Introduction to Parallel Programming For Real-Time Graphics (CPU + GPU)

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What’s In This Talk?

• Overview of parallel programming models used in real-time graphics products and research
  – Abstraction, execution, synchronization
  – Shaders, task systems, conventional threads, graphics pipeline, “GPU” compute languages

• Parallel programming models
  – Vertex shaders
  – Conventional thread programming
  – Task systems
  – Graphics pipeline
  – GPU compute languages (ComputeShader, OpenCL, CUDA)

• Discuss
  – Strengths/weaknesses of different models
  – How each model maps to the architectures
What Goes into a Game Frame? (2 years ago)
Computation graph for *Battlefield: Bad Company* provided by DICE

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Data Parallelism
Task Parallelism
Graphics Pipelines

- Input Assembly
- Vertex Shading
- Primitive Setup
- Geometry Shading
- Rasterization
- Pixel Shading
- Output Merging

Pipeline Flow
Remember: “Our Enthusiast Chip”

Figure by Kayvon Fatahalian
Hardware Resources (from Kayvon’s Talk)

- Core
- Execution Context
- SIMD functional units
- On-chip memory

Figure by Kayvon Fatahalian
Abstraction

• Abstraction enables portability and system optimization
  – E.g., dynamic load balancing, producer-consumer, SIMD utilization

• Lack of abstraction enables arch-specific user optimization
  – E.g., multiple execution contexts jointly building on-chip data structure

• Remember:
  – When a parallel programming model abstracts a HW resource, code written in that programming model scales across architectures with varying amounts of that resource
Definitions: Execution

• **Task**
  – A logically related set of instructions executed in a single execution context (aka shader, instance of a kernel, task)

• **Concurrent execution**
  – Multiple tasks that may execute simultaneously (because they are logically independent)

• **Parallel execution**
  – Multiple tasks whose execution contexts are guaranteed to be live simultaneously (because you want them to be for locality, synchronization, etc)
Synchronization

• Synchronization
  – Restricting when tasks are permitted to execute

• Granularity of permitted synchronization determines at which granularity system allows user to control scheduling
Vertex Shaders: “Pure Data Parallelism”

• Execution
  – Concurrent execution of identical per-vertex tasks

• What is abstracted?
  – Cores, execution contexts, SIMD functional units, memory hierarchy

• What synchronization is allowed?
  – Between draw calls
Shader (Data-parallel) Pseudocode

concurrent_for(i = 0 to numVertices - 1)
{
    ... execute vertex shader ...
}

• SPMD = Single Program Multiple Data
  – This type of programming is sometimes called SPMD
  – Instance the same program multiple times and run on different data
  – Many names: shader-style, kernel-style, SPMD
Conventional Thread Parallelism (e.g., pthreads)

• Execution
  – Parallel execution of N tasks with N execution contexts

• What is abstracted?
  – Nothing (ignoring preemption)

• Where is synchronization allowed?
  – Between any execution context at various granularities
Conventional Thread Parallelism

- Directly program:
  - N execution contexts
  - N SIMD ALUs / execution context
  - ...

- To use SIMD ALUs:
  ```c
  __m128 a_line, b_line, r_line;
  r_line = _mm_mul_ps(a_line, b_line);
  ```

- Powerful, but dangerous...
Game Workload Example
**Typical Game Workload**

- Subsystems given % of overall time “budget”
- Input, Miscellaneous: 5%
- Physics: 30%
- AI, Game Logic: 10%
- Graphics: 50%
- Audio: 5%

**GPU Workload:**

```
I  Physics  AI  Graphics  A
```

“Rendering”
Parallelism Anti-Pattern #1

• Assign each subsystems to a SW thread

- Thread 0
  - I
  - Physics
  - Graphics

- Thread 1
  - Physics

- Thread 2
  - AI

- Thread 3
  - AI
  - Graphics

frame N

• Problems
  – Communication/synchronization
  – Load imbalance
  – Preemption leads to thrashing

• Don’t do this!
Parallelism Anti-Pattern #2

• Group subsystems into HW threads

- Thread 0: I, Physics, AI, A, I, Physics, AI, A
- Thread 1: Graphics, Graphics

• Problems
  – Communication/synchronization
  – Load imbalance
  – Poor scalability (4, 8, ... HW threads)

• Don’t do this either!
Better Solution: Find Concurrency...

