

PC-2019/20 Course Project: 2D Pattern Recognition, CUDA and OpenMP implementations

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Outline

Introduction

- Algorithm

- Time complexity analysis

Parallel implementations

- OpenMP

- CUDA

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- OpenMP results

- CUDA results

- OpenMP and CUDA results comparison

Conclusions

Preview

- ▶ The Pattern Recognition technique consists in individuating a specific query in a data target
- ▶ We focus on 2D Pattern Recognition, our data are matrices (e.g. images)
- ▶ We have to define a matching metric, i.e. a measure that shows the similarity (closeness) between queries and targets.

$$SAD(T, Q, i, j) = \sum_{k=0}^r \sum_{l=0}^c |T_{i+k, j+l} - Q_{k,l}| \quad (1)$$

Algorithm

1	2	1	3
2	1	2	4
0	1	2	3

Target Matrix

0	3
2	1

Query Matrix

1	2	1	3
2	1	2	4
0	1	2	3

compute SAD[1][1]

1	2	1	3
2	1	2	4
0	1	2	3

compute SAD[1][2]

1	2	1	3
2	1	2	4
0	1	2	3

compute SAD[1][3]

1	2	1	3
2	1	2	4
0	1	2	3

compute SAD[2][1]

1	2	1	3
2	1	2	4
0	1	2	3

compute SAD[2][2]

1	2	1	3
2	1	2	4
0	1	2	3

compute SAD[2][3]

2	6	4
6	4	5

SADMatrix



Algorithm

Algorithm 1: computeSAD

Data: queryMatrix Q,
 targetMatrix T,
 startRowIndex i,
 startColIndex j

Result: localSadValue

```

1 localSadValue = 0
2 for from  $k = 0$  to  $Q.rows$  do
3   for from  $l = 0$  to  $Q.cols$  do
4     targetV =  $T[i+k][j+l]$ 
5     queryV =  $Q[k][l]$ 
6     localSadValue +=
      | targetV - queryV |
7 return localSadValue
  
```

Algorithm 2: PatternRecognition

Data: queryMatrix Q,
 targetMatrix T

Result: SADMatrix S

```

1 Define SADMatrix S
2  $S.rows = T.rows - Q.rows + 1$ 
3  $S.cols = T.cols - Q.cols + 1$ 
4 for from  $i = 0$  to  $S.rows$  do
5   for from  $j = 0$  to  $S.cols$  do
6      $S[i][j] =$ 
      | computeSAD(P,Q,i,j)
7  $cx, cy = \text{argmin}(S)$ 
  
```

Time Complexity

- ▶ Our algorithm has 4 nested loops: 2 in the outer cycle (*Algorithm2*) and 2 in the computation of each SAD matrix value (*Algorithm1*).

Time complexity in sequential implementation is

$$(T_r - Q_r + 1) * (T_c - Q_c + 1) * (Q_r * Q_c) \quad (2)$$

- ▶ **Algorithm 2** is embarrassingly parallel, so if we use a number of threads equal to **Nt**, in an ideal situation the complexity of this parallel algorithm becomes:

$$\frac{(T_r - Q_r + 1) * (T_c - Q_c + 1)}{N_t} * (Q_r * Q_c) \quad (3)$$

OpenMP

Algorithm 2: PatternRecognition

Data: queryMatrix Q,
targetMatrix T

Result: SADMatrix S

```

1 Define SADMatrix S
2 S.rows = T.rows - Q.rows + 1
3 S.cols = T.cols - Q.cols + 1
4 for from i = 0 to S.rows do
5   |   for from j = 0 to S.cols do
6   |   |   S[i][j] =
6   |   |   |   computeSAD(P,Q,i,j)
7 cx, cy = argmin(S)

```

Algorithm 3: PatternRecognition *OpenMP version*

Data: queryMatrix Q, targetMatrix
T, numThread Nt

Result: SADMatrix S

```

1 Define SADMatrix S
2 S.rows = T.rows - Q.rows + 1
3 S.cols = T.cols - Q.cols + 1
4 #pragma omp parallel for
4   |   num_threads(Nt) collapse(2)
4   |   schedule(static)
5 for from i = 0 to S.rows do
6   |   for from j = 0 to S.cols do
7   |   |   S[i][j] =
7   |   |   |   computeSAD(P,Q,i,j)
8 cx, cy = argmin(S)

```

OpenMP

Algorithm 2: PatternRecognition

Data: queryMatrix Q,

targetMatrix T

Result: SADMatrix S

```

1 Define SADMatrix S
2 S.rows = T.rows - Q.rows + 1
3 S.cols = T.cols - Q.cols + 1
4 for from i = 0 to S.rows do
5   |   for from j = 0 to S.cols do
6   |   |   S[i][j] =
7   |   |   computeSAD(P,Q,i,j)
8 cx, cy = argmin(S)

