Image Segmentation Across Domains using Parallel Markov Random Field Technique

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Introduction

- Image-based data from experiments across different science domains
- Lack of image analysis software tools capable of extracting valuable and hidden information
- Challenges: amount of data, broad variety of sensors, specific characteristics of the image data

Goal

Design software applications that deal with complex large datasets using pattern recognition and machine learning techniques allied with advanced computer architectures

Outline

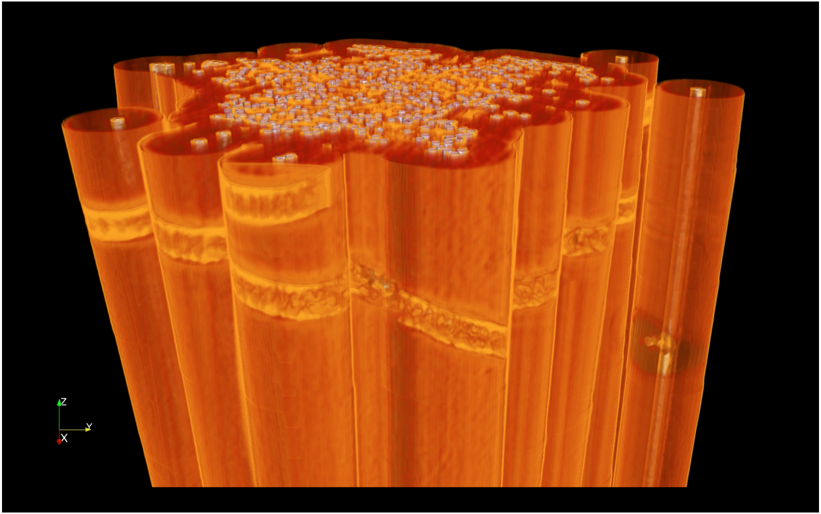
Projects being developed at LBNL

Image acquisition techniques

Micro-Tomography

- Materials: fibrous composites, geological samples
- Resolution: $0.65 - 2.5\mu m$
- Physics at pixel: X-ray attenuation contrast
- Allows non-destructive 3-Dimensional imaging of solid objects

Why image segmentation?



Parallel Markov Random Field





Perciano, Ushizima, Bethel, Mizrahi, Parkinson and Sethian. *Reduced-complexity image segmentation under parallel Markov random field formulation using graph partitioning*, ICIP 2016.

Parallelization of Markov Random Field Techniques

Methodology

- MRF algorithms are powerful tools to explore contextual information of image data
- Problem: application to large data is unfeasible due to the NP-hard complexity of the optimization process
- We developed a MRF-based framework using graph partitioning
  - Threaded-based
  - Optimization and parameter estimation are done in parallel in small subgraphs decreasing the computational complexity

Parallelization of Markov Random Field Techniques

Methodology

- MRF model: optimization process uses a global energy function to find the best solution to a similarity problem, such as the best pixel space partition or the best matching
- Energy function: consists of a data term (likelihood) and a smoothness term (prior)
    - Image segmentation: the mean of the intensity values of a region can serve as the data term, and the smoothness term takes into account the similarity between regions
- Goal: find the best labeling for the regions, so that the similarity between two regions with the same labels is optimal for all pixels

Parallelization of Markov Random Field Techniques
Methodology

Problems:

- Fitting MRF models to data is a challenge
- Gradient of the models is intractable
- Maximum likelihood is data efficient but not model efficient: computation of expectations over the model distribution, i.e., evaluation of a sum with exponentially many terms

