# INTRODUCTION TO GPU COMPUTING

Marwan Abdellah Blue Brain Project, EPFL

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# Agenda

- What (was, is) the GPU?
- Why GPU Computing?
- GPU Vs. CPU
  - Architectures
- GPU APIs
- CUDA Programming Model
- CUDA API Basics
- Vector Addition Example
- GPU (CUDA)-accelerated Libraries

#### **GPU** was

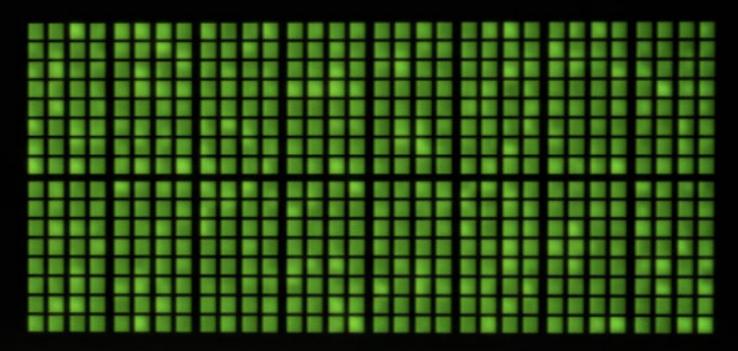
- It was a Graphics (ONLY) Processing Units
- A Processor added to the computer to accelerate graphics operations.
- It addresses the demands of real-time high-resolution 3D graphics compute-intensive tasks.





## Now, GPU is

- High performance co-processor linked to the CPU to solve complex computational data-parallel problems.
- Massively Parallel Floating-Point CoProcessors

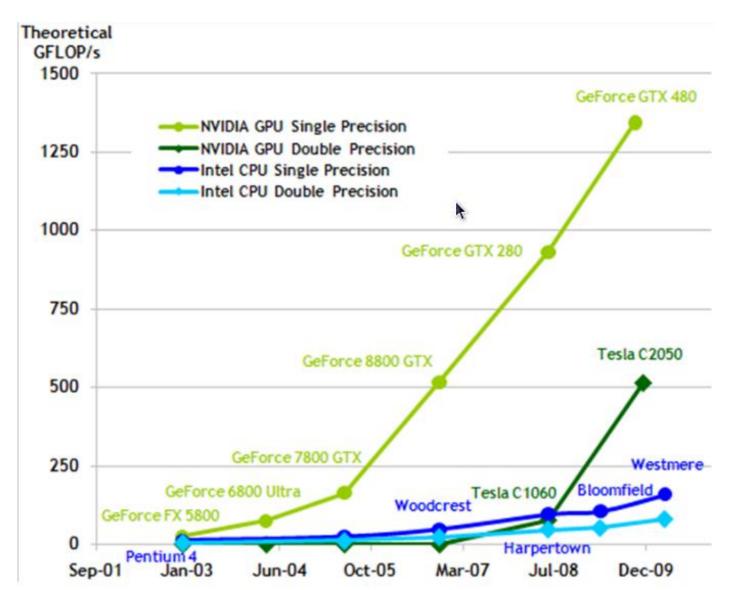


# Why GPU Computing?

- Inexpensive (Compared to a Multi-Core CPU)
- Idle (Unless you are playing Games !!!)
- Designed to well perform for handling floating point arithmetic.
- Outperform the CPU on a per-\$ basis.

	Intel Quad Core Xeon	NVIDIA GTX 257
FP Performance	68 GFlops	304 GFlops
Memory Bandwidth	19/GB/s	127 GB/sec
Cost	1500 \$	300+\$

