Graph Based Processing of Big Images

HUI HAN CHIN
DSO NATIONAL LABORATORIES, SINGAPORE

31 OCT 2014

Introduction

- Member of Technical Staff at
  Signal Processing Laboratory, Sensors Division,
  DSO National Laboratories, Singapore.
- Research / Engineering Interests
  - Compressive Sensing for Synthetic Aperture Radar
  - Electro-Optics Satellite Exploitation
  - Big Image Processing and Visualization

Overview

1. Big Image Challenge
2. Image Processing as Graph Problems
3. Practical Approaches to Big Image Processing

Big Data

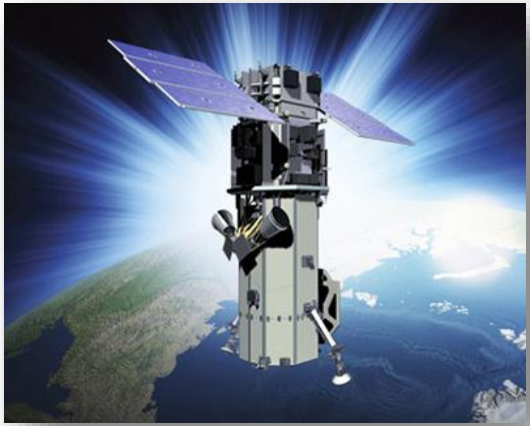
4Vs of Big Data
Volume, Variety, Velocity, Variability

Big Data is mostly represented in blue color!

Big Data ≠ Big Image

- Big Data is highly unstructured.
  Goal is to learn the structure.
  - Deep Learning, Deep Belief Nets, Manifold learning, etc.
- Images are structured. Can structure be exploited for efficient computations?

Commercial Sensors Today



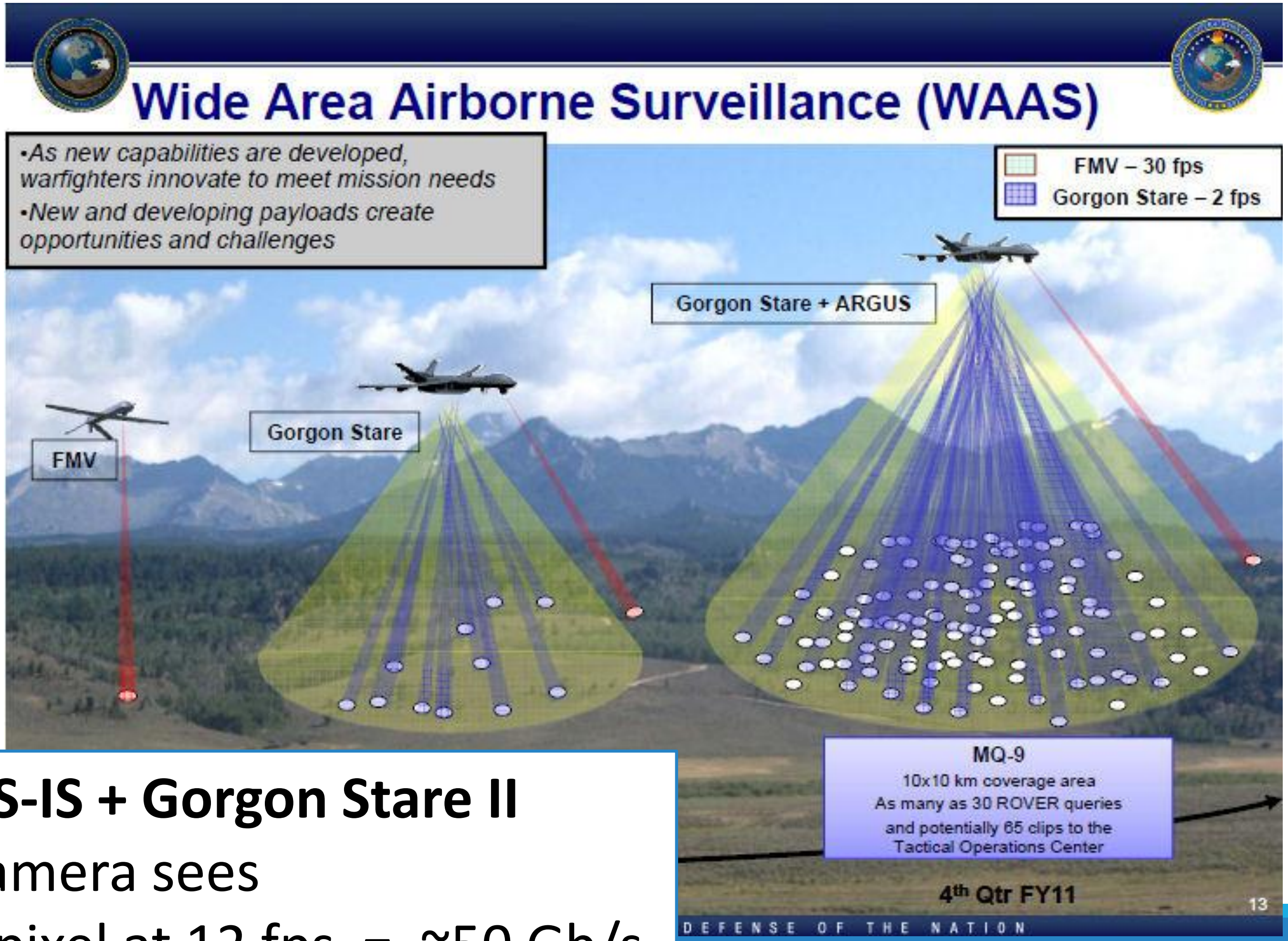
Big Scale and Volume:
World View 3 Satellite

