ECE 571 – Advanced Microprocessor-Based Design Lecture 23

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Project/HW Reminder

Homework #11 was posted



Graphics and Video Cards



Old CRT Days

- Electron gun
- Horizontal Blank, Vertical Blank
- Atari 2600 only enough RAM to do one scanline at a time
- Apple II video on alternate cycles, refresh RAM for free
- Bandwidth key issue. SNES / NES, tiles. Double buffering vs only updating during refresh



Old 2D Video Cards

- Framebuffer (possibly multi-plane), Palette
- Dual-ported RAM, RAMDAC (Digital-Analog Converter)
- Interface (on PC) various io ports and a 64kB RAM window
- Mode 13h
- Acceleration often commands for drawing lines, rectangles, blitting sprites, mouse cursors, video overlay



Modern Graphics Cards

- Can draw a lot of power
- 2D (optional these days)
- 3D
- Video decoders



Interface

- Integrated or stand alone
- Integrated traditionally less capable, but changing. Share Memory bandwidth, take memory.



GPUs

- Display memory often broken up into tiles (improves cache locality)
- Massively parallel matrix-processing CPUs that write to the frame buffer (or can be used for calculation)
- Texture control, 3d state, vectors
- Front-buffer (written out), Back Buffer (being rendered)
 Z-buffer (depth)
- Originally just did lighting and triangle calculations. Now shader languages and fully generic processing



Video RAM

- VRAM dual ported. Could read out full 1024Bit line and latch for drawing, previously most would be discarded (cache line read)
- GDDR3/4/5 traditional one-port RAM. More overhead, but things are fast enough these days it is worth it.
- Confusing naming, GDDR3 is equivalent of DDR2 but with some speed optimization and lower voltage (so higher frequency)



Busses

- DDC i2c bus connection to monitor, giving screen size, timing info, etc.
- PCIe (PCI-Express) most common bus in x86 systems
 Original PCI and PCI-X was 32/64-bit parallel bus
 PCIe is a serial bus, sends packets
 Can power 25W, additional power connectors to supply
 can have 75W, 150W and more
 Can transfer 8GT/s (giga-transfers) a second
 In general PCIe is limiting factor to getting data to GPU.



Connectors

CRTC (CRT Controller) Can point to same part of memory (mirror) or different.

- RCA composite/analog TV
- VGA − 15 pin, analog
- DVI digital and/or analog. DVI-D, DVD-I, DVD-A
- HDMI compatible with DVI (though content restrictions). Also audio. HDMI 1.0 165MHz, 1080p



or 1920x1200 at 60Hz. TMDS differential signaling. Packets. Audio sent during blanking.

- Display Port similar but not the same as HDMI
- Thunderbolt combines PCle and DisplayPort. Intel/Apple. Originally optical, but also Copper. Can send 10W of power.
- LVDS Low Voltage Differential Signaling used to connect laptop LCD



LCD Displays

- Crystals twist in presence of electric field
- Asymmetric on/off times
- Passive (crossing wires) vs Active (Transistor at each pixel)
- Passive have to be refreshed constantly
- Use only 10% of power of equivalent CRT



- Circuitry inside to scale image and other post-processing
- Need to be refreshed periodically to keep their image
- New "bistable" display under development, requires no power to hold state



Interfaces

- OpenGL SGI
- DirectX Microsoft
- For consumer grade, driven by gaming



GPGPUs

- Interfaces needed, as GPU companies do not like to reveal what their chips due at the assembly level.
 - CUDA (Nvidia)
 - OpenCL (Everyone else) can in theory take parallel code and map to CPU, GPU, FPGA, DSP, etc
 - OpenACC?



Why GPUs?

- Old example:
 - 3GHz Pentium 4, 6 GFLOPS, 6GB/sec peak
 - GeForceFX 6800: 53GFLOPS, 34GB/sec peak
- Newer example
 - Raspberry Pi, 700MHz, 0.177 GFLOPS
 - On-board GPU: Video Core IV: 24 GFLOPS



Key Idea

- using many slimmed down cores
- have single instruction stream operate across many cores (SIMD)
- avoid latency (slow textures, etc) by working on another group when one stalls



Latency vs Throughput

- CPUs = Low latency, low throughput
- GPUs = high latency, high throughput
- CPUs optimized to try to get lowest latency (caches);
 with no parallelism have to get memory back as soon as possible
- GPUs optimized for throughput. Best throughput for all better than low-latency for one



GPU Benefits

- Specialized hardware, concentrating on arithmetic.
 Transistors for ALUs not cache.
- Fast 32-bit floating point (16-bit?)
- Driven by commodity gaming, so much faster than would be if only HPC people using them.
- Accuracy? 64-bit floating point? 32-bit floating point?
 16-bit floating point? Doesn't matter as much if color slightly off for a frame in your video game.
- highly parallel



GPU Problems

- optimized for 3d-graphics, not always ideal for other things
- Need to port code, usually can't just recompile cpu code.
- Companies secretive.
- serial code
- a lot of control flow
- lot of off-chip memory transfers



Older / Traditional GPU Pipeline

- In old days, fixed pipeline (lots of triangles).
- Modern chips much more flexible, but the old pipeline can still be implemented in software via the fancier interface.