## Performance: CPU Vs. GPU



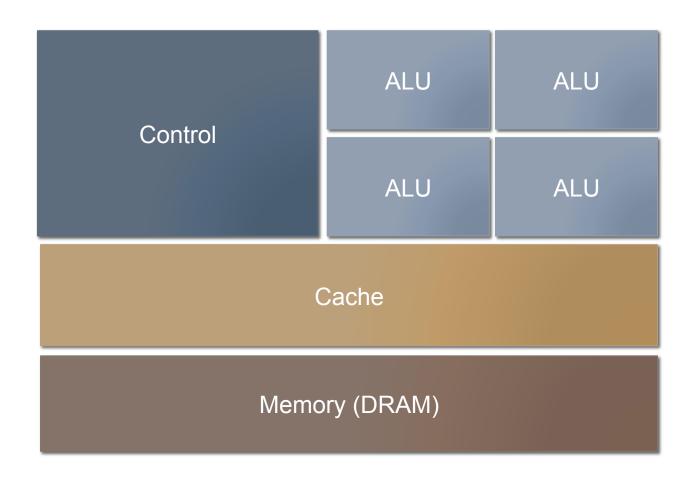
## Tesla Arch.



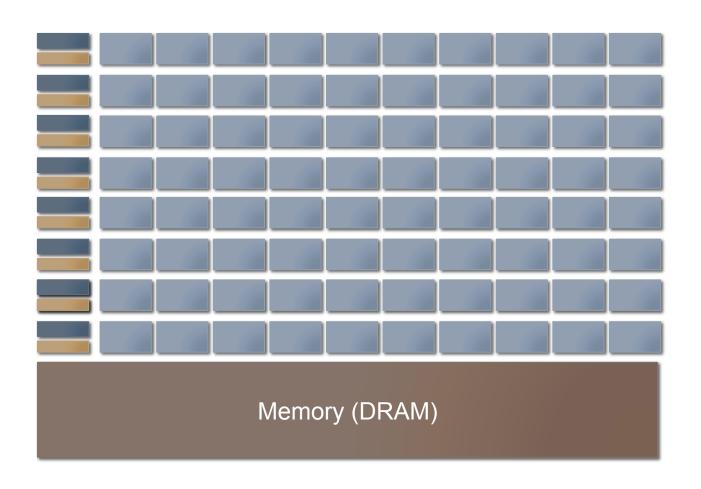




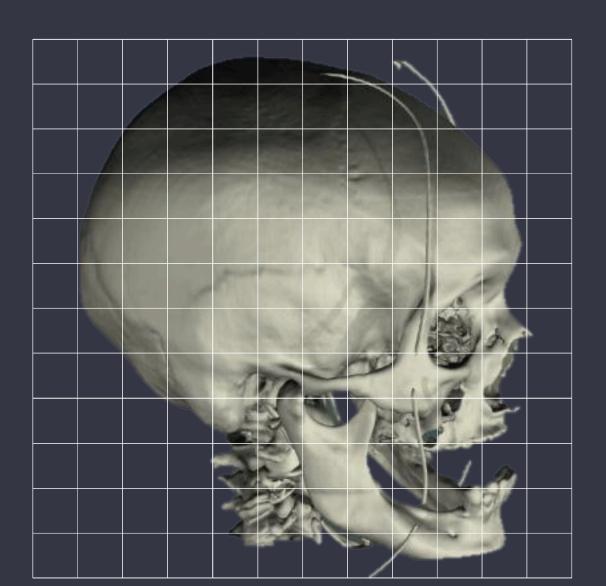
# Architectures (CPU)



# Architectures (GPU)



# Use Case: Image Correction

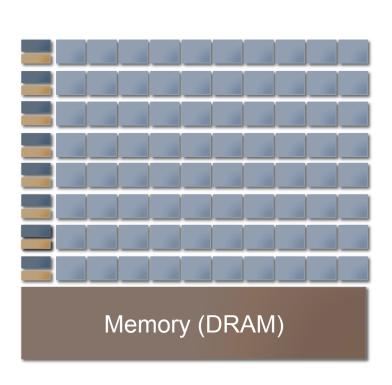


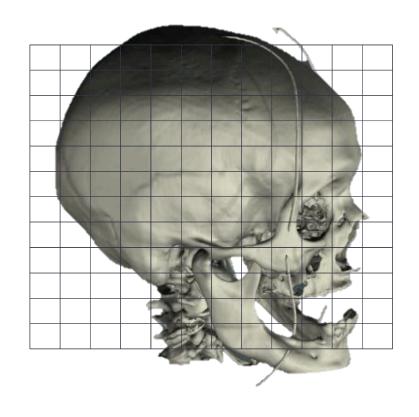
## **CPU-Approach**

This operation could be done in a C programming environment by a simple **for** Loop

```
for (int i = 0; i < numPixels; i++)
{
    pixel[i] += 10;
}</pre>
```

