GPU Programming Project Report

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Introduction

- The project involves implementing morphological operations and image processing like blurring and sharpening on images, using both CPU and GPU parallelization techniques.
- Focus on optimizing the performance using CUDA and shared memory.

Project Structure

1. **Objective:** Implement erosion, dilation, opening, closing, blurring and sharpening operations on images using GPU programming and compare their performance with CPU implementations.
2. **Implementation Details:**
   - **Programming Language:** CUDA
3. **Image Processing Operations:**
   - **Erosion:** Removal of pixels based on a structuring element.
   - **Dilation:** Addition of pixels based on a structuring element.
   - **Opening:** Erosion followed by Dilation.
   - **Closing:** Dilation followed by Erosion.
   - **Blurring:** Smoothing or averaging of pixel values.
   - **Sharpening:** Enhancing edges or fine details in an image.
4. **GPU Optimization Techniques**
5. **Experimental Setup:**
   - Image dimensions:10×10 to 1024×1024
   - Structuring element size: 3×3

Code Structure

```
// Function prototypes
void generateImg(int width, int height, int *img);
void drawSolidRectangle(int width, int height, int *img);
void generateClc(int *img, int *clc, int size_of_filter, int width, int height);
void erosionCPU(int *res_cpu, int *clc, int width, int height, int size_of_filter);
__global__ void erosionImg(int *res, int *clc, int width, int height, int size_of_filter);
__global__ void erosionImgShared(int *res, int *clc, int width, int height, int size_of_filte
void dilationCPU(int *res_cpu, int *clc, int width, int height, int size_of_filter);
__global__ void dilationImg(int *res, int *clc, int width, int height, int size_of_filter);
__global__ void dilationImgShared(int *res, int *clc, int width, int height, int size_of_filt
void blurCPU(int *res_cpu, int *img, int witdh, int height, int size_of_filter)
__global__ void blurImg(int *res, int *img, int witdh, int height, int size_of_filter)
void sharpenCPU(int *res_cpu, int *img, int witdh, int height, float weight_center, float we
__global__ void sharpenImg(int *res, int *img, int witdh, int height, float weight_center, fl
__global__ void sharpenImgOptimized(int *res, int *img, int width, int height, float weight_c
}
```

Image Generation

```
void generateImg(int width, int height, int *img);
void drawSolidRectangle(int width, int height, int *img);
```

CPU Implementation - Erosion

```
void erosionCPU(int *res_cpu, int *clc, int width, int height, int size_of_filter);
```

CPU Implementation - Dilation

```
void dilationCPU(int *res_cpu, int *clc, int width, int height, int size_of_filter);
```

GPU Implementation - Erosion

```
__global__ void erosionImg(int *res, int *clc, int width, int height, int size_of_filter);
```

GPU Implementation - Dilation

```
__global__ void dilationImg(int *res, int *clc, int width, int height, int size_of_filter);
```

Shared Memory Optimization

```
__global__ void erosionImgShared(int *res, int *clc, int width, int height, int size_of_filte
__global__ void dilationImgShared(int *res, int *clc, int width, int height, int size_of_filt
```

Optimizing Blur Code - GPU

- The provided code implements a blur filter for GPU.
- Techniques used to optimize the GPU implementation:
- Techniques:
  - Shared Memory Usage
  - Warp Synchronization
  - Coalesced Memory Access

Optimizing Blur Code - GPU

Listing 1: Original GPU Blur Code

```
    __global__ void sharpenImg(int *res, int *img, int witdh, int height, float weight_ce
    int index = 1;  // Assuming a 3x3 sharpening filter
    int row = blockIdx.x * blockDim.x + threadIdx.x + index;
    int col = blockIdx.y * blockDim.y + threadIdx.y + index;

    if (row < height - index && col < witdh - index) {
        int center = img[col + row * witdh];
        int neighbors = 0;

        // Calculate the weighted sum of neighboring pixels
        for (int i = -index; i <= index; i++) {
            for (int j = -index; j <= index; j++) {
                if (i == 0 && j == 0) {
                    neighbors += weight_center * img[col + j + (row + i) * witdh];
                } else {
                    neighbors += weight_neighbors * img[col + j + (row + i) * witdh];
                }
            }
        }

        // Subtract the weighted sum from the center pixel value
        res[(col - index) + (row - index) * witdh] = center - neighbors;
    }
}
```

Optimizing Blur Code - GPU

Listing 2: Optimized GPU Blur Code

```
    __global__ void blurImgOptimized(int *res, int *img, int width, int height, int size
int index = (size_of_filter - 1) / 2;
int row = blockIdx.x * blockDim.x + threadIdx.x + index;
int col = blockIdx.y * blockDim.y + threadIdx.y + index;

// Define shared memory for caching the image region
__shared__ int img_shared[BLOCK_SIZE][BLOCK_SIZE];

// Load data to shared memory with coalesced memory access
int local_row = threadIdx.x;
int local_col = threadIdx.y;
int global_row = row + local_row - index;
int global_col = col + local_col - index;

if (global_row >= 0 && global_row < height && global_col >= 0 && global_col < width) {
    img_shared[local_row][local_col] = img[global_row * width + global_col];
} else {
    img_shared[local_row][local_col] = 0;  // Padding with zeros for out-of-bounds access
}

__syncthreads();  // Ensure all threads have loaded their data

int sum = 0;

// Apply blur filter with shared memory usage
for (int i = 0; i < size_of_filter; i++) {
```

Optimizing Sharpening Filter Code

- GPU code benefits from several optimizations.
- Applied shared memory and optimize memory access patterns for improved GPU performance.