• Identify where ordering constraints are needed and run concurrently between constraints

I P P P P P P A I G G G G G G G G G G A

• Visualize as a graph

Slide by Tim Foley
...And Distribute Work to Threads

• Dynamically distribute medium-grained concurrent tasks to hardware threads
• (Virtualize/abstract the threads”

Slide by Tim Foley
“Task Systems” (Cilk, TBB, ConcRT, GCD, …)

• Execution
  – Concurrent execution of many (likely different) tasks

• What is abstracted?
  – Cores and execution contexts
  – Does not abstract: SIMD functional units or memory hierarchy

• Where is synchronization allowed?
  – Between tasks
Mental Model: Task Systems

• Think of task as asynchronous function call
  – “Do F() at some point in the future…”
  – Optionally “… after G() is done”

• Can be implemented in HW or SW
  – Launching/spawning task is nearly as fast as function call
  – Usage model: “Spawn 1000s of tasks and let scheduler map tasks to execution contexts”

• Usually cooperative, not preemptive
  – Task runs to completion – no blocking
  – Can create new tasks, but not wait
void myTask(...some arguments...)
{
  
  ...
}

void main()
{
  
  for( i = 0 to NumTasks - 1 )
  {
    cilk_spawn myTask(...);
  }
  
  cilk_sync;
}

Task Parallel Code (Cilk)

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Task Parallel Code (Cilk)

```c
void myTask(...some arguments...)
{
    ...
}

void main()
{
    cilk_for( i = 0 to NumTasks - 1 )
    {
        myTask(...);
    }
    cilk_sync;
}
```
Nested Task Parallel Code (Cilk)

void barTask(...some parameters...)
{
    ...
}

void fooTask(...some parameters...)
{
    if (someCondition) {
        cilk_spawn barTask(...);
    }
    else {
        cilk_spawn fooTask(...);
    }
    // Implicit cilk_sync at end of function
}

void main()
{
    cilk_for( i = 0 to NumTasks - 1 ) {
        fooTask(...);
    }
    cilk_sync;
    ...
    ... More code ...
}
“Task Systems” Review

• Execution
  – Concurrent execution of many (likely different) tasks

• What is abstracted?
  – Cores and execution contexts
  – *Does not abstract: SIMD functional units or memory hierarchy*

• Where is synchronization allowed?
  – Between tasks
DirectX/OpenGL Rendering Pipeline (Combination of multiple models)

• Execution
  – Data-parallel concurrent execution of identical task within each shading stage
  – Task-parallel concurrent execution of different shading stages
  – No parallelism exposed to user

• What is abstracted?
  – (just about everything)
  – Cores, execution contexts, SIMD functional units, memory hierarchy, and fixed-function graphics units (tessellator, rasterizer, ROPs, etc)

• Where is synchronization allowed?
  – Between draw calls
GPU Compute Languages (Combination of Multiple Models)

- DX11 DirectCompute
- OpenCL
- CUDA

- There are multiple possible usage models. We’ll start with the “text book” hierarchical data-parallel usage model
GPU Compute Languages

• Execution
  – Hierarchical model
  – Lower level is parallel execution of identical tasks (work-items) within work-group
  – Upper level is concurrent execution of identical work-groups

• What is abstracted?
  – Work-group abstracts a core’s execution contexts, SIMD functional units
  – Set of work-groups abstracts cores
  – Does not abstract core-local memory

• Where is synchronization allowed?
  – Between work-items in a work-group
  – Between “passes” (set of work-groups)
GPU Compute Pseudocode

```c
void myWorkGroup()
{
    parallel_for(i = 0 to NumWorkItems - 1)
    {
        ... GPU Kernel Code ... (This is where you write GPU compute code)
    }
}

void main()
{
    concurrent_for( i = 0 to NumWorkGroups - 1)
    {
        myWorkGroup();
    }
    sync;
}
```
DX CS/OCL/CUDA Execution Model

• Fundamental unit is work-item
  – Single instance of “kernel” program (i.e., “task” using the definitions in this talk)
  – Each work-item executes in single SIMD lane

• Work items collected in work-groups
  – Work-group scheduled on single core
  – Work-items in a work-group
    – Execute in parallel
    – Can share R/W on-chip scratchpad memory
    – Can wait for other work-items in work-group

• Users launch a grid of work-groups
  – Spawn many concurrent work-groups

Void f(...) {
  int x = ...;
  ...;
  ...
  if(...) {
    ...
  }
}

Figure by Tim Foley
GPU Compute Models

Slide by Tim Foley
GPU Compute Use Cases

- 1:1 Mapping
- Simple Fork/Join
- Switching Axes of Parallelism

Increasing Sophistication
**1:1 Mapping**

- One work item per ray / per pixel / per matrix element
- Every work item executes the same kernel
- Often first, most obvious solution to a problem
- “Pure data parallelism”

```c
void saxpy( int i,
            float a,
            const float* x,
            const float* y,
            float* result )
{
    result[i] = a * x[i] + y[i];
}
```
Simple Fork/Join

• Some code must run at work-group granularity
  – Example: work items cooperate to compute output structure size
  – Atomic operation to allocate output must execute once