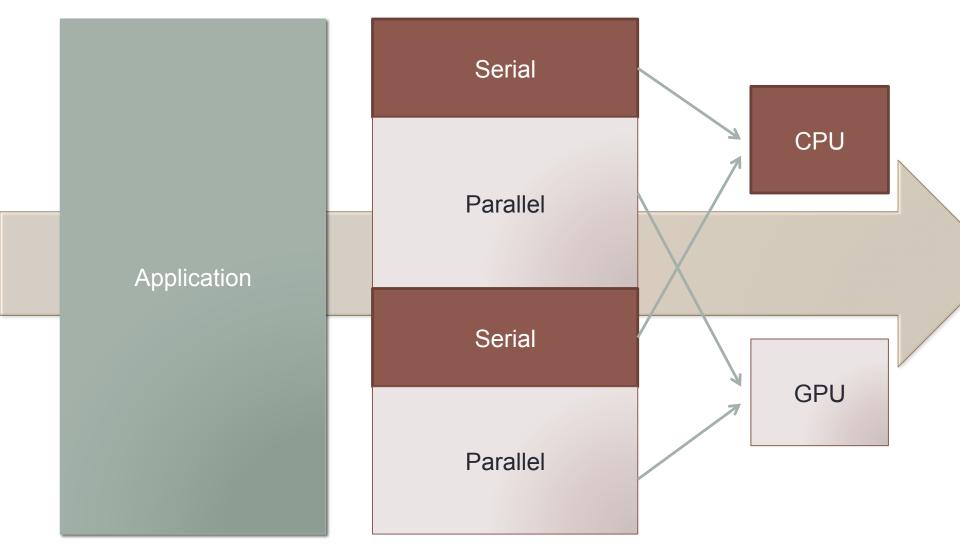
# **GPU-Approach**





# Quite Similar!

# To Make it Short (Application Flow)



### **GPU Evolution**

- Multi core design
- SIMD core optimized for floating point arithmetic
- Dozens of multi cores per card
- Early GPGPU Efforts
  - Fixed Function Pipelines (Graphics APIs)
    - (OpenGL or DirectX Mapping)
- Programmable Pipelines
  - Shader Mapping
    - GLSL
    - NVIDIA Cg
    - Microsoft HLSL
- GPU Programming APIs
  - Unleash your application

#### **APIs**

#### CUDA (Compute Unified Device Architecture)

- Released by NVIDIA
- Supported on all modern NVIDIA GPUs (notebook GPUs, high-end GPUs, mobile devices)
- OpenCL (Open Computing Language)
  - Released by Apple, and now under the maintenance of Khronous.
  - Open standard, targeting NVIDIA, AMD/ATI GPUs, Cell, multicore x86, ...





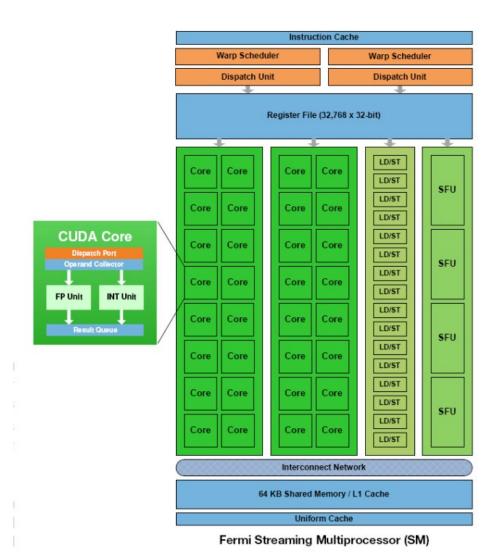
#### **CUDA**

- Parallel Computing Platform and programming model released by NVIDIA in 2004.
- Version 5.0 has been released in October 2012.
- The CUDA platform is accessible to software developers through
  - CUDA-accelerated libraries
  - Compiler directives
  - Extensions to industry-standard programming languages, including C, C++ and Fortran.
- CUDA provides both a low level API and a higher level API.
- Supported GPUs.

