Rendering fractal flames on the GPU

Matt Znoj Michael Semeniuk Nicolas Mejia Steven Robertson

September 29, 2011

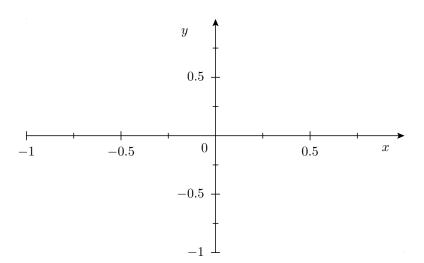


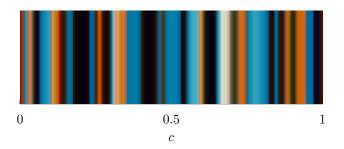
$$(\mathbf{x}_{n+1}, \mathbf{y}_{n+1}) = (0.5\mathbf{x}_n, 0.5\mathbf{y}_n)$$

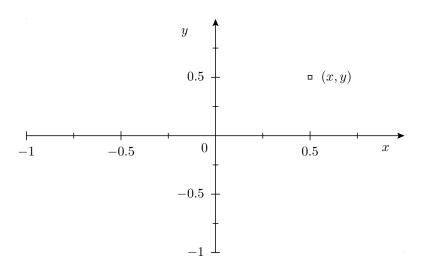
 $(\mathbf{x}_{n+1}, \mathbf{y}_{n+1}) = (0.5(\mathbf{x}_n + 1), 0.5\mathbf{y}_n)$
 $(\mathbf{x}_{n+1}, \mathbf{y}_{n+1}) = (0.5\mathbf{x}_n, 0.5(\mathbf{y}_n + 1))$

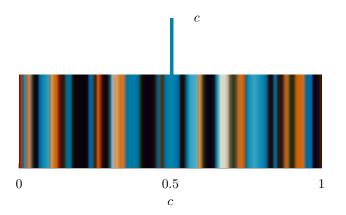
```
<flame name="electricsheep.244.04653" time="0" size="1024 1024"
center="-0.0304807 0.152945" scale="640" rotate="0"
supersample="4" filter="1" filter shape="gaussian"
temporal_filter_type="box" temporal_filter_width="1"
quality="1000" passes="1" temporal_samples="1000" background="0 0
0" brightness="73.7913" gamma="4.28" vibrancv="1"
estimator_radius="14" estimator_minimum="0" estimator_curve="1"
gamma_threshold="0.01" palette mode="linear"
interpolation_type="log" url="">
 <xform weight="0.122" color="0" symmetry="0" polar="0.003"</pre>
 coefs="-0.223176 1.64498 -1.64498 -0.223176 0.00173 -0.00881"/>
 <xform weight="1.829" color="1" symmetry="0" juliascope="1"</pre>
  juliascope_power="2" juliascope_dist="1"
  coefs="0.256909 0 0 0.256909 0 0" />
 <xform weight="0.458" color="0" symmetry="0" hyperbolic="2.051"</pre>
  coefs="-0.841582 -1.07778 1.07778 -0.841582 0 0" />
  <finalxform color="0" symmetry="1" perspective="1"</pre>
  perspective angle="0.530779" perspective dist="1.46989"
  coefs="2.01414 0 0 2.01414 0 0" />
  <!-- palette omitted -->
</flame>
```

4□ > 4個 > 4 = > 4 = > = 900





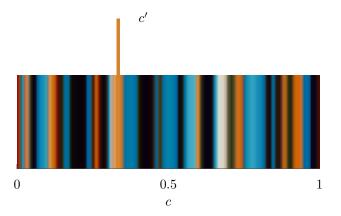


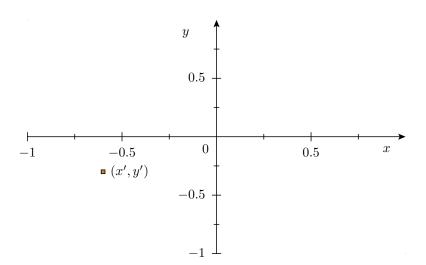


$$f_1(x, y, c)$$

 $f_2(x, y, c)$
 $f_3(x, y, c)$

$$(\mathbf{x}',\mathbf{y}',\mathbf{c}')=f_1(\mathbf{x},\mathbf{y},\mathbf{c})$$





40,000,000,000 iterations



Normalized to 16 Amazon EC2 compute units:

- 14.3M points per second
- 290 seconds per frame
- 116 hours per minute of video

Slow as balls.

