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U.S. DEPARTMENT OF ENERGY

Distributed Memory Parallel Markov Random Fields Using Graph Partitioning

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December 11, 2017

Overview

- What is MRF-based image segmentation?
  - Why is it a challenging and relevant problem?
- Distributed-memory parallel MRF-based image segmentation algorithm
- How well does it perform on modern platforms?
- How can we improve it in the future?

Image Segmentation for Material Science

- Study the properties of material samples by identifying different phases
- Asset 3D architecture of materials
- Challenges: amount of data, broad variety of sensors, specific characteristics of the image data
- Current single socket approaches unable to accommodate growing data sizes
- Our approach: Markov Random Field model with graph partitioning for parallelization through MPI

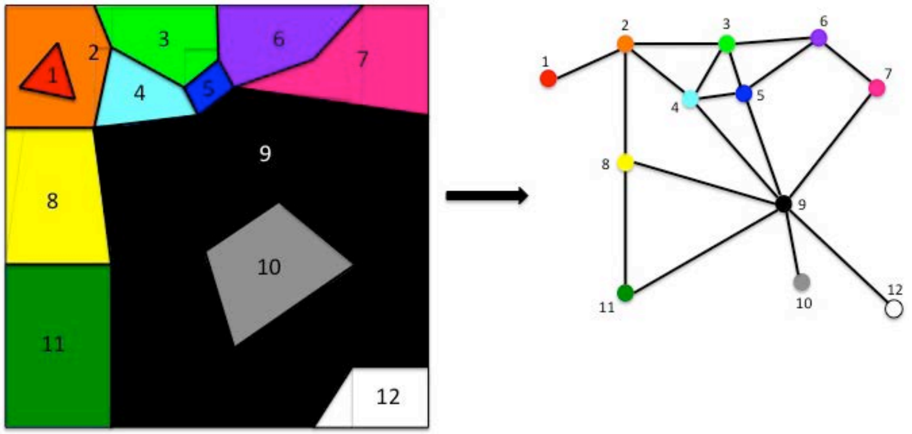
Markov Random Fields (MRF)

- MRF algorithms are accurate and capable of parallelizing
  - Use raw image and oversegmented image
- Problem: application to large data unfeasible due to NP-hard complexity
- Use graph partitioning to assist in making problem parallelizable