Older / Traditional GPU Pipeline

- CPU send list of vertices to GPU.
- Transform (vertex processor) (convert from world space to image space). 3d translation to 2d, calculate lighting.
 Operate on 4-wide vectors (x,y,z,w in projected space, r,g,b,a color space)
- Rasterizer transform vertexes/vectors into a grid.
 Fragments. break up to pixels and anti-alias



- Shader (Fragment processor) compute color for each pixel. Use textures if necessary (texture memory, mostly read)
- Write out to framebuffer (mostly write)
- Z-buffer for depth/visibility



GPGPUs

- Started when the vertex and fragment processors became generically programmable (originally to allow more advanced shading and lighting calculations)
- By having generic use can adapt to different workloads, some having more vertex operations and some more fragment



Graphics vs Programmable Use

Vertex	Vertex Processing	Data	MIMD processing
Polygon	Polygon Setup	Lists	SIMD Rasterization
Fragment	Per-pixel math	Data	Programmable SIMD
Texture	Data fetch, Blending	Data	Data Fetch
Image	Z-buffer, anti-alias	Data	Predicated Write



Example for Shader 3.0, came out DirectX9

They are up to Pixel Shader 5.0 now



Shader 3.0 Programming – Vertex Processor

- 512 static / 65536 dynamic instructions
- Up to 32 temporary registers
- Simple flow control
- Texturing texture data can be fetched during vertex operations



- Can do a four-wide SIMD MAD (multiply ADD) and a scalar op per cycle:
 - EXP, EXPP, LIT, LOGP (exponential)
 - RCP, RSQ (reciprocal, r-square-root)
 - SIN, COS (trig)



Shader 3.0 Programming – Fragment Processor

- 65536 static / 65536 dynamic instructions (but can time out if takes too long)
- Supports conditional branches and loops
- fp32 and fp16 internal precision
- Can do 4-wide MAD and 4-wide DP4 (dot product)



Program

- Typically textures read-only. Some can render to texture, only way GPU can share RAM w/o going through CPU.
 In general data not written back until entire chunk is done. Fragment processor can read memory as often as it wants, but not write back until done.
- Only handle fixed-point or floating point values
- Analogies:
 - Textures == arrays



- Kernels == inner loops
- Render-to-texture == feedback
- Geometry-rasterization == computation. Usually done as a simple grid (quadrilateral)
- Texture-coordinates = Domain
- Vertex-coordinates = Range



Flow Control, Branches

- only recently added to GPUs, but at a performance penalty.
- Often a lot like ARM conditional execution



Terminology (CUDA)

- Thread: chunk of code running on GPU.
- Warp: group of thread running at same time in parallel simultaneously
- Block: group of threads that need to run
- Grid: a group of thread blocks that need to finish before next can be started



Terminology (cores)

 Confusing. Nvidia would say GTX285 had 240 stream processors; what they mean is 30 cores, 8 SIMD units per core.



CUDA Programming

- Since 2007
- Use nvcc to compile
- *host* vs *device*
 host code runs on CPU
 device code runs on GPU
- Host code compiled by host compiler (gcc), device code by custom NVidia compiler



- __global__ parameters to function means pass to CUDA compiler
- cudaMalloc() to allocate memory and pointers that can be passed in
- call global function like this add<<<1,1>>>(args)
 where first inside brackets is number of blocks, second is threads per block
- cudaFree() at the end
- Can get block number with blockldx.x and thread index



with threadIdx.x

Can have 65536 blocks and 512 threads (At least in 2010)

- Why threads vs blocks?
 Shared memory, block specific
 _shared__ to specify
- __syncthreads() is a barrier to make sure all threads finish before continuing



CUDA Programming

- See the NVIDIA "CUDA C Programming Guide"
- Compute Unified Device Architecture
- From CUDA C Programming guide from NVIDIA
- CUDA introduced in 2006
- Heterogeneous programming there is a host executing a main body of code (a CPU) and it dispatches code to run on a device (a GPU)
- CUDA assumes host and device each have own separate DRAM memory



 CUDA C extends C, define C functions "kernels" that are executed N times in parallel by N CUDA threads



CUDA Coding

- version compliance can check version number. New versions support more hardware but sometimes drop old
- nvcc wrapper around gcc. global code compiled into PTX (parallel thread execution) ISA
- can code in PTX code directly which is sort of like assembly language. Won't give out actual assembly language. Why?
- CUDA C has mix of host and device code. Compiles the global stuff to PTX, compiles the <<< ... >>> into



- code that can launch the GPU code
- PTX code is JIT compiled into native by the device driver
- You can control JIT with environment variables
- Only subset of C/C++ supported in the device code