Not complete.

flam3: simple and complete

flam4: simple and fast

Chaotica: complete and fast

Chaotica: complete and less slow

Our project: complete, fast, GPU

Our project: complete, fast, GPU (...project goals)

- ► AWS EC2 instance type cg1.4xlarge
 - 2 NVIDIA Tesla M2050 GPUs
 - 33.5 EC2 compute units (2×8 cores)
- CPU: 15M iter/sec per processor
- ▶ GPU: 1030B FMA/sec / (100 instr/iter) ≤ 1B iter/sec

Upper bound: 68.6× faster

Practical target: 20× faster

Project specifications

- Runs on NVIDIA Tesla M2050 (among others)
- Supports full 24,000-parameter genome feature space
- Runs at 1920×1080 with 4× ISAA
- Renders at 20× the rate of 16 EC2 CU

Implementation: Overview

Bottlenecks occur in surprising places, so don't try to second guess and put in a speed hack until you have proven that's where the bottleneck is. (Rob Pike)

Premature optimization is the root of all evil... look carefully at the critical code; but only after that code has been identified. (Donald Knuth)

Implementation: Overview

Bottom-up design process

Implementation: Overview

Implementation: RNG

Step 1: Randomly select a transform function.

Implementation: RNG

A "good" RNG

Implementation: RNG

Cryptographic properties

Don't care

Statistical properties

Period

n-dimensional linear correlation

Practical properties

Speed

Block size

State size

Lots

Approximately lots

"Won't fit"

No stack

No dynamic heap

High latencies for global memory

16 bytes/thread shared memory

20 registers

Register spilling

Early termination and selective restart

Huge pool of random numbers

Mersenne Twister

ISAAC

Linear Congruential Generator

Multiply-With-Carry

Multiply-With-Carry

- ▶ Batch size: 1
- State: 8 bytes (12 for independent multiplier)

Multiply-With-Carry

- ▶ Batch size: 1
- State: 8 bytes (12 for independent multiplier)
- Passes the Diehard tests

- Seeding strategy to avoid cross-correlation
- Multiplier selection and distribution
- Spectral properties under shared multiplier

Step 2: Apply the transform function.

Linear variation

$$x'' = w \cdot x'$$
$$y'' = w \cdot y'$$

Flux variation

$$x'' = w \cdot (2 + flux_spread \cdot \sqrt{\frac{\sqrt{y'^2 + (x' + w)^2}}{\sqrt{y'^2 + (x' - w)^2}}} + \cos(\arctan\frac{y'}{x' - w} - \arctan\frac{y'}{x' + w})$$

$$y'' = w \cdot (2 + flux_spread \cdot \sqrt{\frac{\sqrt{y'^2 + (x' + w)^2}}{\sqrt{y'^2 + (x' + w)^2}}} + \sin(\arctan\frac{y'}{x' - w} - \arctan\frac{y'}{x' + w})$$

```
if(genome.weights[VAR_LINEAR]) {
  double w = genome.weights[VAR_LINEAR];
  xf += w * xt;
  yf += w * yt;
}
if(genome.weights[VAR_SINE])
...
```

Common subexpression elimination

```
// Original code: fx += sin(x) * sin(x);
double tmp000 = sin(x);
fx += tmp000 * tmp000;
```