#### **CUDA**

- To Start writing Hello World (Vector Addition )on CUDA, we have to understand
  - GPU Architecture
  - Basic Terminology
  - CUDA Programming Model
  - CUDA Threading Hierarchy
  - CUDA Memory Model

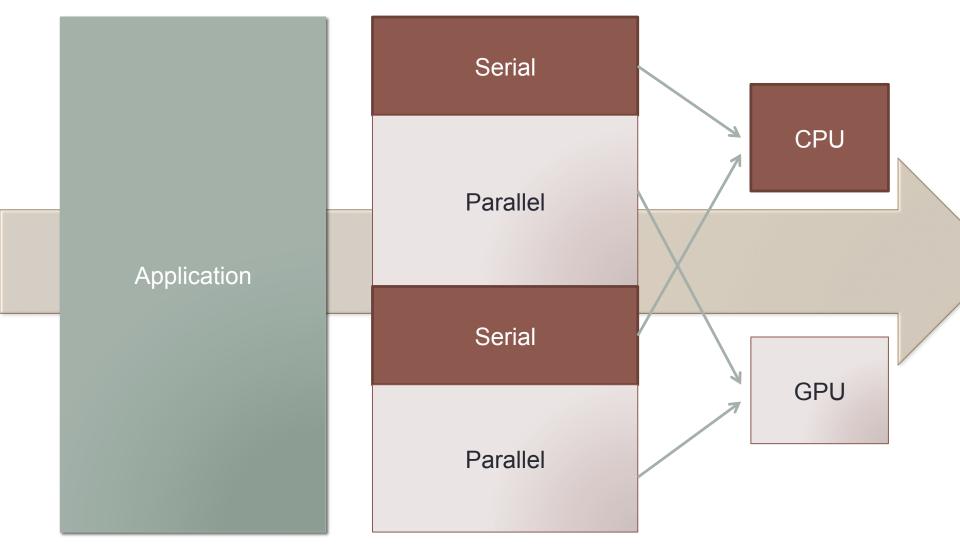
## **CUDA** Architecture



# **GPU Programming Model**

- GPU = Compute Device (Compute Capability)
- GPU can execute a portion of an application that
  - Has to be executed many times (as a for loop)
  - Can be isolated as a function
  - Works independently on different data
- This function is compiled to be executed on the device as a kernel.
- The kernel will be executed on the different data processing thousands of elements of the data in parallel.

# Programming Model (Recall)



# Programming Model

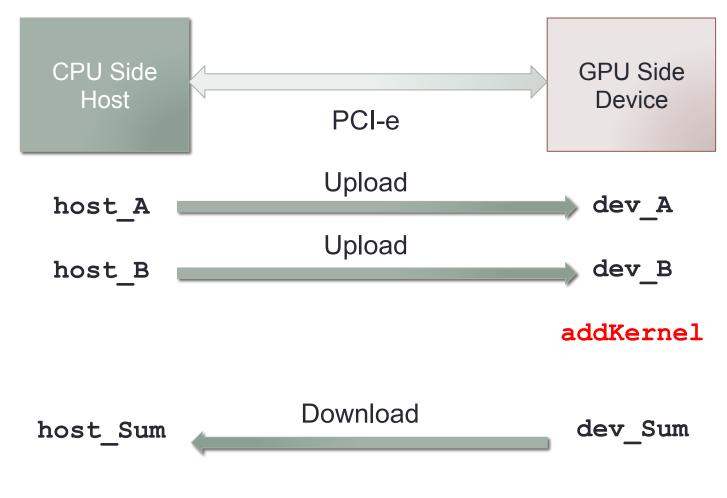
Assuming a perfect parallel problem (Vector Addition)

$$Sum = A + B$$

CPU Solution (for loop)

```
for (int i = 0; i < size(Sum); i++)
{
    Sum[i] = A[i] + B[i];
}</pre>
```

