

Pattern Recognition with C++ OpenMP and CUDA

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Parallel Computing, April 2020

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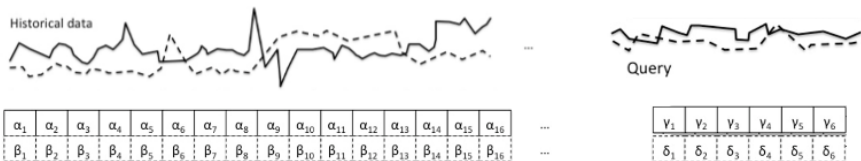
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Introduction

SAD and Pattern Recognition

Pattern Recognition

- Search some Queries inside Historical data
- The goal is to find the data subset which matches query
- Difficult to find the exact subset



Parallel Pattern Recognition

- Sum of absolute differences (SAD)
 - Similarity measure between data subsets
 - Calculated by the absolute difference between each subset values
 - Find the *nearest* data subset
- SAD computation for Patter Recognition can be parallelized, since

$$R_q[i] = \sum_{j=0}^{\text{len}(q)} |D[i+j] - q[j]|$$

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Parallel solutions

- CUDA
- OpenMP

Sequential

Sequential approach

Algorithm 1 Pattern Recognition

- 1: Generate the Historical Data
 - 2: Generate all the Queries
 - 3: Create a vector R with length equal to Queries number
 - 4: **for** query q in Queries **do**
 - 5: Create a vector R_q with length $\text{len}(\text{Data}) - \text{len}(q) + 1$
 - 6: Compute $R_q[i] = \sum_{j=0}^{\text{len}(q)} |D[i+j] - q[j]|$
 - 7: $R[q] = \arg \min R_q$
 - 8: **end for**
 - 9: return R
-

Sequential approach

- Analyze all queries
- Scrolls across the Historical Data
- Has to find min SAD value for each query
- Total computation time $\Rightarrow O(nrq) + O(nr)$

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Problems

- very long Historical Data
- a lot of queries

OpenMP

OpenMP approach

- Use OpenMP library to leverage the CPU multi-threads computation
- Use OpenMP *for* loop, *critical* section, *parallel* section

Parallelism levels

- Parallelism on Queries
- Parallelism on Historical Data

Parallelism on queries

- Is the higher parallelism level in Pattern Recognition
- Each thread computes one query through a OpenMP *for* loop
- Each thread analyzes its query like in the Sequential approach
- Each thread computes the min SAD value for the query

Parallelism on data

- Use *parallel* section to analyze Historical Data in parallel
- Each thread computes SAD values w.r.t. the same Query
- Threads wait the other threads termination through implicit *barrier*

Different approaches

- Privatization method
- Lock method

Parallelism on data

Privatization method

- Private variables for each thread
- Thread stores min SAD privately
- Each result vector (R_q) length depends on threads number

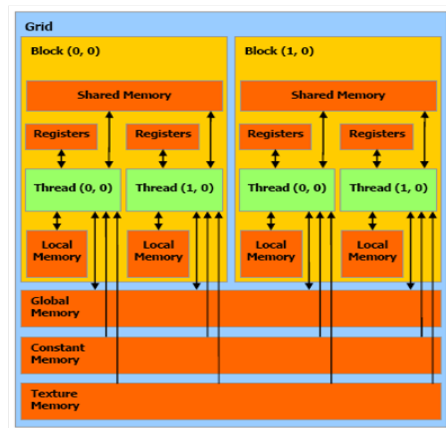
Lock method

- No minimum SAD value search
- Shared variable stores query min SAD
- Critical section (with *flush*) to write SAD values

CUDA

CUDA approach

- Each block has a Shared memory
- Each thread has a personal and block id
- The total blocks number depends on Historical Data length and threads per block
- Four different implementations



Naive Implementation

- The Queries and Historical Data are stored in Global memory
- Each thread reads a Historical Data chunk and compare it with all queries
- The Result vector is in global memory