Parallelization of Markov Random Field Techniques

Methodology

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Methodology

$$s \longrightarrow X_s \qquad \mathbb{L}$$

Parallelization of Markov Random Field Techniques

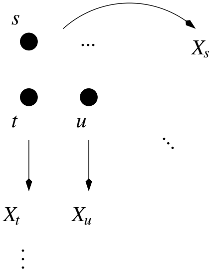
Methodology

s

X_s $\mathbb{L}$ $X_s = x_s$

Parallelization of Markov Random Field Techniques

Methodology



$\mathbb{L}$

$X_s = x_s$

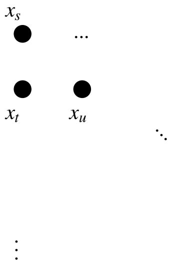
⋱

$X = (X_s; X_t; \dots)$

$(X_s = x_s; X_t = x_t; \dots)$

Parallelization of Markov Random Field Techniques

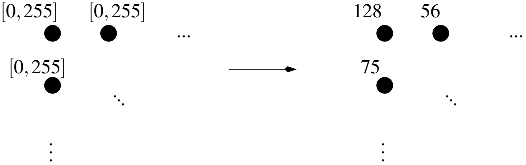
Methodology



$$x = (x_s; x_t; \dots)$$

Parallelization of Markov Random Field Techniques

Methodology



Parallelization of Markov Random Field Techniques
Methodology

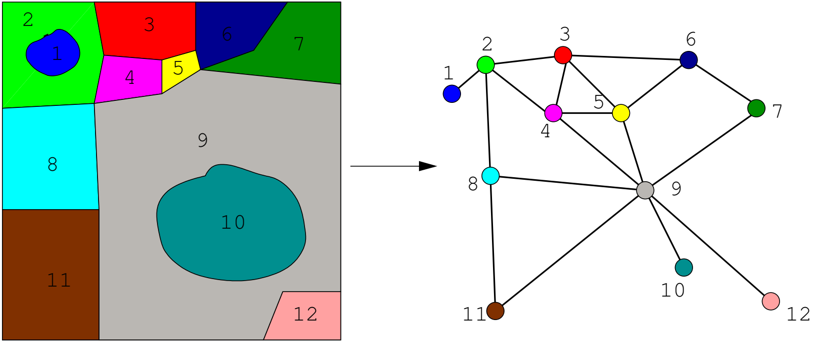


Figure: Obtaining a region graph from an oversegmentation.

Parallelization of Markov Random Field Techniques

Methodology

- Given an image represented by $\mathbf{y} = (y_1, \dots, y_N)$, where each y_i is a region
- Goal: configuration of labels $\mathbf{x} = (x_1, \dots, x_N)$ where $x_i \in L$ and L is the set of all possible labels, $L = \{0, 1, 2, \dots, M\}$
- MAP criterion: find a labeling $\mathbf{x}^*$ that satisfies $\mathbf{x}^* = \underset{x}{\operatorname{argmax}}\{P(\mathbf{y}|\mathbf{x}, \Theta)P(\mathbf{x})\}$, which can be rewritten in terms of the energies as $\mathbf{x}^* = \underset{x}{\operatorname{argmin}}\{U(\mathbf{y}|\mathbf{x}, \Theta) + U(\mathbf{x})\}$

Parallelization of Markov Random Field Techniques

Methodology

- LAP (Linear and Parallel): model and data efficient method for MRF parameter estimation
- Divide the joint parameter estimation process into several fully independent sub-problems
- For a fixed clique q, the 1-neighborhood is used: $A_q = \bigcup_{c \cap q \neq \varnothing} c$

Require: MRF with maximal cliques $\mathcal{C}$

1: **for** $q \in \mathcal{C}$ **do**
2: Construct auxiliary MRF $\mathcal{M}_q$ on variables in A_q
3: Estimate parameters $\theta^{\mathcal{M}_q}$
4: Set $\theta_q \leftarrow \theta_q^{\mathcal{M}_q}$
5: **end for**

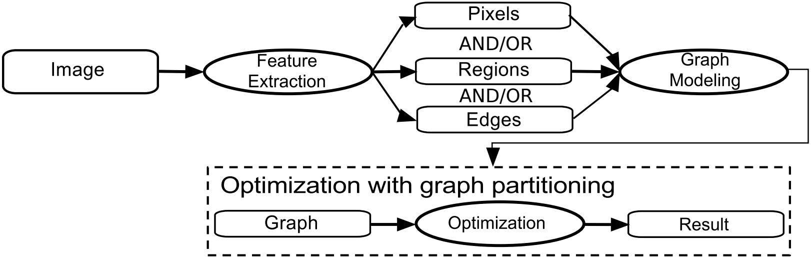
Parallelization of Markov Random Field Techniques

Methodology

Require: Original image, oversegmentation, number of classes
Ensure: Segmented image and estimated parameters

```
k ← number of classes
Initialize parameters and output randomly
Create graph from oversegmentation
for each EM iteration do
    Use LAP to partition the graph
    for each maximal clique of the graph do
        MAP estimation computed in parallel
    end for
    Update parameters
end for
```

Parallelization of Markov Random Field Techniques
Methodology



Computational complexity: (**before**) exponential in the size (m) of the largest clique of the graph i.e., $O(k^m N)$, k being the number of classes (**after**) optimization is applied separately for each subgraph, decreasing drastically m and N. Additionally, LAP is linear in the number of cliques.

Parallelization of Markov Random Field Techniques

Results

Figure: Boundary detection for three images from BSDS 300: 3096, 42049 and 101087 (481x321px). Original grayscale images are shown in the first row, human-labeled images on second row and the parallel MRF results on third row.