# **Programming Model**



## Sequence

- Allocate CPU arrays
- Pack them with Signals
- 3. Allocate GPU arrays
- Send (Upload) arrays to GPU
- Configure GPU
- Execute addition kernel
- 7. Send (Download) the Sum array

Main CPU Memory Copy processing data Instruct the processing Copy the result Memory for GPU Execute parallel GPU I in each core (GeForce 8800) Processing flow on CUDA

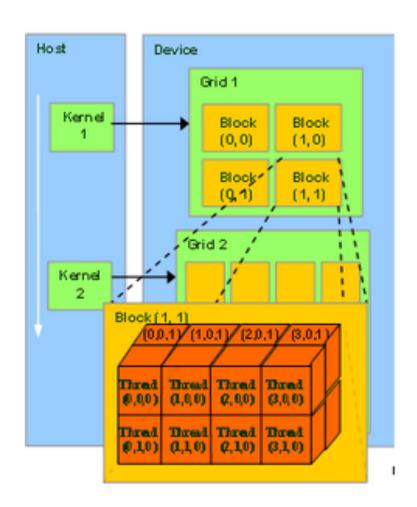
# Threading Hierarchy (Transparent)

- GPU Cores (Resources) are Configurable in
  - Grids
    - Blocks
      - Threads
- Kernel lunches a gird that contains several blocks where every block wraps a group of threads.
- This process is kernel-dependent and configurable for every kernel

# Threading Hierarchy (Transparent)

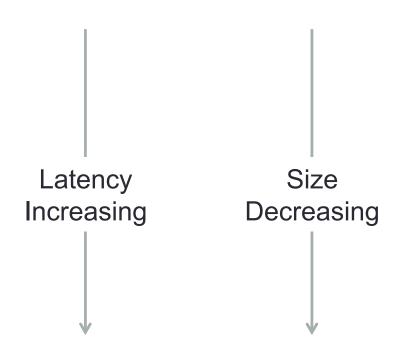
```
threadID 0 1 2 3 4 5 6 7

...
float x = input[threadID];
float y = func(x);
output[threadID] = y;
...
```

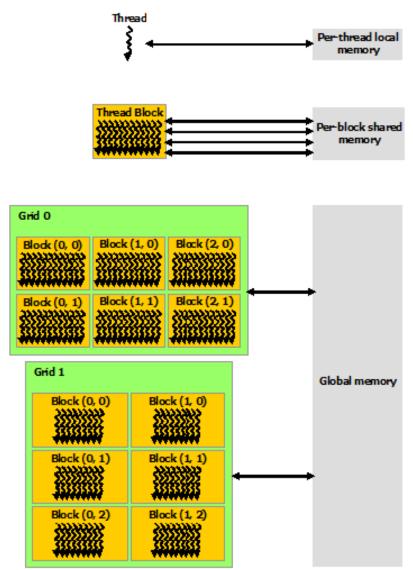


# Memory Model

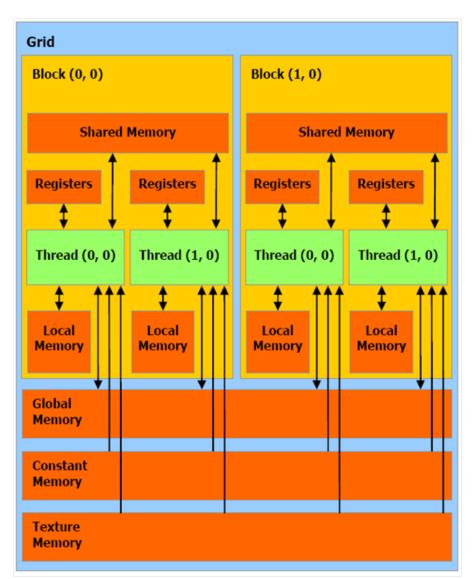
- Memory is divided into
  - Host Memory (CPU)
  - Device Memory (GPU)
    - Global Memory
    - Shared Memory
    - Texture Memory
    - Constant Memory
    - Local Memory
    - Register