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A lot of reads/writes in/from Global memory

Private Implementation

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- Each thread has a private variable
- The threads compute SAD values w.r.t. its data chunk
- Make local SAD computations and write once

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- Use the Constant memory to store the Queries
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- In each block Shared memory is written a Historical Data chunk
- A thread can see only a fragment of data to compute SAD
 - Each thread in each block compute the remaining SAD values for a query

```

if ( $idx - r \geq 0$  and ( $idx - r < len(R)$ )
     $R_q[idx - r] += |Ds[threadId] - Qc_q[r]|$ 
    
```

Constant Implementation

- Use the Constant memory to store the Queries
- In each block Shared memory is written a Historical Data chunk
- A thread can see only a fragment of data to compute SAD
 - Each thread in each block compute the remaining SAD values for a query

```
if (idx - r) ≥ 0 and (idx - r) < len(R)
    Rq[idx - r] += |Ds[threadId] - QCq[r]|
```

Possible race condition \Rightarrow *atomic* write

Tiling Implementation

- Both Historical Data and Queries are stored in Shared memory
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 - Need multiple Queries loads in Shared memory (at least 1 for each Query)
 - Different Query portions loaded in the same block Shared memory ($t < q$)

if $(idx - (r + p \cdot T)) \geq 0$ **and** $(idx - (r + p \cdot T)) < len(R)$
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Experiments

Testing Hypothesis

One Historical Data vector and multiple Queries

- Pattern Recognition tested on:
 - Variable Historical Data length
 - Variable Query length
 - Variable Queries number
 - Variable CPU and GPU threads

Hyper-parameter	Default Value
Historical Data	100000
Query	1000
Queries Number	10
Threads Number	12
Kernels per Block	128

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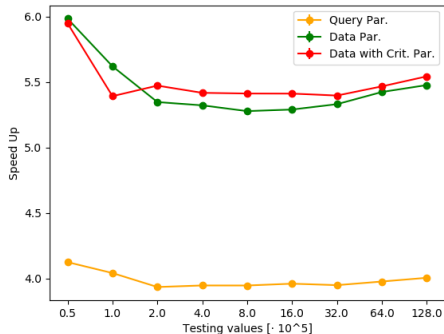
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Stabilize results

For each test configuration are performed 10 run for stable results

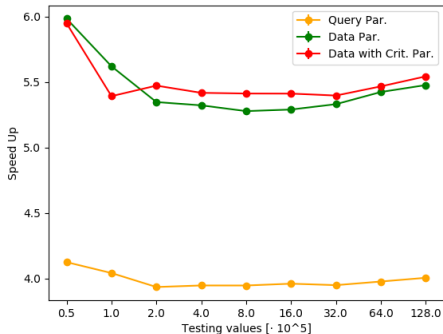
Historical Data length

- Historical Data with size in [50000, 1280000]



Historical Data length

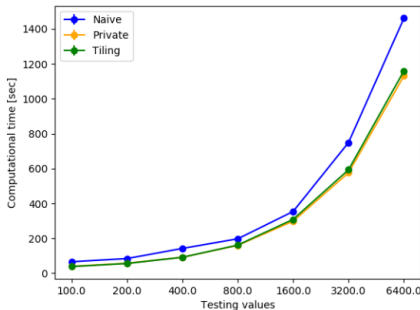
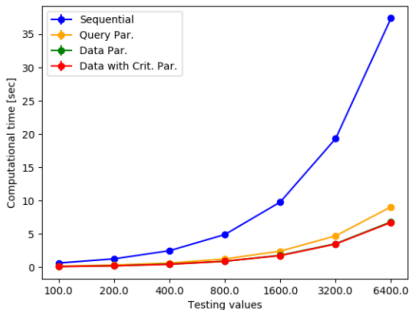
- Historical Data with size in [50000, 1280000]
- Table compares the OpenMP and CUDA implementations w.r.t. the Sequential one (with mean and std)