Ubiquitous and Fast :
GoPro Hero Camera

High Features Dimension:
Lytro Light Field Camera

Current: Process 2 Gb in < 5mins

Future Sensors



ARGUS-IS + Gorgon Stare II
368 Camera sees
1.8e9 pixel at 12 fps = ~50 Gb/s

Big Image Today

Partition big images in smaller subsets and process them in parallel.

Local processing approach will affect the underlying statistics, leaving unwanted artifacts.

Seams from satellite image mosaic from Google Earth

Big Image Challenge

To process image datasets globally in an efficient manner

- Hyperlapse by
  Microsoft Research, SIGGRAPH 14.
- Build upon, Markov Random Field,
  Poisson Blending technologies

First-person Hyper-lapse Videos

Johannes Kopf
Microsoft Research

Michael F. Cohen
Microsoft Research

Richard Szeliski
Microsoft Research

(a) Scene reconstruction (b) Proxy geometry (c) Stitched & blended

Figure 1: *Our system converts first-person videos into hyper-lapse summaries using a set of processing stages. (a) 3D camera and point cloud recovery, followed by smooth path planning; (b) 3D per-camera proxy estimation; (c) source frame selection, seam selection using a MRF, and Poisson blending.*

Signal Processing 101

Problem

Sampled Signal =
Transfer Function * Signal + Noise

Goal

Recover Signal!

Noisy Lenna

Denoise Lenna

Signal Processing 101

Original Lenna?

Key Point

We have a <u>prior belief</u> of the <u>structure</u> of the signal.

Signal Processing 101

Assumptions

1. Band-limited Sampling : Shannon-Nyquist Processing

   Traditional EEE 101, filter design

2. Sparse Signal in Sampling : Compressive Sensing

   [Candès, Romberg, Tao, (2006)."Stable signal recovery from incomplete and inaccurate measurements“] [Donoho 06]

3. Correlation in Signal : <u>Graph-Based Approach</u>

Compressive Sensing Remark

- Assumes <u>sparsity</u> and <u>min separation</u> of signals
- Reduces the number of samples required to reconstruct signal
  - Faster to sense but work is pushed to reconstruction part of the algorithm
- Cannot beat Shannon - Nyquist Sampling for high resolution due to coherence
  - Have to process entire data cube at some higher resolution

Mumford Shah, 1989

Given image, I, model J, boundary B and domain D. The Mumford-Shah functional is

$$E[J, B] = \lambda \int (I - J)^2 + \mu \int_{D/B} \nabla J \cdot \nabla J + \gamma \int_B$$

Essentially:
Fidelity + Smoothness + Components

Spawned of Total Variation Denoising (ROF92), Chan-Vese Segmentation (99)

