Pattern Recognition with C++ OpenMP and CUDA

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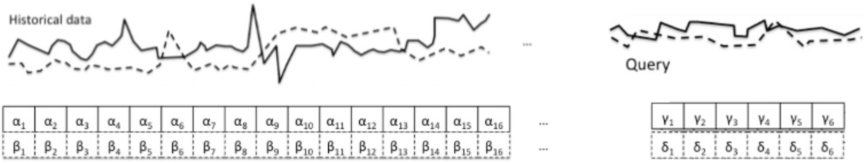
Introduction

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

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

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Parallel solutions

- CUDA
- OpenMP

Sequential

Sequential approach

Algorithm 1 Pattern Recognition

```
Generate the Historical Data
Generate all the Queries
Create a vector R with length equal to Queries number
for query q in Queries do
    Create a vector R_q with length len(Data) - len(q) + 1
    Compute R_q[i] = sum_{j=0}^{len(q)} |D[i + j] - q[j]|
    R[q] = arg min R_q
end for
return R
```

Where:

- Line 5: Create a vector R_q with length len(Data) - len(q) + 1
- Line 6: Compute $R_q[i] = \sum_{j=0}^{len(q)} |D[i+j] - q[j]|$
- Line 7: $R[q] = arg \min R_q$

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 thought 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

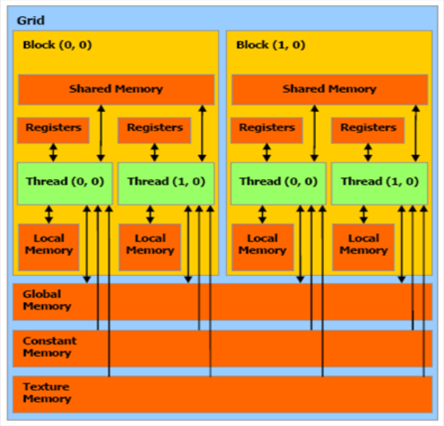
Lock method

- 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 tread 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 chuck and compare it with all queries
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A lot of reads/writes in/from Global memory

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- Make local SAD computations and write once

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Constant Implementation

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- A thread can see only a fragment of data to compute SAD
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$$\textbf{if } (idx - r) \geqslant 0 \textbf{ and } (idx - r) < len(R)$$
$$R_q[idx - r] += |Ds[threadId] - Qc_q[r]|$$

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Possible race condition $\Rightarrow$ *atomic* write

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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 ($t < q$)

$$\textbf{if } (idx - (r + p \cdot T)) \geqslant 0 \textbf{ and } (idx - (r + p \cdot T)) < len(R)$$

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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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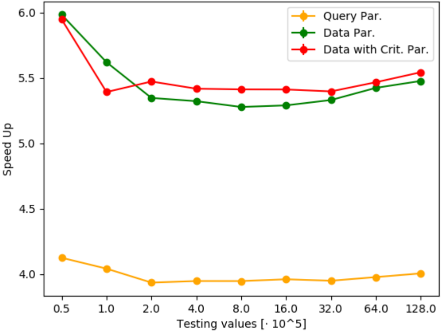
Stabilize results

For each test configuration are performed 10 run for stable results

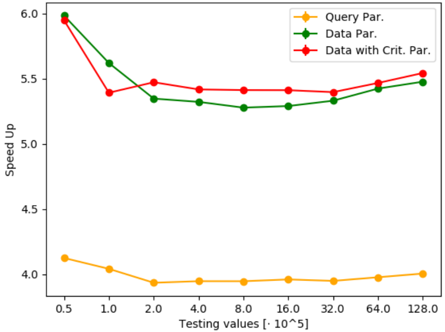
Historical Data length

- Historical Data with size in $[50000, 1280000]$



Historical Data length

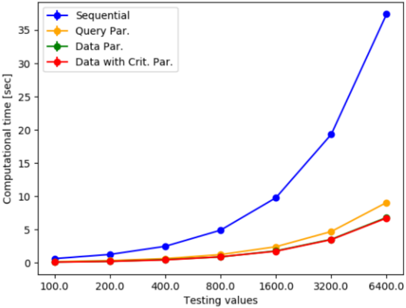
- Historical Data with size in $[50000, 1280000]$
- Table compares the OpenMP and CUDA implementations w.r.t. the Sequential one (with mean and std)

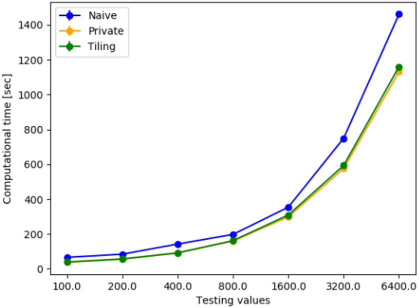


len(Data)	Sequential [*sec*]	OpenMP [*sec*]	CUDA [μsec]
50000	$3.20 \pm 0.37\%$	$0.53 \pm 0.02\%$	$178.6 \pm 5.81\%$
200000	$12 \pm 1.03\%$	$2.24 \pm 0.52\%$	$181.3 \pm 5.51\%$
800000	$47.8 \pm 0.02\%$	$9.05 \pm 1.02\%$	$171.2 \pm 8.61\%$
320000	$191 \pm 0.34\%$	$36 \pm 1.21\%$	$182.8 \pm 2.91\%$
1280000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

Query length

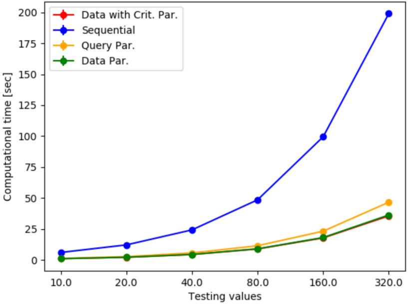
- Query length from 100 to 6400
- CPP computational times reported in *sec*; GPU ones in μsec
- No parallelism on queries $\Rightarrow$ **proportional** grown

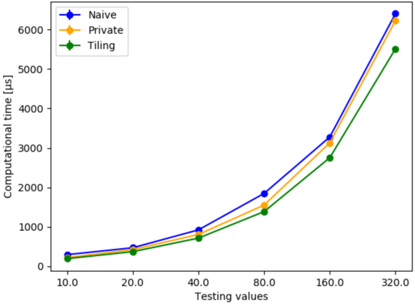




Queries number

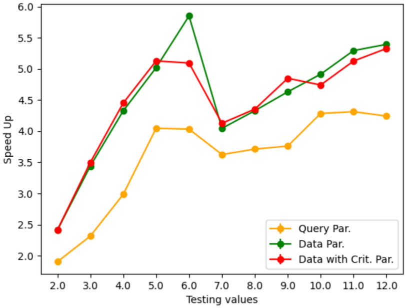
- Queries number in $[10, 320]$
- CUDA Constant implementation can not be tested

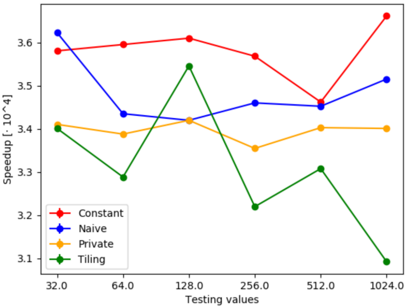




CPU and GPU threads number

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





Evaluation Metrics

	OpenMP			*CUDA*			
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	4.37	4.48	4.15	(-)	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)
- The values are the mean obtained in 10 different runs

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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