GPGPU High-performance computing Dmitry Puzyrev, SPbSU for JASS '09

What is GPGPU?

- General-purpose computing on Graphics Processing Units
- Applications traditionally handled by the CPU
- Programmable stages and higher precision arithmetics on rendering pipelines
- Stream processing of non-graphics data

Why GPGPU can be effective?

- GPUs are built for parallel processing
- Highly effective in data parallel tasks
- High amount of computing units: GPUs have in the range of 128-800 ALUs (compared to 4 ALUs on a typical quad-core)
- High memory bandwidth (100+ GB/s, compared to ≈10-20 GB/s for CPUs)

Computational power of GPU

Floating-point operations per second for the GPU and CPU:



Application areas:

- High-performance computing
- Signal processing
- Image processing
- Computer graphics:
 - Raytracing
 - Rendering tasks

High-performance computing on GPGPU: Scientific applications

- Molecular dynamics
- Astrophysics
- Geophysics

etc.

- Quantum chemistry
- Neural networks

Speedup by GPU:

Not 2x or 3x : Speedups are 20x to 150x



GPGPU hardware:

NVIDIA graphic processors:

- from desktop GPUs (9x or GTX series) to dedicated Tesla and Quadro
- AMD graphic processors
 - AMD FireStream is a dedicated solution
- Cell by Sony, Toshiba and IBM

Specifics of GPU architecture

GPU devotes much more transistors to data processing rather then data caching and flow control



Programming model:

- Small program (called kernel) works on many data elements
- Each data element is processed concurrently
- Communication is effective only inside one execution unit
- Different models:
 - **SIMD** (Single instruction, multiple data)
 - **SPMD** (Single program, multiple data)

GPGPU implementation: NVIDIA CUDA

- General purpose parallel computing architecture
- Works with all modern NVIDIA GPUs
- Uses C as a high-level programming language
- Other languages will be supported in the future



Basic CUDA concepts: Kernels

 C functions, called kernels, that are executed N times in parallel with <<<>>> syntax in main function

```
__global___void vecAdd(float* A, float* B, float* C)
{
    int i = threadIdx.x;
    C[i] = A[i] + B[i];
}
int main()
{
    // Kernel invocation
    vecAdd<<<1, N>>>(A, B, C);
}
```

* This code adds two vectors A and B of size N

Basic CUDA concepts: Thread Hierarchy

 One kernel is executed in one thread, and threads are combined in thread blocks

```
__global__ void matAdd(float A[N][N], float B[N][N],
                                 float C[N][N])
{
    int i = threadIdx.x;
    int j = threadIdx.y;
    C[i][j] = A[i][j] + B[i][j];
}
int main()
{
    // Kernel invocation
    dim3 dimBlock(N, N);
    matAdd<<<1, dimBlock>>>(A, B, C);
}
```

Threads and thread blocks

- Threads within a block have shared memory and can synchronize
- On current GPUs, a thread block may contain up to 512 threads
- A kernel can be executed by multiple equally-shaped thread blocks put in a grid



Thread blocks and grid

Matrix addition on a grid

```
global void matAdd(float A[N][N], float B[N][N],
                       float C[N][N])
{
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    int j = blockIdx.y * blockDim.y + threadIdx.y;
    if (i < N \& \& j < N)
        C[i][j] = A[i][j] + B[i][j];
int main()
{
    // Kernel invocation
    dim3 dimBlock(16, 16);
    dim3 dimGrid((N + dimBlock.x - 1) / dimBlock.x,
                 (N + dimBlock.y - 1) / dimBlock.y);
   matAdd<<<dimGrid, dimBlock>>>(A, B, C);
```

* Thread blocks in a grid are required to execute independently

Basic CUDA concepts: Memory Hierarchy



- Multiple memory spaces
- Additional memory spaces: constant and texture memory
- Different memory usage strategies
- Memory usage: bottleneck of GPGPU applications

Basic CUDA concepts: Host and Device

- CUDA threads may execute on a physically separate device that operates as a coprocessor to the host running the C program
- Both the host and the device maintain their own DRAM, referred to as host memory and device memory, and CUDA runtime manages data transfer.

C Program Sequential Execution		
Serial code	Host	
Parallel kernel	Device	
Kernel0<<<>>>()	Grid 0	
	Block (0, 0) Block (1, 0) >>>>>>>>>>>>>>>>>>>>>>>>>>>>	
Serial code	Host	
	Device	
Parallel kernel Kernel1<<<>>>()	Grid 1	
	Block (0, 0)	Block (1, 0)
	Block (0, 1)	Block (1, 1)
	<u> </u>	
	Block (0, 2)	Block (1, 2)
♥		

CUDA features

- Efficient implementation of FFT on CUDA
- CUDA implementation of BLAS, called CUBLAS
 - Subset of BLAS functions
- CUDA-based plugins for MATLAB
- LAPACK libraries for CUDA are under development
- Efficient dense linear algebra, sparse solvers are under development

CUDA limitations

- Fundamental advantages and limitations come from specific architecture and data-parallel programming model
- Double precision has no deviations from IEEE 754 standard, single precision is not standard
- Still lacks advanced profiler
- Emulation on CPU is slow and often gives different results
- Works only on NVIDIA GPUs

Alternative implementation: Brook

- Alternative architecture is built by AMD, called Stream Computing, based on Brook language
- Brook works on both AMD and NVIDIA GPUs, Brook+ is AMD hardware optimized version
- Faster in some applications, better support of double precision
- Apparently, AMD doesn't actively compete to NVIDIA in highperformance GPGPU market at the moment

Future directions: Larrabee

- Larrabee Intel's upcoming discrete GPU
- Compete with both GPUs and high-performance computing
- Hybrid architecture: 16-32 simple x86 cores with SIMD vector units and per-core L1/L2 cache
- No fixed function hardware, except for texturing units

Larrabee: Programming concepts

- Task-parallel on core level
- Data-parallel on vector units inside the core
- Cores can submit work to itself without the host
- Benefits from Intel C/C++ compiler

Much praise from Intel and much criticism from GPU manufacturers



Future directions: OpenCL

- OpenCL a framework for programming on CPUs, GPUs and other processors
- Proposed by Apple and developed by Khronos Group
- Full support from both AMD and NVIDIA
- Will be introduced with Mac OS X 10.6

Conclusion

GPGPU is a developed branch of computing

NVIDIA CUDA already allows us to utilize the power of GPUs in convenient way

Data parallel programming model is effective in many applications, but GPGPU could become more flexible

A fusion between many-core CPUs and GPUs is a promising direction

Standardized API for GPGPU is highly anticipated