Rudin Osher Fatemi, 1992

Total Variational Denoising

Given S

Recover X

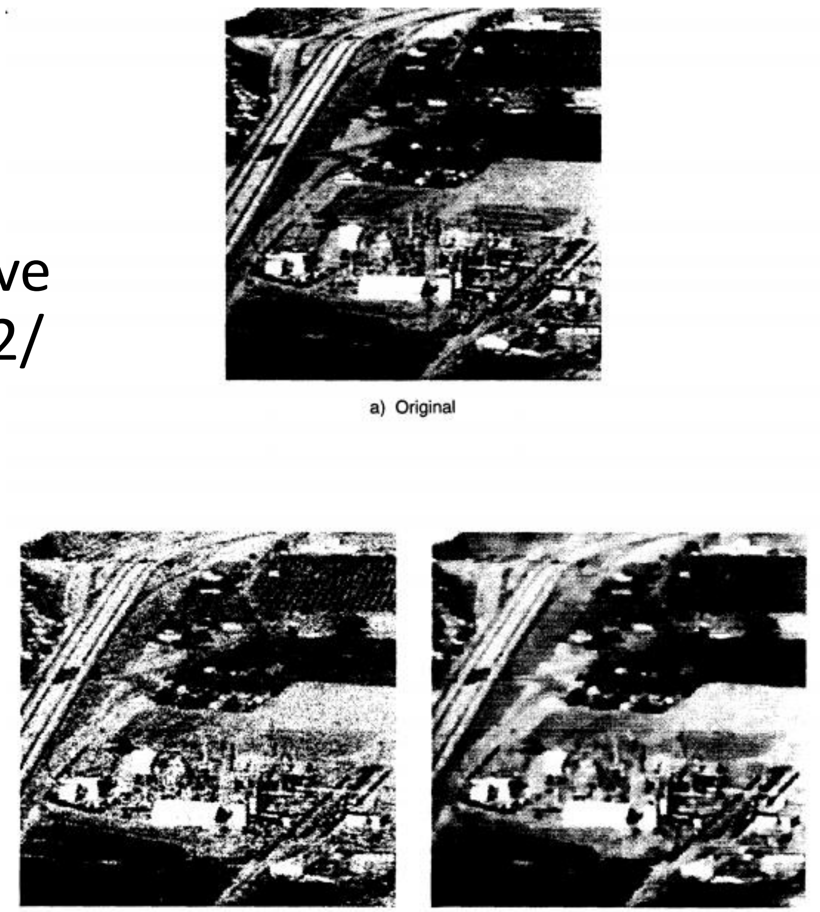
$$\min_X |X - S|_2^2 + \lambda \sum_{(i,j)} |x_i - x_j|$$

Gaussian noise + Laplacian edges

Rudin Osher Fatemi, 1992

ROF92 was original designed for Electro Optics weapon targeting equipment.

“Removing noise without excessive blurring, Cognitech Report #5, (12/ 89), delivered to DARPA US Army Missile Command”



a) Original

b) Multiplicative noise with $\sigma = 0.2$

c) Restoration of "b"

Total Variation

The total variation (TV) of a $\mathcal{C}^1$ function, f, on $[a, b] \in \mathbb{R}$ is

$$TV(f) = \int_a^b |f'(x)| dx$$

- A Bounded Variation (BV) function is a real-valued function whose total variation is finite
- The existence and convergence of minimizers for a large class of BV PDEs is known and TV norm was found suitable for many image processing problems.

TV algorithms

1. **Goldfarb-Yin 04**
   Variations of the objective function can be computed using interior point algorithms.
2. **Kolmogorov-Zabih, Darbon-Sigelle 04**
   Minimum cut applicable to anistropic total variation.
3. **Cai-Osher-Shen 09**
   Bregman iterations
   iterated reweighted least squares.

Solving Linear Systems: Matrix Multiply to Electrical Circuits

1. **Gauss Folklore:**
   Gaussian Elimination
2. **Strassen 69:**
   Strassen Multiplication
3. **Lipton-Rose-Tarjan 80:**
   Direct methods for non-zero structures
4. **Doyle-Snell 00:**
   Electrical resistance are random walks on graphs.
5. **Spielman-Teng 03:**
   Graph Sparsification and solving linear systems.
6. **Koutis-Miller-Peng 10:**
   Approaching Optimality for solving Symmetric Diagonal Dominant (SDD) systems.