```

Algorithm 3: PatternRecognition *OpenMP version*

Data: queryMatrix Q, targetMatrix
T, numThread Nt

Result: SADMatrix S

```

1 Define SADMatrix S
2 S.rows = T.rows - Q.rows + 1
3 S.cols = T.cols - Q.cols + 1
4 #pragma omp parallel for
5   num_threads(Nt) collapse(2)
6   schedule(static)
7 for from i = 0 to S.rows do
8   |   for from j = 0 to S.cols do
9   |   |   S[i][j] =
10  |   |   computeSAD(P,Q,i,j)
11 cx, cy = argmin(S)

```

CUDA

Algorithm 4: Kernel Launch

Data: queryMatrix Q,
targetMatrix T,
SADMatrix S,
TILE_WIDTH

```

1 DimGrid(
    ceil(S.rows / TILE_WIDTH),
    ceil(s.cols / TILE_WIDTH));
2 dimBlock(TILE_WIDTH,
    TILE_WIDTH)
3 PatternRecognitionKernel
  <<<dimGrid, dimBlock>>>(Q,T,S)
  
```

Algorithm 5: PatternRecognitionKernel

Data: queryMatrix Q, targetMatrix T,
SADMatrix S

```

1 bx = blockIdx.x
2 by = blockIdx.y
3 tx = threadIdx.x
4 ty = threadIdx.y
5 col = bx * blockDim.x + tx
6 row = by * blockDim.y + ty
7 if row < S.rows and col < S.cols then
8     for from i = 0 to Q.rows do
9         for from j = 0 to Q.cols do
10             tV = T[i+row][j+col]
11             qV = Q[i][j]
12             localSadValue +=
                | tV - qV |
13             S[row][col] = localSadValue
  
```

CUDA points of interest

- ▶ In **Algorithm 5** we can notice that the access to the target matrix is coalesced, in fact $T[i+row][j+col]$ is of the form $T[(\text{expression with terms independent of } tx) + tx]$
- ▶ Target Matrix and Query Matrix are not modified, so we can mark them as **const** and **restrict**, this way the compiler is sure that both matrices are read-only data and can use a cache designed for this type of data, available for devices with compute capability greater than 3.5.
- ▶ Tiling is useless due to the low reuse of same values within the same block

Equipment, metrics and profiling

- ▶ The tests have been conducted on an Ubuntu 18.04 LTS machine equipped with:
 - ▶ Intel Core i7-4790 3.6GHz with Turbo Boost up to 4Ghz, 4 core/8 thread processor
 - ▶ RAM 16 GB DDR4
 - ▶ NVidia GeForce 750 2GB compute-capability 5.0 (running on CUDA 10.1)
- ▶ The metrics used are execution time and SpeedUp S_P , which is calculated as

$$S_P = \frac{t_s}{t_p}$$

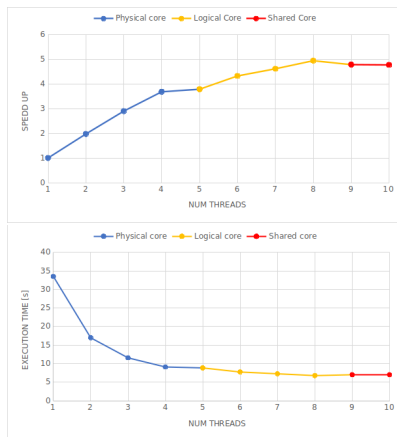
- ▶ The high precision C++11 library *chrono* has been used for measuring the execution time.

Tests

- ▶ Each time has been measured running each test 5 times and taking the average as a result
- ▶ We have conducted experiments on three different combinations of query matrix and target matrix size:
 - ▶ **Test1:** target matrix with dimension 1500×1500 and query matrix with dimension 150×150
 - ▶ **Test2:** target matrix with dimension 2000×2000 and query matrix with dimension 200×200
 - ▶ **Test3:** target matrix with dimension 2500×2500 and query matrix with dimension 250×250

OpenMP Test1

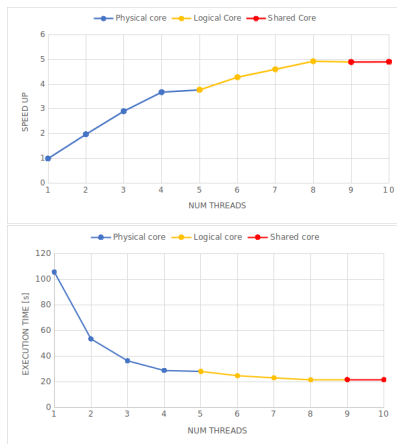
Test1: target matrix with dimension 1500×1500 and query matrix with dimension 150×150



OpenMP Test1		
Num threads	Execution time	SpeedUp
1	33,52s	1,00x
2	16,98s	1,97x
3	11,57s	2,90x
4	9,11s	3,68x
5	8,86s	3,78x
6	7,76s	4,32x
7	7,27s	4,61x
8	6,79s	4,94x
9	7,01s	4,78x
10	7,03s	4,77x