Markov Random Fields for Image Segmentation

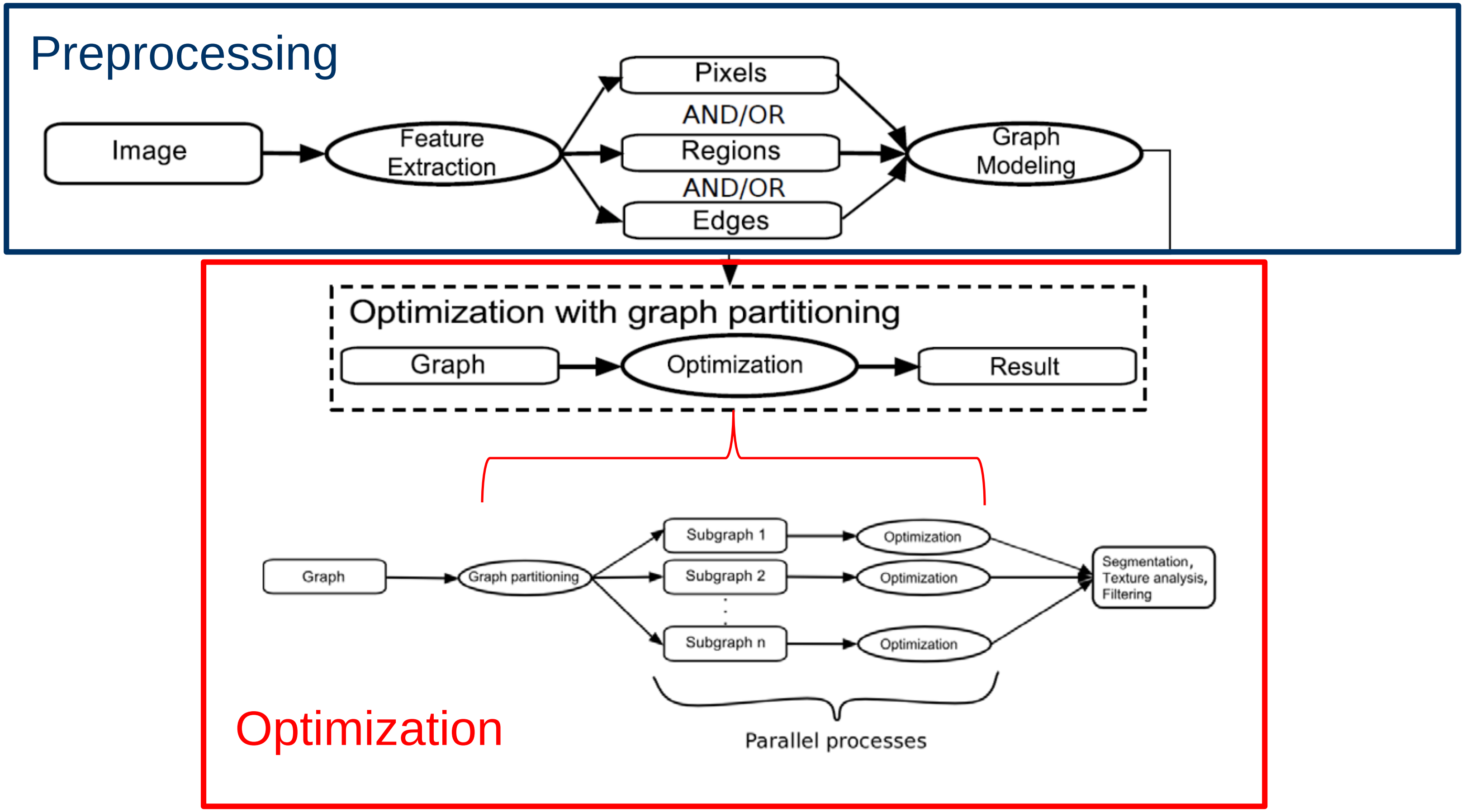
- Given an image represented by $\mathbf{y} = (y_1, \ldots, y_N)$ where each y_i is a region
- Goal: configuration of labels $\mathbf{x} = (x_1, \ldots, x_N)$ where $x_i \in L$ and L is the set of all possible labels, $L = \{0, 1, 2, \ldots, M\}$
- MAP criterion: find a labeling that satisfies:

$$\mathbf{x}^* = \underset{x}{\operatorname{argmin}} \{U(\mathbf{y}|\mathbf{x}, \Theta) + U(\mathbf{x})\}$$



Obtaining a region graph from an oversegmentation

Markov Random Fields for Image Segmentation



T. Perciano, D. Ushizima, E. W. Bethel, Y. D. Mizhahi, and J. A. Sethian, "Reduced-complexity Image Segmentation under Parallel Markov Random Field Formulation using Graph Partitioning," in *2016 IEEE International Conference on Image Processing*, Phoenix, AZ, USA, Sep. 2016, lBNL-1005703.

MPI - Parallel Markov Random Fields (MPI-PMRF)

Algorithm 1 Distributed memory version of the Markov Random Field algorithm using graph partitioning and parameter estimation (MPI-PMRF). Line 8 is run in parallel to distribute the largest amount of work to increase performance.