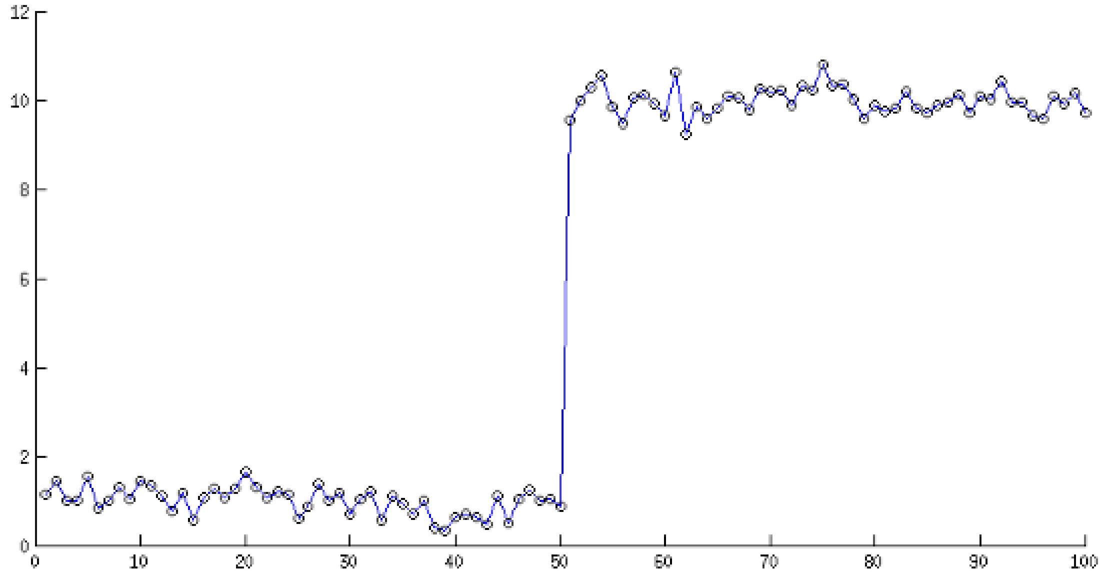
Laplacian Paradigm

"An emerging for the design of efficient algorithm for massive graphs . . .

We reduce the optimization or combinatorial problem to one or multiple linear algebraic problems that can be solved efficiently by applying the nearly linear time Laplacian solver."

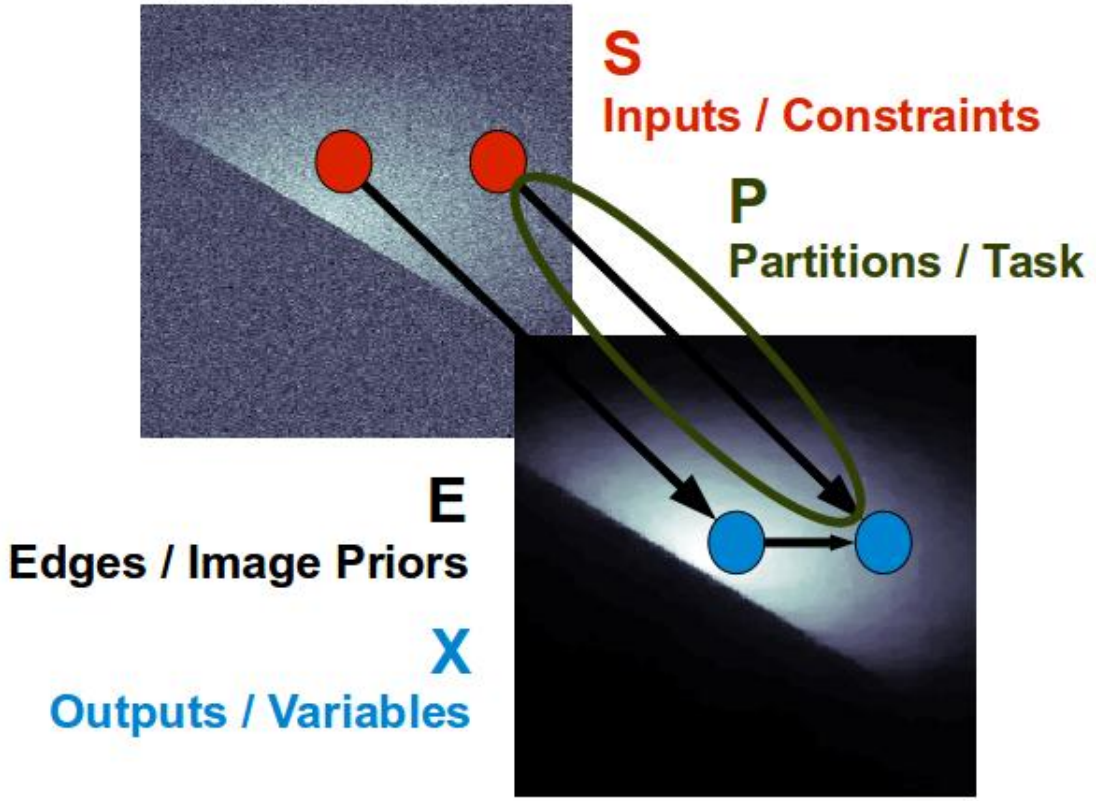
-ShangHua Teng 11

Signals are Graphs



Signals are continuous but physical sensors are discrete.
Sampled signals are vertices of a discrete graph!