• Idiomatic solution
  – Barrier, then make work item #0 do the group-wide operation

```c
void subdividePolygon(...) {
    shared int numOutputPolygons = 0;

    // in parallel, every work item does
    atomic_add( numOutputPolygons, 1);
    barrier();

    Polygon* output = NULL;
    if( workItemID == 0 ) {
        output = allocateMemory( numOutputPolygons );
    }
    barrier();
    ...  
}
```
Multiple Axes of Parallelism

• Deferred rendering with DX11 Compute Shader
  – Example from Johan Andersson (DICE)
  – 1000+ dynamic lights

• Multiple phases of execution
  – Work group responsible for a screen-space tile
  – Each phase exploits work items differently:
    – Phase 1: pixel-parallel computation of tile depth bounds
    – Phase 2: light-parallel test for intersection with tile
    – Phase 3: pixel-parallel accumulation of lighting

• Exploits producer-consumer locality between phases
### Terminology Decoder Ring

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<td>multiprocessor</td>
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<td>Set of work-groups</td>
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When Use GPU Compute vs Pixel Shader?

• Use GPU compute language if your algorithm needs on-chip memory
  – Reduce bandwidth by building local data structures

• Otherwise, use pixel shader
  – All mapping, decomposition, and scheduling decisions automatic
  – (Easier to reach peak performance)
GPU Compute Languages Review

• “Write code from within two nested concurrent/parallel loops”

• Abstracts
  – Cores, execution contexts, and SIMD ALUs

• Exposes
  – Parallel execution contexts on same core
  – Fast R/W on-core memory shared by the execution contexts on same core

• Synchronization
  – Fine grain: between execution contexts on same core
  – Very coarse: between large sets of concurrent work
  – *No medium-grain synchronization “between function calls” like task systems provide*
Conventional Thread Parallelism on GPUs

• Also called “persistent threads”

• “Expert” usage model for GPU compute
  – Defeat abstractions over cores, execution contexts, and SIMD functional units
  – Defeat system scheduler, load balancing, etc.
  – Code not portable between architectures
Conventional Thread Parallelism on GPUs

• Execution
  – Two-level parallel execution model
  – Lower level: parallel execution of $M$ identical tasks on $M$-wide SIMD functional unit
  – Higher level: parallel execution of $N$ different tasks on $N$ execution contexts

• What is abstracted?
  – Nothing (other than automatic mapping to SIMD lanes)

• Where is synchronization allowed?
  – Lower-level: between any task running on same SIMD functional unit
  – Higher-level: between any execution context
Why Persistent Threads?

• Enable alternate programming models that require different scheduling and synchronization rules than the default model provides

• Example alternate programming models
  – Task systems (esp. nested task parallelism)
  – Producer-consumer rendering pipelines
  – (See references at end of this slide deck for more details)
Summary of Concepts

• Abstraction
  – When a parallel programming model abstracts a HW resource, code written in that programming model scales across architectures with varying amounts of that resource

• Execution
  – Concurrency versus parallelism

• Synchronization
  – Where is user allowed to control scheduling?
“Ideal Parallel Programming Model”

• Combine the best of CPU and GPU programming models
  – Task systems are great for scheduling (from CPUs)
    – “Asynchronous function call” is easy to understand and use
    – Great load balancing and scalability (with cores, execution contexts)
  – SPMD programming is great for utilizing SIMD (from GPUs)
    – “Write sequential code that is instanced N times across N-wide SIMD”
    – Intuitive: only slightly different from sequential programming

• Why not just “launch tasks that run fine-grain SPMD code?”
  – The future on CPU and GPU?
Conclusions

• Task-, data- and pipeline-parallelism
  – Three proven approaches to scalability
  – Plentiful of concurrency with little exposed parallelism
  – Applicable to many problems in visual computing

• Current real-time rendering programming uses a mix of data-, task-, and pipeline-parallel programming (and conventional threads as means to an end)

• Current GPU compute models designed for data-parallelism but can be abused to implement all of these other models
References

• GPU-inspired compute languages
  – DX11 DirectCompute, OpenCL (CPU+GPU+...), CUDA

• Task systems (CPU and CPU+GPU+...)
  – Cilk, Thread Building Blocks (TBB), Grand Central Dispatch (GCD), ConcRT, Task Parallel Library, OpenCL (limited in 1.0)

• Conventional CPU thread programming
  – Pthreads

• GPU task systems and “persistent threads” (i.e., conventional thread programming on GPU)

• Additional input (concepts, terminology, patterns, etc)
  – Foley, “Parallel Programming for Graphics,”
    – Beyond Programmable Shading SIGGRAPH 2009
    – Beyond Programmable Shading CS448s Stanford course
Questions?

http://www.cs.washington.edu/education/courses/cse558/11wi/