Input: Original image, oversegmentation, number of classes
Output: Segmented image and estimated parameters

```
 1: K ← number of classes
 2: Initialize parameters and initial labels randomly
 3: Create graph from oversegmentation
 4: for each Expectation Maximization iteration do
 5:     Divide graph into subgraphs (cliques) based on number of
        MPI processes to be used
 6:     Distribute cliques to MPI processes
 7:     for each non-zero clique of the graph do
 8:         Run Expectation Maximization and Maximum a Posteriori
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13: Generate resulting output image
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Experiments Overview

- Types of Experiments
  - Verification testing
  - Performance testing
- Scaling characteristics
  - 2 datasets
  - Large-scale platform

(a
)

(b
)

(a) Result from threaded version; (b) Result from MPI-PMRF

Results are identical

Computation Verification

- 98.99% accurate compared to ground truth
- Identical results with threaded version
- Berkeley Dataset Benchmark
  - Higher accuracy than other image segmentations

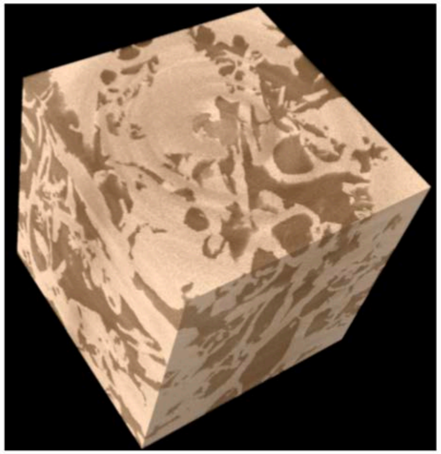
(a) (b)

Synthetic dataset → (a) original image; (b) MPI-PMRF result

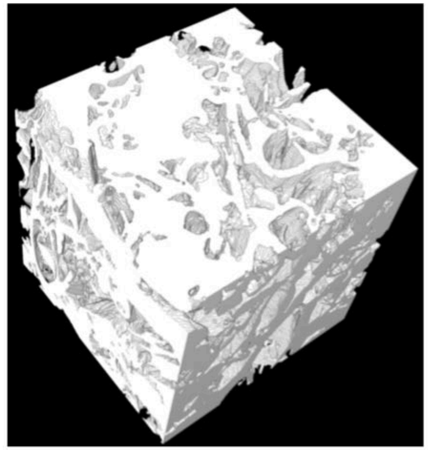
(a) (b)

Experimental dataset → (a) original image; (b) MPI-PMRF result

Results



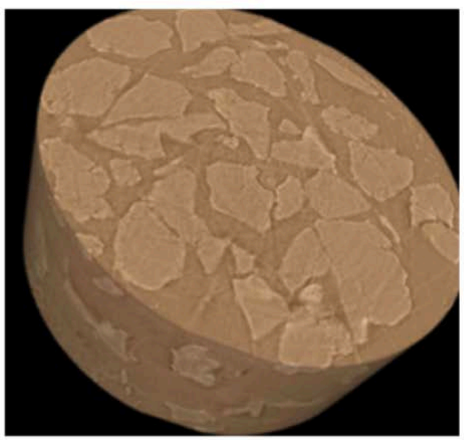
(a)



(b)

(a) 3D rendering of original synthetic data

(b) 3D rendering of MPI-PMRF result



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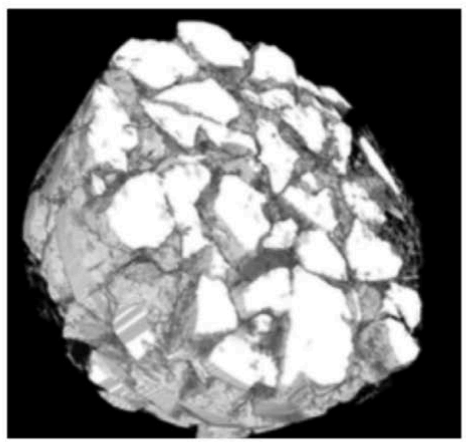