Graph Based Approach



TV as Graph Laplacians

$$|x - s|_2^2 + \lambda |\nabla x|_1$$

$$B \binom{X}{S} = 0$$

$$B \binom{wX}{S} = 0 \text{ , "drop L1 penalty"}$$

$$B^T B \binom{wX}{S} = 0 \text{ , Quadratic Form}$$

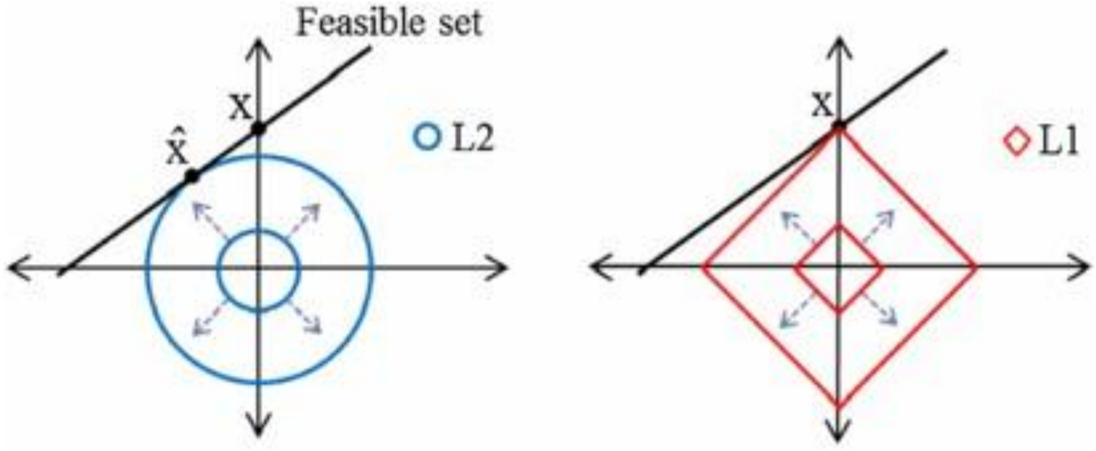
$$\begin{pmatrix} L_{grid} + I & -I \\ -I & I \end{pmatrix} \binom{wX}{S} = 0 \text{ , Graph Laplacian}$$

$$\boxed{L_{grid}(wX) - S = 0 \text{ , linear system}}$$

Not Exactly

LX = S is not guaranteed to have an exactly solution and has to be optimized against a loss function.

ROF92 encoded the loss in the L22 and L1 norm



Grouped Least Squares

Use group least squares to solve for norms from L1 to L2

Suppose we can only minimize norms of the form L_2^2

To minimize L_1 , at convergence, find w such that

$$|x - s| = w(x - s)^2$$

$$\sqrt{(x - s)^2} = w(x - s)^2$$

$$w = ((x - s)^2)^{-1/2}$$

GLS Solutions

1. Sets up graph optimization problem

2. Iterate over

   2.1 Use quadratic coupled flows to solve an instance

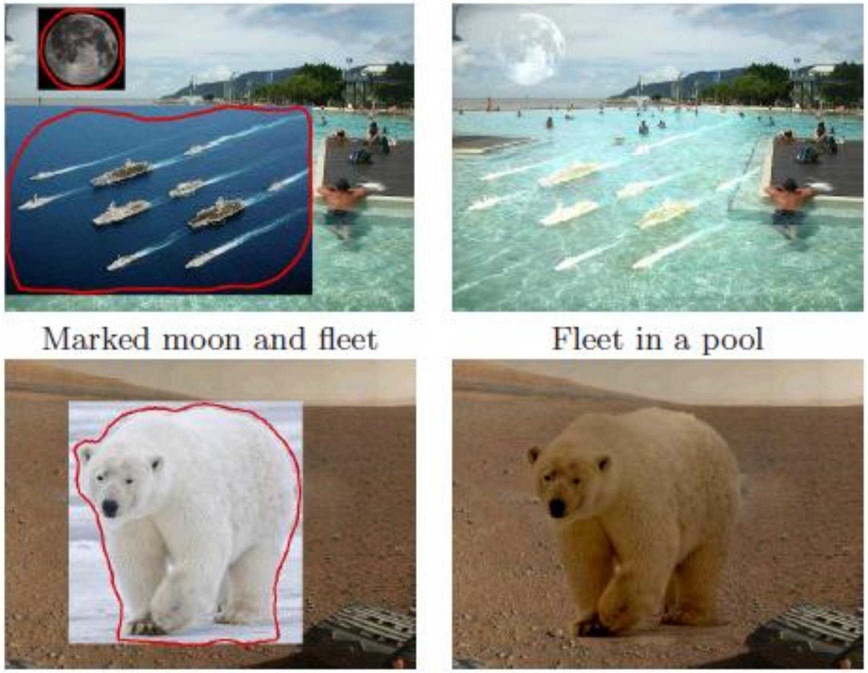
   2.2 Reweight vertex/edge groups accordingly