len(Data)	Sequential [sec]	OpenMP [sec]	CUDA [μ sec]
50000	$3.20 \pm 0.37\%$	$0.53 \pm 0.02\%$	$178.6 \pm 5.81\%$
200000	$12 \pm 1.03\%$	$2.24 \pm 0.52\%$	$181.3 \pm 5.51\%$
800000	$47.8 \pm 0.02\%$	$9.05 \pm 1.02\%$	$171.2 \pm 8.61\%$
320000	$191 \pm 0.34\%$	$36 \pm 1.21\%$	$182.8 \pm 2.91\%$
1280000	$780 \pm 6.58\%$	$142 \pm 2.57\%$	$181.3 \pm 3.72\%$

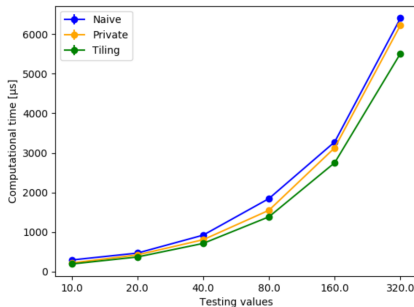
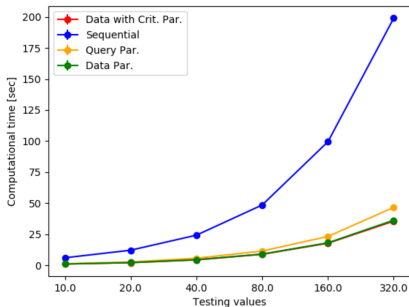
Query length

- Query length from 100 to 6400
- CPP computational times reported in *sec*; GPU ones in μsec
- No parallelism on queries \Rightarrow **proportional** grown



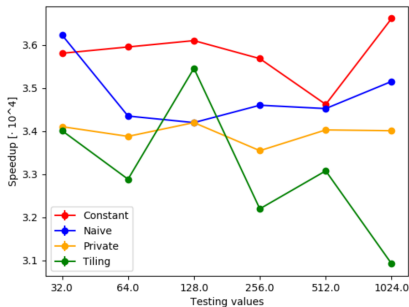
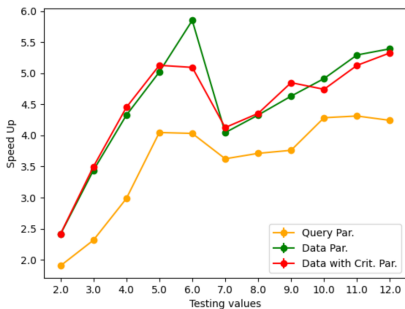
Queries number

- Queries number in [10, 320]
- CUDA Constant implementation can not be tested



CPU and GPU threads number

- Threads number from 1 (for Relative Speedup) to 12
- GPU kernels per block from 32 to 1024 (device maximum)



Evaluation Metrics

	<i>OpenMP</i>			<i>CUDA</i>			
Metric	Query	Privatization	Lock	Naive	Private	Tiling	Constant
S_p	4.03	5.87	5.09	$2.2 \cdot 10^4$	$2.8 \cdot 10^4$	$3.0 \cdot 10^4$	$3.4 \cdot 10^4$
RS_p	4.15	6.02	5.24	(-)	1.24	1.34	1.51
E	0.67	0.97	0.85	0.22	0.28	0.30	0.34

- Reported performances for the parallel Pattern Recognition solutions. All the values are computed with a 100000 Historical Data vector, 1000 Query length, 10 total Queries, 6 CPU threads number and 128 CUDA kernels for each block.
- Relative Speedup is computed w.r.t. the baseline methods (Sequential and Naive)
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Conclusions

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- Experimental results underline the gap between CPU and GPU parallel implementations
- OpenMP Privatization method reports almost linear Speedup and Efficiency close to 1
- CUDA show its parallelism power in all the implementations, in particular thanks to the Shared and Constant memories

Thanks for the attention