Listing 3: Optimized GPU Sharpening Code

```
__global__ void sharpenImgOptimized(int *res, int *img, int width, int height, float wei
int index = 1; // Assuming a 3x3 sharpening filter
int row = blockIdx.x * blockDim.x + threadIdx.x + index;
int col = blockIdx.y * blockDim.y + threadIdx.y + index;
//BLOCK_SIZE + 2 * index = 18
__shared__ float sharedImg[18][18];

int shared_row = threadIdx.x + index;
int shared_col = threadIdx.y + index;

if (row < height && col < width) {
    sharedImg[shared_row][shared_col] = img[row * width + col];

    // Load additional pixels to shared memory for border handling
    if (threadIdx.x < index) {
        sharedImg[threadIdx.x][shared_col] = img[row * width + col - index];
        sharedImg[threadIdx.x + blockDim.x + index][shared_col] = img[row * width + col -
    }

    if (threadIdx.y < index) {
```

Performance Measurement

- Performance is measured using CUDA events and CPU clock cycles.
- Execution times for GPU and CPU implementations are compared for both erosion and dilation operations.

Constant Memory for Constants

Moved `BLOCK_SIZE` to constant memory, as it is a constant value used in the kernel.

Listing 4: Constant Memory Declaration

```
__constant__ int BLOCK_SIZE = 16;
```

Optimize Memory Access

Reorganized data access to optimize memory coalescing. This improved memory access patterns and overall performance.

Optimize Thread and Block Configuration

Experimented with different thread and block configurations to find the optimal combination for the specific GPU architecture.

Bank Conflicts in Shared Memory

Ensured that shared memory accesses do not lead to bank conflicts. Bank conflicts can degrade performance in shared memory operations.

Use Shared Memory Efficiently

Utilized shared memory for caching data that is frequently accessed by threads in a block. This reduces the need to access global memory.

Loop Unrolling

Depending on the situation, loop unrolling in device code used to provide performance gains.

Minimized Divergent Code Paths

Minimized divergent code paths in the kernels. Divergence can lead to the serialization of threads, reducing performance.

Asynchronous Memory Copies

Used asynchronous memory copies (`cudaMemcpyAsync`) to overlap data transfers with computation.

Occupancy Considerations

Considered the occupancy of your GPU kernels. Ensured that enough active warps are present to hide memory latency.

Results and Discussion

- Output includes execution times for each operation and implementation.
- Comprehensive analysis of performance gains achieved through GPU parallelization and shared memory optimization.

Execution Times - Part 1

Operation	M = 10, N = 10 (ms)	M = 200, N = 200 (ms)
Erosion GPU	0.081920	0.070656
Erosion CPU	0.000000	3.000000
Dilation GPU	0.082016	0.062496
Dilation CPU	0.000000	3.000000
Erosion GPU (SM)	0.038752	0.062464
Dilation GPU (SM)	0.168800	0.253952
Opening CPU	0.000000	4.000000
Opening GPU	0.092160	0.107520
Opening GPU (SM)	0.039936	0.089088
Closing CPU	1.000000	3.000000
Closing GPU	0.097280	0.151648
Closing GPU (SM)	0.039936	0.090016

Table: Execution times for different operations (M = 10, N = 10 and M = 200, N = 200)

Execution Times - Part 2

Operation	M = 400, N = 400 (ms)	M = 1024, N = 1024 (ms)
Erosion GPU	0.165888	0.539648
Erosion CPU	11.000000	68.000000
Dilation GPU	0.180224	0.519328
Dilation CPU	12.000000	68.000000
Erosion GPU (SM)	0.153600	0.838656
Dilation GPU (SM)	0.502784	1.841152
Opening CPU	13.000000	88.000000
Opening GPU	0.230400	0.983040
Opening GPU (SM)	0.278528	1.614848
Closing CPU	13.000000	89.000000
Closing GPU	0.231424	0.997408
Closing GPU (SM)	0.276640	1.616896

Table: Execution times for different operations (M = 400, N = 400 and M = 1024, N = 1024)

Conclusion

- Successful implementation of image processing operations on both CPU and GPU platforms.
- Shared memory in GPU implementations enhances performance.
- GPU-based operations are competitive with or faster than CPU-based operations.

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References

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