3. Take average solution

(C-Madry-Miller-Peng 12) solves GLS using electrical flows based methods to obtain $(1+\epsilon)$ *approx in* $O(mk^{-1/3}\epsilon^{-8/3})$ *time.*

Image Blending

[Perez03] Using Poisson Equations with Dirichlet boundary conditions.



Marked moon and fleet

Fleet in a pool

Marked polar bear

Polar Bear on Mars [2]

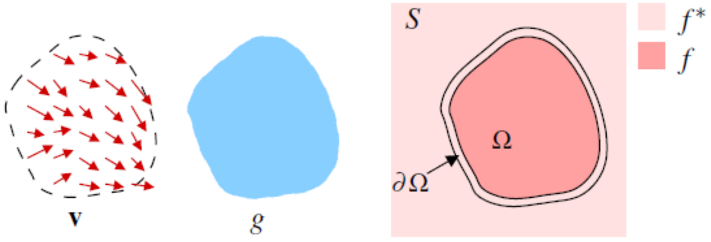


Figure 1: **Guided interpolation notations**. Unknown function f interpolates in domain Ω the destination function f^*, under guidance of vector field $\mathbf{v}$, which might be or not the gradient field of a source function g.

Laplacians in Graphics

Efficient Preconditioning of Laplacian Matrices for Computer Graphics

Dilip Krishnan and Raanan Fattal and Rick Szeliski

detail enhancement — image colorization — mesh geodesic distance and isolines — mesh segmentation using spectral embedding

• D. Krishnan, R. Fattal and R. Szeliski. SIGGRAPH2013

Graph Based Image Processing

- Zeroth Order constraints

  Convolutions filters

- Up to First Order
  - TV Denoising, Poisson Image blending
- Higher Order

Most of image processing can be re-expressed as graph problems!

Graph Based Processing

1. Take advantage of “optimal” linear solvers.
2. Leverage on new graph technologies developed by the machine learning and Big Data community.

Graph Technologies

Technology binned by problem size

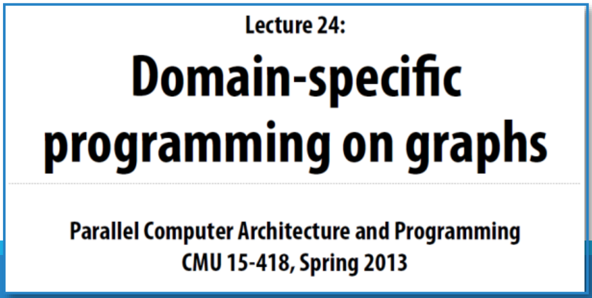
1. <10Gb : GPU accelerated
   Nvidia cuBLAS, ATLAS for LAPACK

Competitive against CMG code

2. 10Gb-1Tb : In Memory solution, Bulk Synchronous
   Ligra, GIRAPH

3. >1Tb : Disk Based, Asynchronous
   GraphLab

Overview of GraphLab, Ligra, Green Marl by Kayvon Fatahalian, CMU



Practical challenges

"Microsoft Hyperlapse uses standard conjugate gradient solver". Why not optimal solvers?