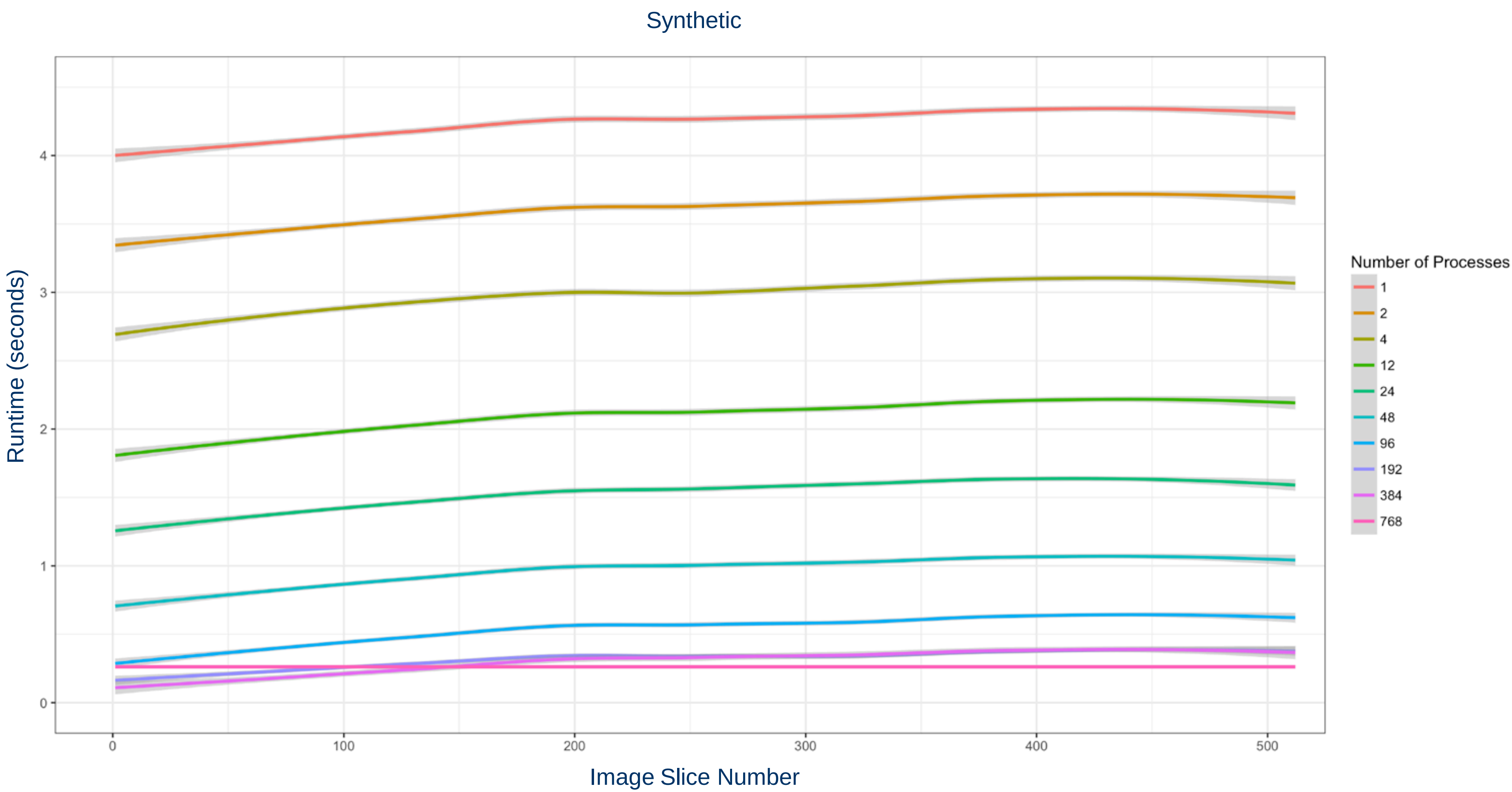
(b)

(a) 3D rendering of original experimental data

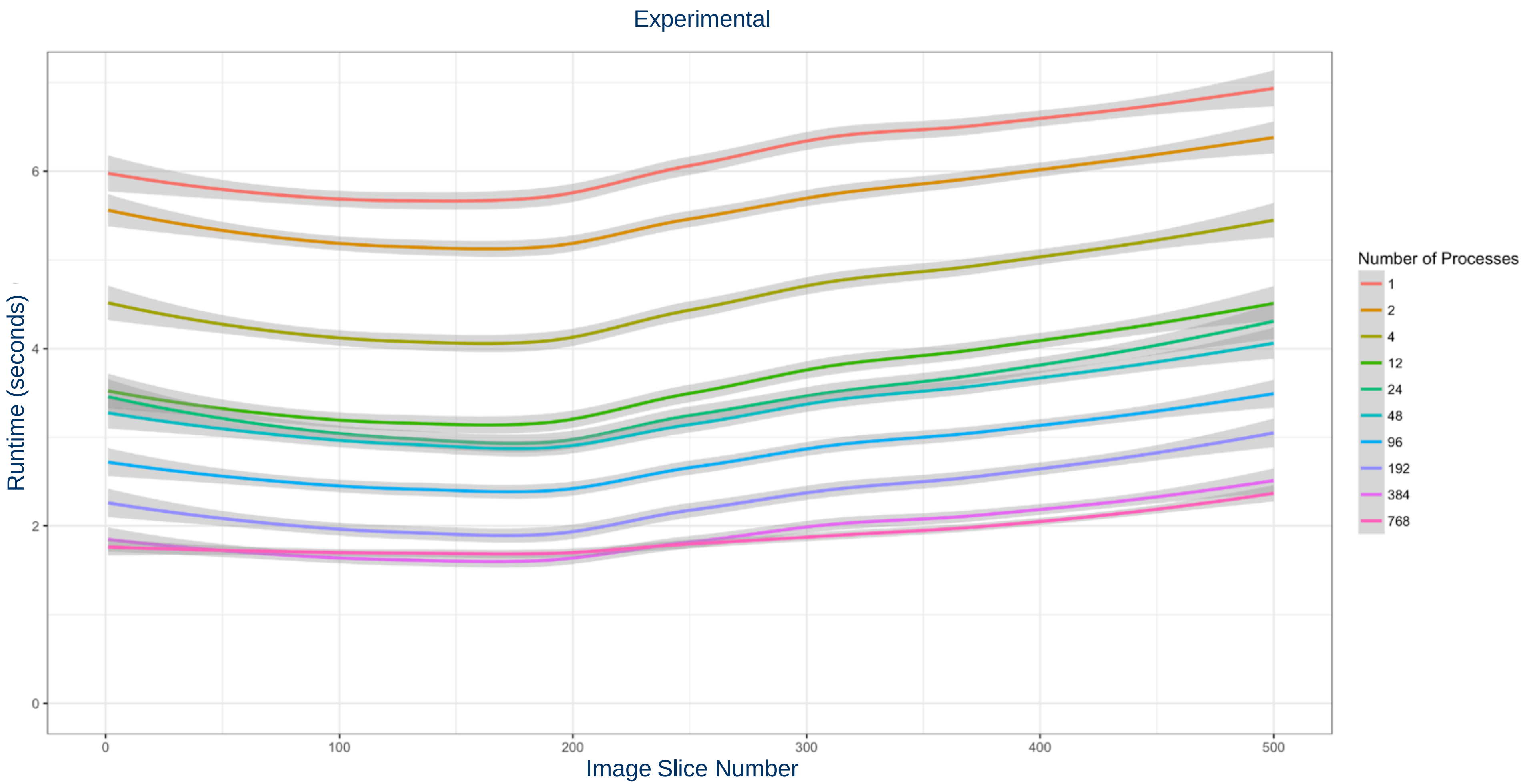
(b) 3D rendering of MPI-PMRF result

Performance Analysis

- Platform
  - Edison supercomputer at NERSC
  - Cray XC30 system
    - 24 cores per node
- Methodology
  - Run 2 datasets
  - Varying levels of concurrency
  - Scalability study
  - Additional performance metrics



When measuring runtime (in seconds) of the synthetic dataset, the results show the overall decrease in runtime as concurrency increases



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Results – Efficiency and Rate

- Use “efficiency” and “rate” metrics to yield insight into scaling performance