# **Memory Model**



# Memory Model



#### **CUDA API Basics**

- Function Qualifiers
  - \_\_global\_\_\_
    - Executed on the device
    - Callable from the host only
  - \_\_device\_\_\_
    - Executed on the device
    - Callable from the device only
  - \_\_host\_\_\_
    - Executed on the host
    - Callable from the host only

#### **CUDA API Basics**

- Execution Configuration or Grid Configuration
  - Must be specified for any call to a \_\_global \_\_function.
  - Defines the dimension of the grid and blocks.
    - grid\_Dim = dim3()
    - block\_Dim = dim3()
  - The function

Device Kernel Function addKernel

```
// Addition kernel that executes on the devices
_alobal__void addKernel(float *A, float *B, float* Sum)
{
    // Calculate array index from the built-in variables
    int idx = blockIdx.x * blockDim.x + threadIdx.x;

    // Execute the addition operation
    Sum[idx] = A[idx] + B[idx];
}
```

Main Function – Memory Allocation

```
// Number of elements in arrays
const int N = 10000;
// Pointer to host & device arrays
float *host_A, *host_B, host_Sum;
float *dev_A, *dev_B, dev_Sum;
// Array size in bytes
size_t sizeBytes = N * sizeof(float);
// Host allocation
hotst_A = (float *) malloc(sizeBytes);
hotst_B = (float *) malloc(sizeBytes);
hotst_Sum = (float *) malloc(sizeBytes);
// Device allocation
cudaMalloc((void **) &dev_A, sizeBytes);
cudaMalloc((void **) &dev_B, sizeBytes);
cudaMalloc((void **) &dev_Sum, sizeBytes);
```

Main Function – Memory Upload

```
// Upload the arrays to the device
cudaMemcpy(dev_A, host_A, sizeBytes, cudaMemcpyHostToDevice);
cudaMemcpy(dev_B, host_B, sizeBytes, cudaMemcpyHostToDevice);
```

Main Function – Kernel Configuration & Execution

```
// Grid Configuration
int blockSize = 4;
int numBlocks = N/block_size + (N % block_size == 0 ? 0:1);

// Execute kernel on the device
addKernel <<< numBlocks, blockSize >>> (dev_A, dev_B, dev_Sum);
```

Main Function – Download Results and Printing …

```
// Download the result to the CPU
cudaMemcpy(a_h, a_d, sizeof(float)*N, cudaMemcpyDeviceToHost);
// Print results
for (int i=0; i<N; i++)
    printf("%d %f\n", i, host_Sum[i]);</pre>
```

Main Function – Cleaning & Freeing Memory

```
// Cleanup and release memory on host side
free(host_A);
free(host_B);
free(host_Sum);

// Release device memory
cudaFree(dev_A);
cudaFree(dev_B);
cudaFree(dev_Sum);
```

#### **GPU Accelerated Libraries**

- cuFFT (10X)
  - MATLAB (fft, fft2, fft3), FFTW, FFTW++
- cuBLAS (6X ~ 17X)
  - Standard BLAS
- cuSPARSE (8X)
  - Collection of basic linear algebra subroutines for sparse matrices
- cuRAND
- AccelErEyes ArrayFire
  - Image processing and signal processing
- NPP (NVIDIA PEFROAMNCE PRIMITIVES)
- Thrust
- cuYURI (To be released)

## Take Home Message

• If you have a code that contains a core **for** loop, then it is time to learn

# **How To Drive a GPU**

# Thanks for Paying Attention