1. Any matrix multiplication must use the GPU to be competitive
2. The memory overhead must be less than problem size
3. Smart data prepositioning across computation nodes
   Not much work done in this area even in the machine learning community

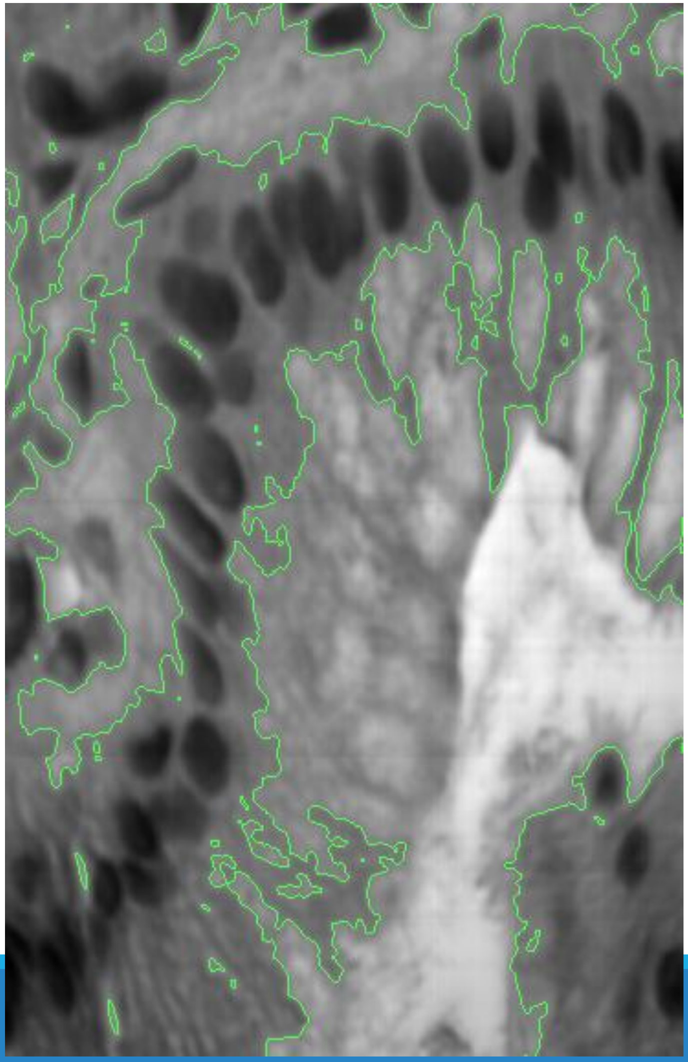
Applications

Graph Based Image processing allows the mix and match of various processing techniques