- **Efficiency**: measure degree to which code scales compared to serialized version
- **Rate:** measure degree to which performance time increases as function of workload size and concurrency
- Measuring workload imbalance?

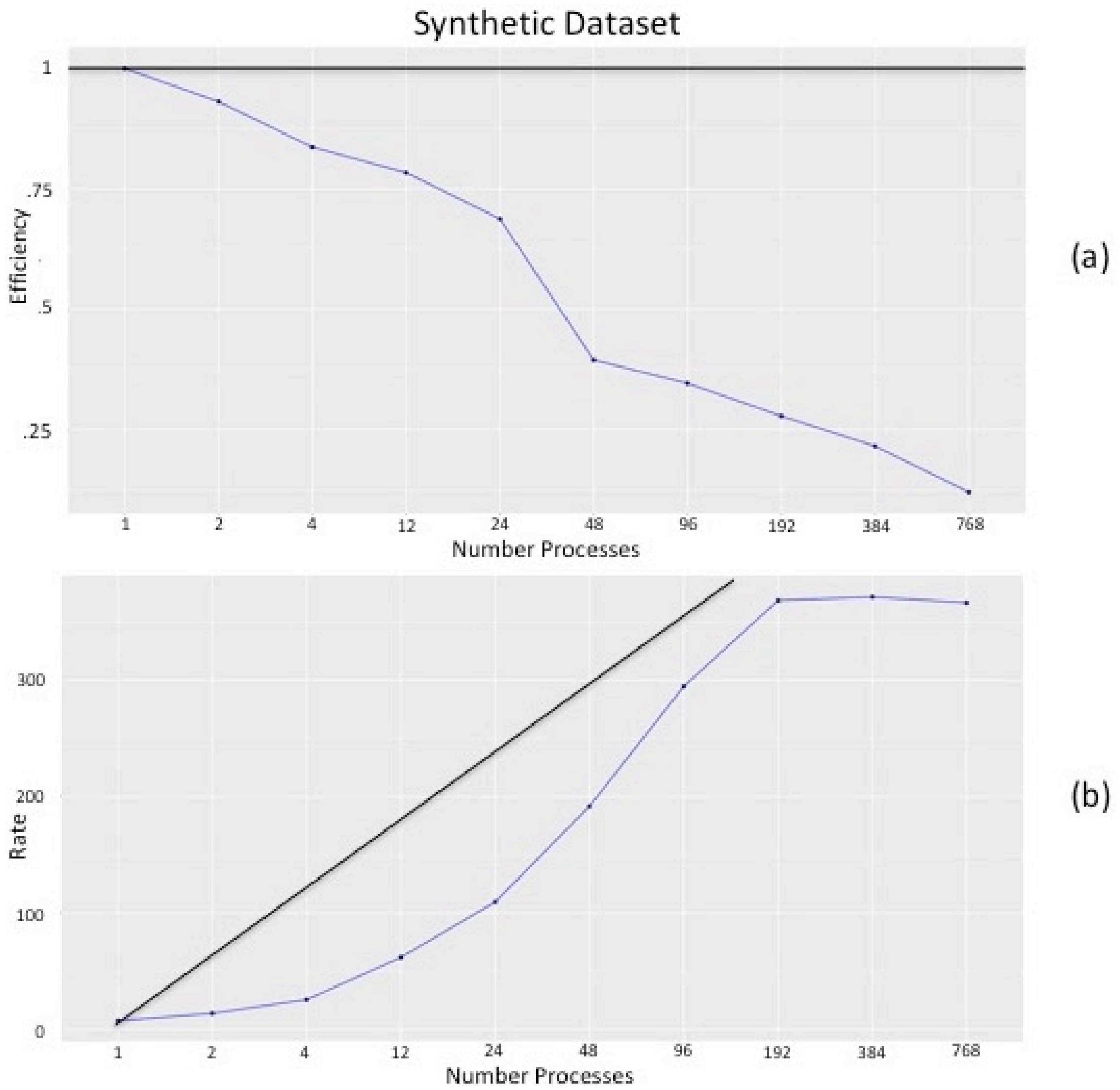
Efficiency

$$E(n,p) = \frac{C^*(n)}{C(n,p)}$$

Rate

$$R(n,p) = \frac{n}{T(n,p)}$$

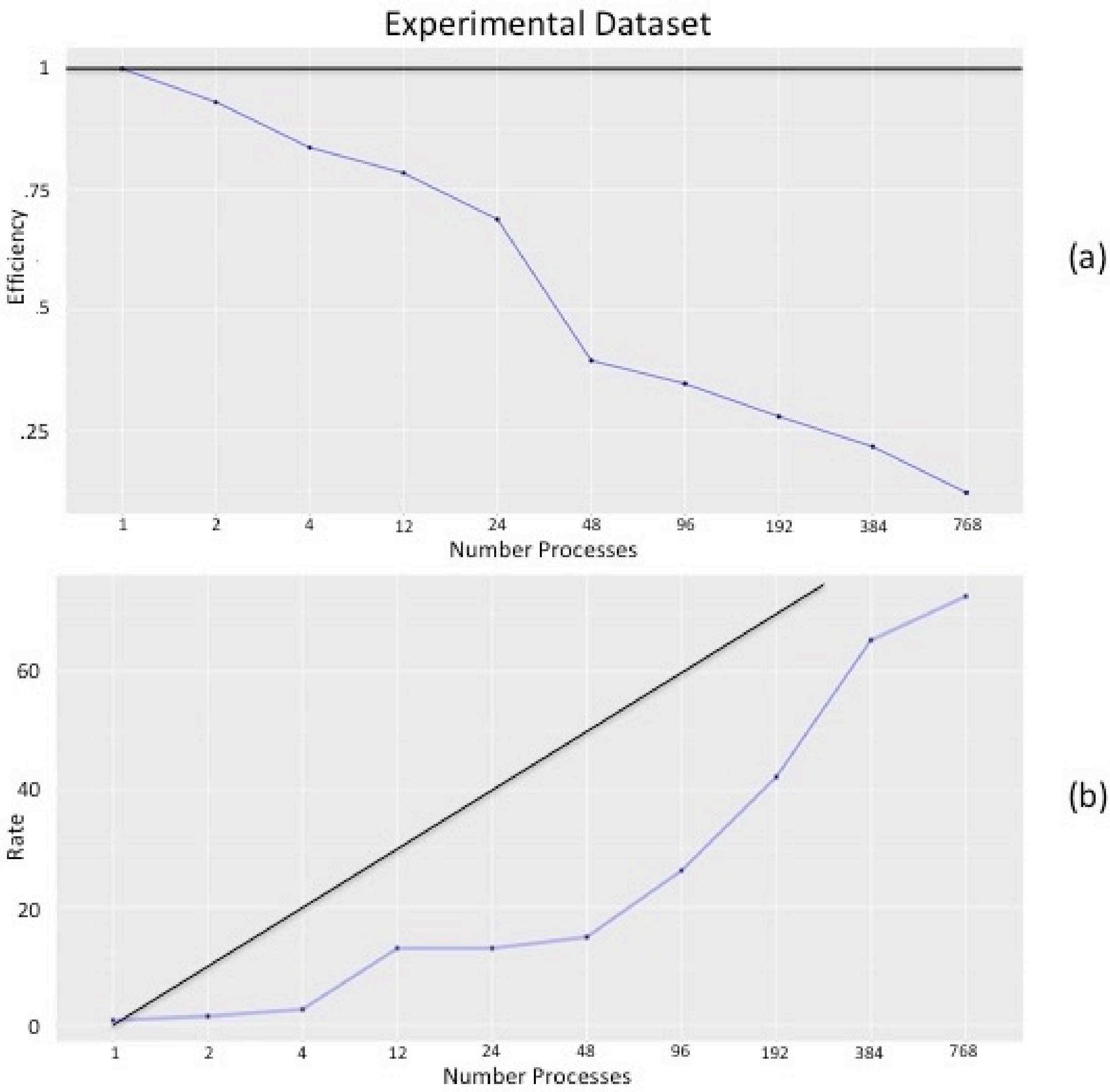
K. Moreland and R. Oldfield, “Formal metrics for large- scale parallel performance,” in *Proceedings of International Supercomputing Conference*, 2015.



(a) Efficiency of the synthetic dataset; does not follow ideal efficiency of 1, but still provides an increase in performance

(b) Rate of the synthetic dataset does not follow ideal rate with a slope equal to 1, but provides a performance increase at different concurrencies and executes faster than when running in serial

Insufficient workload
Workload imbalance
Communication



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Summary of Results

- MPI-PMRF shows decrease in runtime as concurrency increases
- Limits to efficiently scaling:
  - Workload imbalance
  - Serialization due to inter-processor communication
  - Insufficient workload
- Future work
  - Increase problem size and complexity
  - Workload balance
  - Extend algorithm to work with 3D image volumes

Conclusion

- Promising new approach for scalable image segmentation to help meet scientific needs
- Take advantage of large computational resources and process large data
- Additional work needed to improve performance

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