Bitmasked conditional cascade

<ロト < 回 > < 巨 > < 巨 > 三 の Q で

Stack-based data structures

```
int next_xf_id = POPi();
if (next_xf_id == VAR_LINEAR) {
    float w = POPf();
    fx += w * tx;
    fy += w * ty;
    next_xf_id = POPi();
}
if (next_xf_id == VAR_SINE) {
...
```

$$\sum_{0 \le k \le n} \binom{n}{k} = 2^n = 633825300114114700748351602688$$

```
if (genome.xf[1].weights[VAR_LINEAR]) {
    float w = genome.xf[1].weights[VAR_LINEAR];
    fx += w * tx;
    fy += w * ty;
}
if (genome.xf[1].weights[VAR_SINE]) {
    ...
}
```

```
float w = genome.xf[1].weights[VAR_LINEAR];
fx += w * tx;
fy += w * ty;
float w = genome.xf[1].weights[VAR_SINE];
...
```

```
float w = xf1_weights_linear;
fx += w * tx;
fy += w * ty;
float w = xf1_weights_sine;
...
```

Mission accomplished!

haha j/k

GPUs are vector machines

Divergent branch

This kills performance.

But...

We choose at runtime.

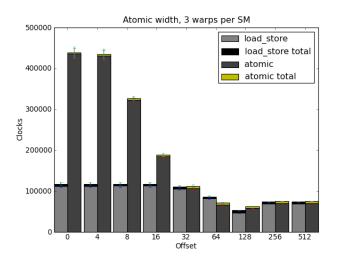
"I bet pervasive use of runtime code generation results in its own set of subtle problems."

Memory Management Unit

Thread block

Contiguous shared memory region

- Number of registers
- Grid dimensions
- Block dimensions
- Parameter sizes
- Shared memory size
- Local memory size
- Texture references



DynaTune™

(we're kidding about the name)





Compute platform





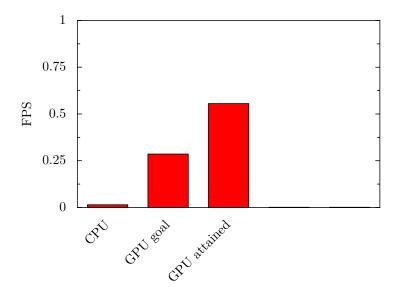
Not that different

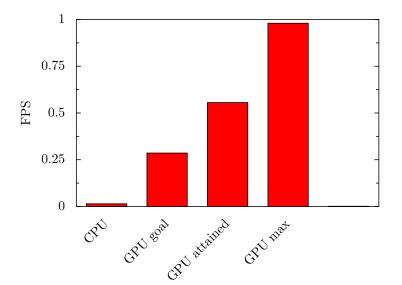
We're "done"!

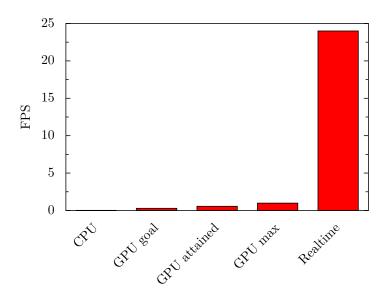
Task	Completeness
Research	100%
Planning	100%
Prototyping	100%
Discovering how wrong our plan was	100%
Performance optimizations	100% (of goal)
Feature parity	100%
Image quality testing	100%

- ▶ OpenCL support
- Multi-card rendering
- Sorted writeback
- Machine-learning tuner
- Parallel MWC research

Not done done







Item	Cost
AWS GPU instance (3 hours)	\$6.30

Item	Cost
AWS GPU instance (3 hours)	\$6.30
Matt's laptop (Lenovo ThinkPad W520)	\$1691.00
Mike's laptop (Alienware M17XR3)	\$1749.00
Steve's card (NVIDIA GTX 460 OC)	\$229.99



Matt Filtering, image enhancement, AA

Mike Colorspace, tonemapping, writeback

Nick RNG, malloc() emulation

Steve Prototype, language tools

Questions?