Solver allows control of the degree which a technique is applied

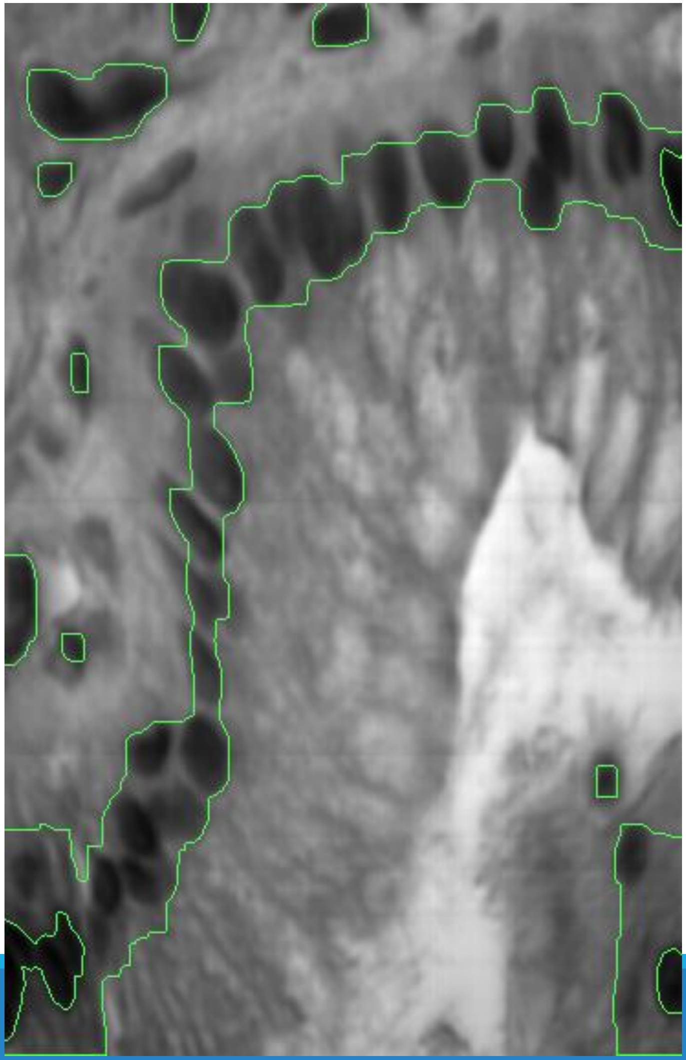
Spectral Segmentation

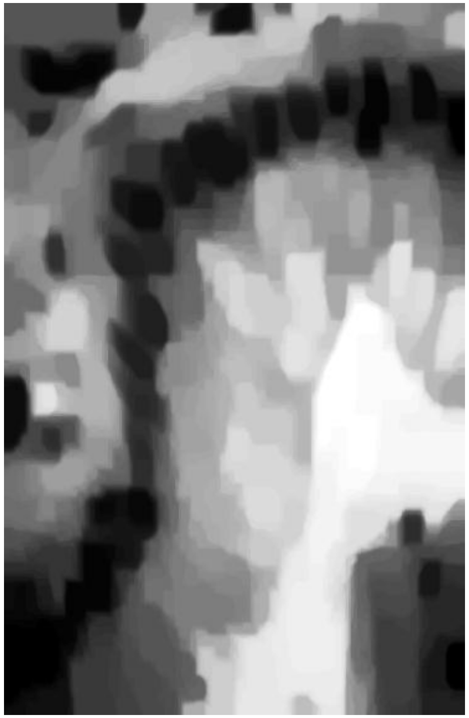
Cell Spectral Segmentation with Virginia Burger, UPitts



Spectral Segmentation

Adding TV norm aids segmentation in noisy scans



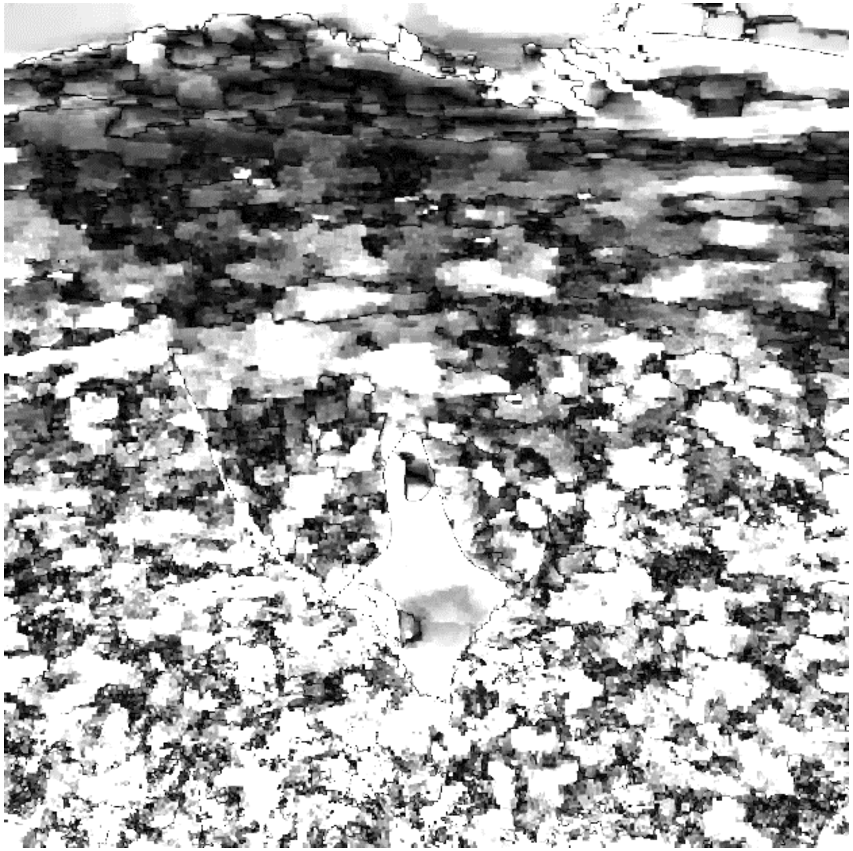


Camouflage Detection

Hyperstealth Biotechnology Corp Stealth Cloak

Camouflage Detection

Control the rate of diffusion of TVD to find breaks



Camouflage Detection

Shadow Enhancement

Shadow Retrieval
With
Pang Sze Kim,
Cheryl Seow,
DSO National Labs

Shadow Enhancement

Contrast Limited
Adaptive
Histogram
Equalization

Shadow Enhancement

Halo due to penumbra correction errors.

Conclusion

1. Data generated from sensors will out pace traditional approaches to process them efficiently.
2. Image processing task can be reformulated as graph optimization problems.
3. Graph based image processing will be able to take advantages of linear solvers and graph technologies.
4. There is a lot of room for research and development in linear solvers for graph and image processing.