Parallelization of Markov Random Field Techniques

Results

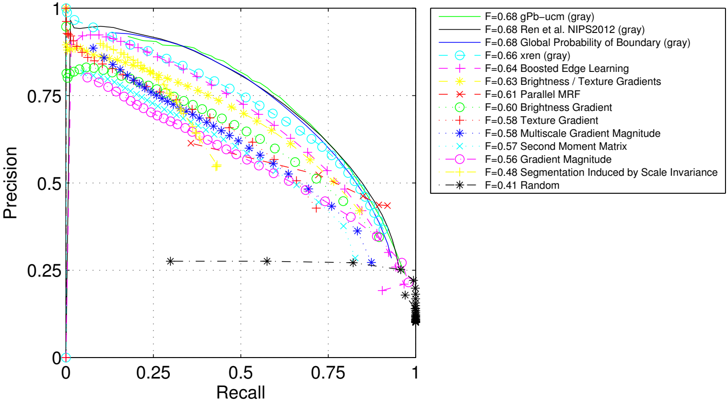
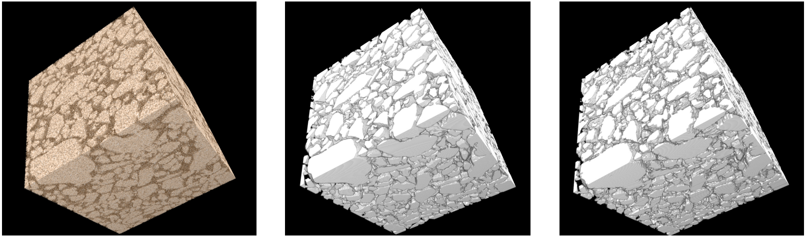


Figure: Precision and Recall curves for all the algorithms included in the BSDS 300 Benchmark and PMRF.

Parallelization of Markov Random Field Techniques

Results

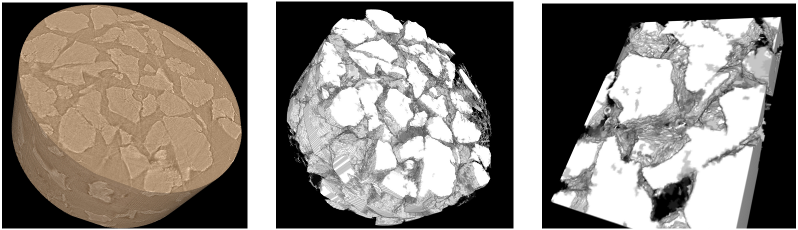


(a) (b) (c)

Figure: 3D visualization of the synthetic dataset (512x512x512px). (a) Original noisy image (b) Ground-truth (c) Result using the proposed segmentation framework. The values of *precision*, *recall* and *accuracy* are 0.9512, 0.85 and 0.88, respectively.

Parallelization of Markov Random Field Techniques

Results



(a) (b) (c)

Figure: 3D visualization of the real microCT dataset (1813x1830x500px). (a) Original image (b) Result using PMRF (c) Zoomed region from the segmentation result.

Parallelization of Markov Random Field Techniques

Results

Table: Timings for optimization process using three different versions of the framework implementation.

Dataset	Version of the code	Mean # cliques	Mean # regions	Time opt.(s)
Real	`C++`, thread `C++`, serial `Matlab`	26671	6562	83.09 746.76 20035.2
Synthetic	`C++`, thread `C++`, serial `Matlab`	16302	4500	10.56 62 1587.01

Parallelization of Markov Random Field Techniques

Current Advances and Future Work

1. Distributed-memory parallel implementation
2. Alternative VTK-m version
3. Parallel I/O

Fast 3D Non-Linear Filtering





Fast 3D Non-Linear Filtering

- 3D non-linear filters are essential part of preprocessing steps in image analysis
- Problem: computational time of usual implementations is unfeasible when applied to large datasets
- F3D is a package that provides accelerated 3D nonlinear filters, with OpenCL kernels that explores graphics cards technology
  - Communication of Java code with OpenCL kernels
  - In-memory streaming
  - Scripting
- Broad range of applications and different collaborations
- `https://github.com/CameraIA/F3D`

Streaming Ptychography








Real-time ptychographic reconstruction

- Ptychography: imaging modality that enables one to build up very large images at wavelength resolution
- Problem: challenges involved with the image acquisition system and the ptychographic image reconstruction
- Solution: real-time streaming pipeline for ptychographic image acquisition and reconstruction
  - **Frontend**: control of the experiment by the user, real-time feedback and visualization
  - **Backend**: different modules and communication, reconstruction algorithm, and the parallelization scheme
  - Overcomes I/O operations and the complexity of the common pipelines and provides real-time feedback while the experimental acquisition is in process

Real-time ptychographic reconstruction

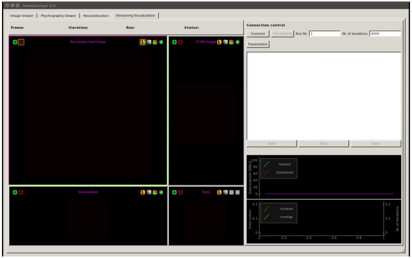


Figure: Real-time ptychographic reconstruction.

Conclusions

Conclusions

- Scalable method to allow practical MRF computations for large datasets, particularly the parameter estimation and optimization
- Use of a MRF-based segmentation approach at scale
- The `C++` parallel version of the code is $26\times$ faster than its serial version, and it is $241\times$ faster then the `Matlab` version
- Evaluation of the method using the BSDS 300 Benchmark, where our algorithm ranks 7th place among 15 methods

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Thank you! Contact: `tperciano@lbl.gov`