CUDA Hardware

- GPU is array of Streaming Multiprocessors (SMs)
- Program partitioned into blocks of threads that execute independently from each other.
- Manages/Schedules/Executes threads in groups of 32 parallel threads (warps) (weaving terminology) (no relation)
- Threads have own PC, registers, etc, and can execute independently
- When SM given thread block, partitions to warps and



- each warp gets scheduled
- One common instruction at a time. If diverge in control flow, each way executed and thread not taking that path just waits.
- Full context stored with each warp; if warp is not ready (waiting for memory) then it may be stopped and another warp that's ready can be run



CUDA Threads

- kernel defined using __global__ declaration. When called use <<<...>>> to specify number of threads
- each thread that is called is assigned a unique ThreadID
 Use threadIdx to find what thread you are and act
 accordingly

```
__global__ void VecAdd(float *A, float *B
    int i = threadIdx.x;
    C[i]=A[i]+B[i];
```



- threadIdx is 3-component vector, can be seen as 1, 2 or 3 dimensional block of threads (thread block)
- Much like our sobel code, can look as 1D (just x), 2D, (thread iD is ((y*xsize)+x) or (z*xsize*ysize)+y*xsize+x
- Weird syntax for doing 2 or 3d.



```
__global__ void MatAdd(float A[N][N], flo
        int i=threadIdx.x;
        int j=threadIdx.y;
        C[i][j]=A[i][j]+B[i][j];
int numBlocks=1;
dim3 threadsPerBlock(N,N);
MatAdd <<< numBlocks, threadsPerBlock >>> (A,
```



- Each block made up of the threads. Can have multiple levels of blocks too, can get block number with blockldx
- Thread blocks operate independently, in any order. That way can be scheduled across arbitrary number of cores (depends how fancy your GPU is)



CUDA Memory

- Per-thread private local memory
- Shared memory visible to whole block (lifetime of block)
- Global memory
- also constant and texture spaces. Have special rules.
 Texture can do some filtering and stuff
- Global, constant, and texture persistent across kernel launches by same app.



More Coding

- No explicit initialization, done automatically first time you do something (keep in mind if timing)
- Global Memory: linear or arrays.
 - Arrays are textures
 - Linear arrays are allocated with cudaMalloc(), cudaFree()
 - To transfer use cudaMemcpy()
 - Also can be allocated cudaMallocPitch() cudaMalloc3D()
 for allignment reasons



- Access by symbol (?)
- Shared memory, __shared__. Faster than Global also __device__

Manually break your problem into smaller sizes



Misc

Can lock host memory with cudaHostAlloc(). Pinned, can't be paged out. Can load store while kernel running if case. Only so much available. Can be marked writecombining. Not cached. So slow for host to read (should only write) but speeds up PCI transaction.



Async Concurrent Execution

- Instead of serial/parallel/serial/parallel model
- Want to have CUDA running and host at same time, or with mem transfers at same time
 - Concurrent host/device: calls are async and return to host before device done
 - Concurrent kernel execution: newer devices can run multiple kernels at once. Problem if use lots of memory
 - Overlap of Data Transfer and Kernel execution
 - Streams: sequence of commands that execute in order,



but can be interleaved with other streams complicated way to set them up. Synchronization and callbacks



Events

- Can create performance events to monitor timing
- PAPI can read out performance counters on some boards
- Often it's for a full synchronous stream, can't get values mid-operation
- NVML can measure power and temp on some boards?



Multi-device system

- Can switch between active device
- More advanced systems can access each others device memory



Other features

- Unified virtual address space (64 bit machines)
- Interprocess communication
- Error checking



Texture Memory

Complex



3D Interop

- Can make results go to an OpenGL or Direct3D buffer
- Can then use CUDA results in your graphics program



Code Example

```
#include <stdio.h>
#define N 10
__global__ void add (int *a, int *b, int *e
         int tid=blockIdx.x;
         if (tid < N) {
                 c[tid]=a[tid]+b[tid];
```



```
int main(int arc, char **argv) {
        int a[N], b[N], c[N];
        int *dev_a,*dev_b,*dev_c;
        int i;
        /* Allocate memory on GPU */
```



```
cudaMalloc((void **)&dev_a,N*sizeo
cudaMalloc((void **)&dev_b,N*sizeo
cudaMalloc((void **)&dev_c,N*sizeo
/* Fill the host arrays with values
for (i = 0; i < N; i++)
        a[i]=-i;
        b[i]=i*i;
```

cudaMemcpy(dev_a,a,N*sizeof(int),ci

```
cudaMemcpy(dev_b,b,N*sizeof(int),ci
add <<< N,1>>> (dev_a, dev_b, dev_c);
cudaMemcpy(c,dev_c,N*sizeof(int),ci
/* results */
for (i=0; i<N; i++)
        printf("%d+%d=%d\n",a[i],b
```



```
cudaFree(dev_a);
cudaFree(dev_b);
cudaFree(dev_c);
return 0;
```

