Adam Harries

CUDA, or how I stopped worrying and learned to love the GPU

Tuesday October 15th 2013

Overview

The talk

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- Coherent

History

First, some history

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- Dedicated cards for handling graphical rendering
- Generally 3d acceleration today, but started off with 2d acceleration
- Arguably first card: Intel iSBX 275 Video Graphics Controller Multimodule Board

Intel iSBX 275

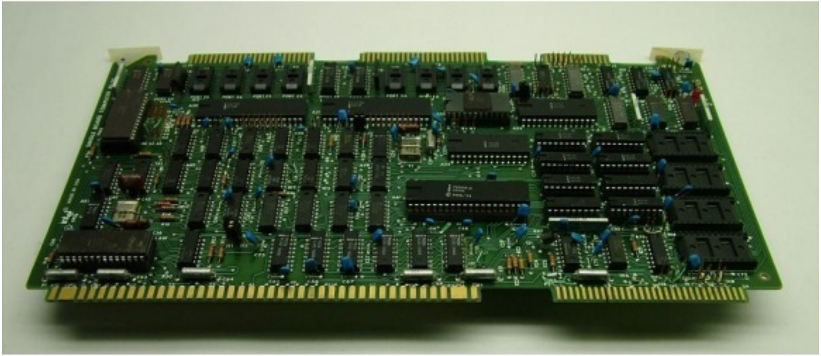

Figure : The Intel ISBX, because everyone loves dual in line packaging. . .

The arrival of 3d

Dedicated 3d graphics hardware speedup

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- Dedicated 3d graphics card
- needed to be piggybacked with a 2d card

Voodoo 1 card

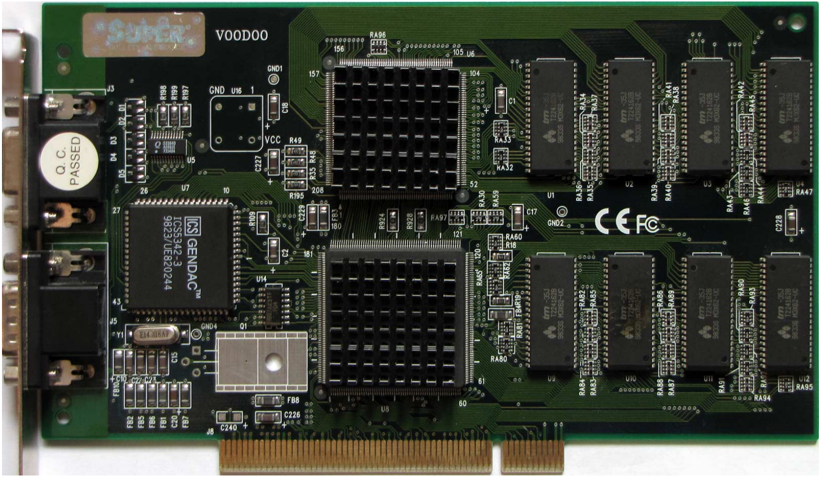

Figure : The 3dfx voodoo 1 card. Note the dual VGA ports, for piggybacking off a 2d card.

Programmable pipeline

The advent of programming on the graphics card

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- First graphics card with support: nVidia GeForce 3
- Only 12 years ago - in 2001

nVidia Geforce 3

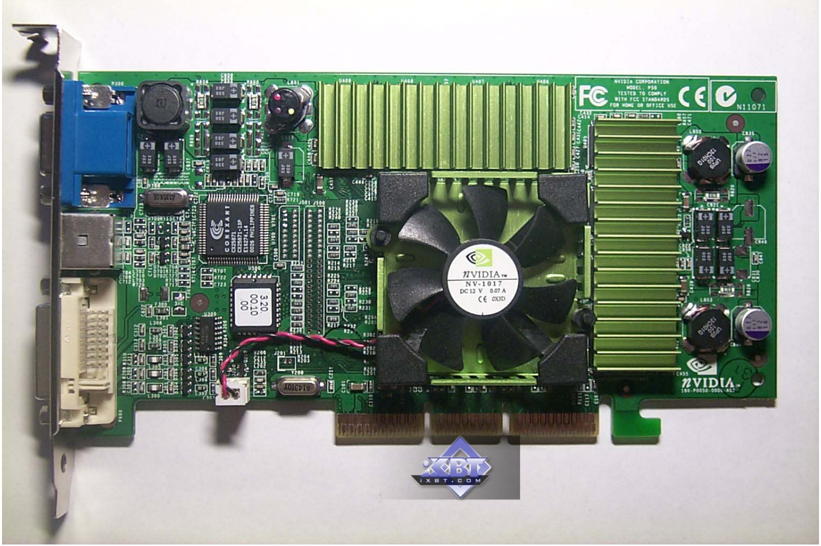

Figure : The first graphics card with a programmable pipeline

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- First supporting card: 8800GTX

8800GTX

CUDA: an overview

Kernels

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Example:

```
__global__ void double(int *a)
{
    const int id = threadIdx.x;
    a[id] = 2*a[id];
}
```

