another need before they can be used.

**The right distance:**

The “prefetch distance” is how far ahead the prefetch memory is than the memory we are using right now.

Too far, and the values sit in cache for too long, and possibly get evicted.

Too near, and the program is ready for the values before they have arrived.
The Effects of Prefetching on SIMD Computations

Array Multiplication
Length of Arrays (NUM): 1,000,000
Length per SIMD call (ONETIME): 256

for(  int i = 0;  i < NUM;  i += ONETIME )
{
    __builtin_prefetch ( &A[i+PD],  WILL_READ_ONLY , LOCALITY_LOW );
    __builtin_prefetch ( &B[i+PD],  WILL_READ_ONLY , LOCALITY_LOW );
    __builtin_prefetch ( &C[i+PD],  WILL_READ_AND_WRITE,  LOCALITY_LOW );
    SimdMul( A, B,  C,  ONETIME );
}

Array Size (M)  Speed (MFLOPS)

This all sounds great!
What is the catch?

The catch is that compilers haven’t caught up to producing really efficient SIMD code. So, while there are great ways to express the desire for SIMD in code, you won’t get the full potential speedup ... yet.

One way to get a better speedup is to use assembly language.

Here are two assembly functions:
1. SimdMul: \( C[0:len] = A[0:len] \times B[0:len] \)
2. SimdMulSum: return \( \sum A[0:len] \times B[0:len] \)

Warning – due to the nature of how different compilers and systems handle local variables, these two functions only work on flip using gcc/g++, without –O3 !!!

Getting at the full SIMD power until compilers catch up

This only works on flip using gcc/g++, without –O3 !!!

Combining SIMD with Multicore

#define NUM_ELEMENTS_PER_CORE  ARRAYSIZE / NUMT
...
omp_set_num_threads( NUMT );
maxMegaMultsPerSecond = 0.;
for( int t = 0; t < NUM_TRIES; ++t )
{
    double time0 = omp_get_wtime( );
#pragma omp parallel
    {
        int first = omp_get_thread_num( ) * NUM_ELEMENTS_PER_CORE;
        SimdMul( &A[first], &B[first], &C[first], NUM_ELEMENTS_PER_CORE );
    }
    double time1 = omp_get_wtime( );
    double megaMultsPerSecond = (float)ARRAYSIZE / ( time1 - time0 ) / 1000000.;
    if( megaMultsPerSecond > maxMegaMultsPerSecond )
        maxMegaMultsPerSecond = megaMultsPerSecond;
}

This only works on flip using gcc/g++, without –O3 !!!
Combining SIMD with Multicore

Speedups for Multicore, SIMD, and Multicore+SSE

- Speedups are with respect to a function with no multicore or SIMD.
- "cores alone" = a for-loop with "#pragma omp parallel for".
- "cores + SIMD" = as the code looks on the previous page.

Avoiding Assembly Language: the Intel Intrinsics

Intel has a mechanism to get at the SSE SIMD without resorting to assembly language. These are called Intrinsics.

<table>
<thead>
<tr>
<th>Intrinsic</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>_mm_loadu_ps</td>
<td>Load a __m128 word from memory</td>
</tr>
<tr>
<td>_mm_storeu_ps</td>
<td>Store a __m128 word into memory</td>
</tr>
<tr>
<td>__m128</td>
<td>Declaration for a 128 bit 4-float word</td>
</tr>
<tr>
<td>_mm_mul_ps</td>
<td>Multiply two __m128 words</td>
</tr>
<tr>
<td>_mm_add_ps</td>
<td>Add two __m128 words</td>
</tr>
</tbody>
</table>

SimdMul using Intel Intrinsics

```c
#include <xmmintrin.h>
#define SSE_WIDTH               4

void
SimdMul( float *a, float *b, float *c, int len )
{
    int limit = ( len/SSE_WIDTH ) * SSE_WIDTH;
    register float *pa = a;
    register float *pb = b;
    register float *pc = c;
    for( int i = 0; i < limit; i += SSE_WIDTH )
    {
        _mm_storeu_ps( pc, _mm_mul_ps( _mm_loadu_ps( pa ), _mm_loadu_ps( pb ) ) );
        pa += SSE_WIDTH;
        pb += SSE_WIDTH;
        pc += SSE_WIDTH;
    }
    for( int i = limit; i < len; i++ )
    {
        c[i] = a[i] * b[i];
    }
}
```

SimdMulSum using Intel Intrinsics

```c
float
SimdMulSum( float *a, float *b, int len )
{
    float sum[4] = { 0., 0., 0., 0. };
    int limit = ( len/SSE_WIDTH ) * SSE_WIDTH;
    register float *pa = a;
    register float *pb = b;
    __m128 ss = _mm_loadu_ps( &sum[0] );
    for( int i = 0; i < limit; i += SSE_WIDTH )
    {
        ss = _mm_add_ps( ss, _mm_mul_ps( _mm_loadu_ps( pa ), _mm_loadu_ps( pb ) ) );
        pa += SSE_WIDTH;
        pb += SSE_WIDTH;
    }
    _mm_storeu_ps( &sum[0], ss );
    for( int i = limit; i < len; i++ )
    {
        sum[0] += a[i] * b[i];
    }
}
```

Why do the Intrinsics do so well with a small dataset size?

It's not due to the code in the inner-loop:

```
for( int i = 0; i < len; i++ )
{
    c[i] = a[i] * b[i];
}
```

It's actually due to the setup time. The Intrinsics have a tighter coupling to the setting up of the registers. A smaller setup time makes the small dataset size speedup look better.
When we get to OpenCL, we could compute projectile physics like this:

\[
\begin{align*}
\text{float4 } pp &\equiv p + v \cdot DT \; \text{; } \quad \text{ if } p' \\
pp.x &= p.x + v.x \cdot DT; \\
pp.y &= p.y + v.y \cdot DT + \frac{1}{2} DT \cdot DT \cdot G.y; \\
pp.z &= p.z + v.z \cdot DT; \\
\end{align*}
\]

But, instead, we will do it like this:

\[
\begin{align*}
\text{float4 } pp &\equiv p + v \cdot DT + \frac{1}{2} DT \cdot DT \cdot G; \\
\end{align*}
\]

We do it this way for two reasons:
1. Convenience and clean coding
2. Some hardware can do multiple arithmetic operations simultaneously

The whole thing will look like this:

```c
constant float4 G = (float4) ( 0., -9.8, 0., 0. );
constant float DT = 0.1;

kernel void Particle(  global float4 * dPobj,  global float4 * dVel,  global float4 * dCobj )
{
    int gid = get_global_id( 0 ); // particle #
    float4 p = dPobj[gid];       // particle gid's position
    float4 v = dVel[gid];        // particle gid's velocity

    float4 pp = p + v*DT + \frac{1}{2} DT \cdot DT \cdot G;   // p' \\
    float4 vp = v + G*DT;     // v'

    dPobj[gid] = pp;           // p' \\
    dVel[gid] = vp;            // v'
}
```