OpenMP Test2

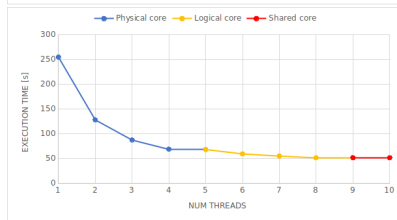
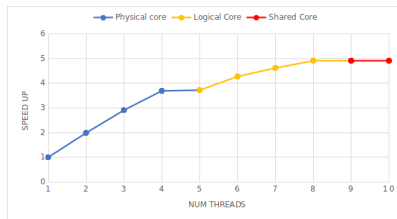
Test2: target matrix with dimension 2000×2000 and query matrix with dimension 200×200



OpenMP Test2		
Num threads	Execution time	SpeedUp
1	105,68s	1,00x
2	53,47s	1,98x
3	36,34s	2,91x
4	28,76s	3,67x
5	28,04s	3,77x
6	24,70s	4,28x
7	22,99s	4,60x
8	21,47s	4,92x
9	21,61s	4,89x
10	21,59s	4,90x

OpenMP Test3

Test3: target matrix with dimension 2500×2500 and query matrix with dimension 250×250



OpenMP Test3		
Num threads	Execution time	SpeedUp
1	254,50s	1,00x
2	128,09s	1,99x
3	87,53s	2,91x
4	69,01s	3,69x
5	68,40s	3,72x
6	59,60s	4,27x
7	55,16s	4,61x
8	51,80s	4,91x
9	51,85s	4,91x
10	51,88s	4,91x

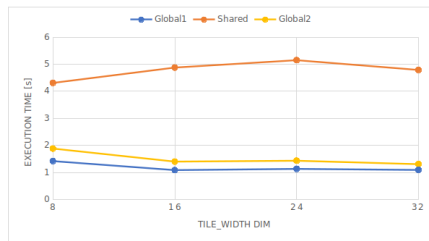
CUDA results

In the following slides the results of our CUDA implementations are shown, in each test we have used four TILE_WIDTH dimensions and three different implementations:

- ▶ The implementation which uses global memory and the optimization for pointer aliasing (blue line in the graph with the name **Global1**)
- ▶ The implementation which uses global memory but does not use the optimization for pointer aliasing (yellow line in the graph with the name **Global2**)
- ▶ The implementation which uses shared memory (orange line in the graph with the name of **Shared**)

CUDA Test1

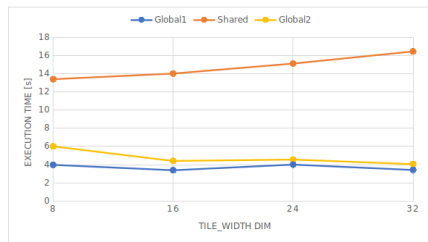
Test1: target matrix with dimension 1500×1500 and query matrix with dimension 150×150



CUDA Test1			
TILE_WIDTH	Global1	Shared	Global2
8	1,42s	4,31s	1,88s
16	1,08s	4,88s	1,40s
24	1,13s	5,15s	1,43s
32	1,10s	4,79s	1,31s

CUDA Test2

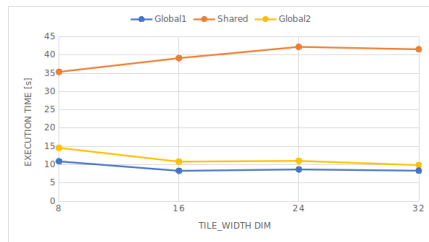
Test2: target matrix with dimension 2000×2000 and query matrix with dimension 200×200



CUDA Test2			
TILE.WIDTH	Global1	Shared	Global2
8	3,97s	13,40s	6,01s
16	3,39s	14,02s	4,41s
24	4,00s	15,12s	4,56s
32	3,42s	16,45s	4,05s

CUDA Test3

Test3: target matrix with dimension 2500×2500 and query matrix with dimension 250×250



CUDA Test3			
TILE_WIDTH	Global1	Shared	Global2
8	10,90s	35,40s	14,59s
16	8,31s	39,15s	10,82s
24	8,69s	42,23s	11,03s
32	8,34s	41,56s	9,86s

- └ Experimental results
 - └ OpenMP and CUDA results comparison

OpenMP and CUDA results comparison

- ▶ Both CUDA and OpenMP experiments use the same matrices, so the comparison between implementations is fair
- ▶ For each test has been taken the best time achieved with each different implementation.

	<i>Sequential time</i>	<i>OpenMP time</i>	<i>OpenMP speedUp</i>	<i>CUDA time</i>	<i>CUDA SpeedUP</i>
Test1	33,52s	6,79s	4,94x	1,09s	30,75x
Test2	105,68s	21,47s	4,92x	3,39s	31,17x
Test3	254,50s	51,80s	4,91x	8,31s	30,62x

Conclusions

- ▶ 2D Pattern Recognition algorithm achieves a powerful boost if executed in a parallel implementation
- ▶ In our tests OpenMP implementations reach a **5x** SpeedUP and the GPU version based on CUDA reach a **31x** SpeedUP
- ▶ In embarrassingly parallel algorithm the use of GPUs outperforms the traditional CPU processing