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```
__device__ int square(int x)
{
    return x*x;
}
__global__ void double_and_square(int *a)
{
    const int id = threadIdx.x;
    a[id] = 2*square(a[id]);
}
```

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- define a dimension for threads within blocks
- limitations depending on card being used
- use variables based on dimensions to tell kernel what ID it is

Some examples

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Visualising the interference of waves using a discrete grid of cells

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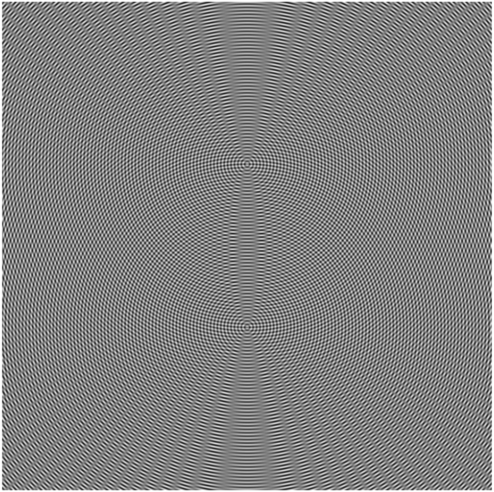
- nested for Loops over an array to calculate the value at each cell
- both versions (cuda and traditional) use the same formula to calculate the value at each cell, from each wave (sin of hypotenuse):

$$Wavevalue = \sin(\sqrt{(x - s_x)^2 + (y - s_y)^2})$$

The result



“Tradtional” loops version:

```
from numpy import *
import matplotlib.pyplot as plt
wav_array = zeros((300,300), dtype=float32)
pa = (300,450)
pb = (600,450)
for i in range(300):
    for j in range(300):
        adist = sin( sqrt( (i-pa[0])**2 + (j-pa[1])**2))
        bdist = sin( sqrt( (i-pb[0])**2 + (j-pb[1])**2))
        wav_array[i][j] = (adist+bdist)/2
plt.imshow(wav_array)
plt.clim(-1,1);
plt.set_cmap('gray')
plt.axis('off')
plt.show()
```

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  real 0m12.579s

  user 0m10.220s

  sys 0m0.070s

- still faster than the way recommended by the physics department

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- a little longer - but due to structuring, not difficulty
- comprised of two main parts: kernel code, and calling/structure (CPU) code
- all CPU code in Python
- kernel written in CUDA (somewhat like C)

The structure/CPU code

```
from numpy import *
import matplotlib.pyplot as plt
import pycuda.compiler as comp
import pycuda.driver as drv
import pycuda.autoinit
mod = comp.SourceModule("""
#kernel declaration, of "wave_kernel"
""")
wav_array = zeros((900,900), dtype=float32)
wav_array_gpu = drv.mem_alloc(wav_array.nbytes)
make_waves = mod.get_function("wave_kernel")
make_waves(wav_array_gpu,block=(30,30,1), grid=(30,30))
drv.memcpy_dtoh(wav_array, wav_array_gpu)
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They respectively:

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- interface with CUDA, and provide a host of useful abstractions
- initialise much of what CUDA does, including getting kernels ready to launch

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The kernel code

```
__global__ void wave_kernel(float *wa)
{
    const int j = threadIdx.y+(blockIdx.y*gridDim.y);
    const int i = threadIdx.x+(blockIdx.x*gridDim.x);
    const int lID = i+(j*blockDim.y*gridDim.y);
    float pa[] = {300,450};
    float pb[] = {600,450};
    float a,b;
    a = sqrt(((i-pa[0])*(i-pa[0]))+((j-pa[1])*(j-pa[1])));
    b = sqrt(((i-pb[0])*(i-pb[0]))+((j-pb[1])*(j-pb[1])));
    wa[lID] = (sin(a)+sin(b))/2;
}
```

Strolling through the kernel

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- Threads getting information about themselves
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- in this case, (i,j) is the cell, while lID is the element of the final array

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- note disparity between real and user/sys: very little CPU time, lots of GPU
- however, still faster than serial.

But still not faster than C

```c
#include <stdio.h>
#include <stdlib.h>
#include <math.h>
int main(int argc, char** argv){
 float *wav_array = malloc(sizeof(float)*900*900);
 float pa[] = {300,450};
 float pb[] = {600,450};
 int index = 0; float a,b;
 for(int i = 0;i<900;i++){
  for(int j = 0;j<900;j++){
   index = i+(j*900);
   a = sqrt(((i-pa[0])*(i-pa[0]))+((j-pa[1])*(j-pa[1])));
   b = sqrt(((i-pb[0])*(i-pb[0]))+((j-pb[1])*(j-pb[1])));
   wav_array[index] = (sin(a)+sin(b))/2;
  }
 }
 return 0;
}
```

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- what???
- not the fault of CUDA, more the fault of python and poor programming
- for larger problems, with more complex processing, we get a bigger speedup with CUDA

Rewrite the CUDA in C?

```
/*Same kernel definition */
int main(int argc, char** argv){
    float *wav_array = (float*)malloc(sizeof(float)*900*90
    float *gpu_wav_array;
    cudaMalloc(&gpu_wav_array, 900*900*sizeof(float));
    dim3 block_size;
    block_size.x = 30;
    block_size.y = 30;
    block_size.z = 1;
    dim3 grid_size;
    grid_size.x = 30;
    grid_size.y = 30;
    sin_dist<<<block_size, grid_size>>>(gpu_wav_array);
    cudaMemcpy(wav_array, gpu_wav_array, 900*900*sizeof(fl
        cudaMemcpyDeviceToHost);
    return 0;
}
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- however, faster than PyCUDA - so some speedup gaineds
- more importantly, we use the same CUDA code, so if we want to squeeze speed out, we can rewrite in C

Questions!

Any questions?