

# Auto-Segmentation of Spine CT for Data-Intensive Analysis of Surgical Outcome

Group 21

Niko Eng

# Team Members and Mentors

## Team Members



Ben Ramsay  
*Biomedical Engineering 2018*



Niko Eng  
*Biomedical Engineering 2018*

## Mentors



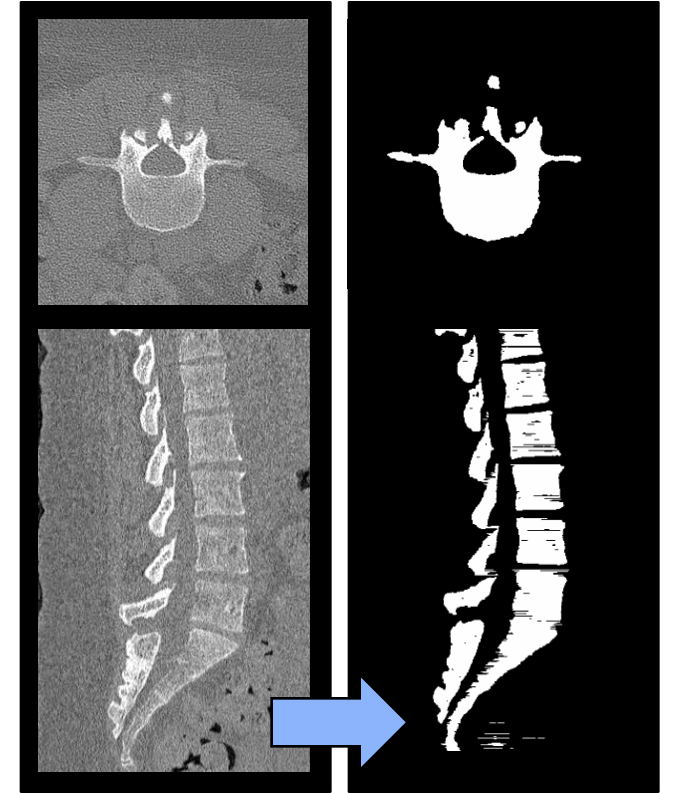
Tharindu De Silva, PhD  
*Post-Doctorate at I-STAR Lab*



Jeffrey Siewerdsen, PhD  
*Professor*  
*Dept. of Biomedical*  
*Engineering*  
*Dept. of Computer Science*

# Project Goals

- Overall: To Develop and Test the “max-flow/min-cut” segmentation method for spine CT images
- **Main Deliverable 04/20:** Accurate segmentation of N=200 spine CT dataset provided by Dr. Siewerdsen



# Paper Selection

## Fast Approximate Energy Minimization via Graph Cuts

Yuri Boykov

Olga Veksler

Ramin Zabih

Computer Science Department

Cornell University

Ithaca, NY 14853

**1999**

**Conference Paper**

International  
Conference for  
Computer Vision

**2001**

**Journal Paper** IEEE

Transactions on PAMI,  
vol. 23, no. 11, pp.  
1222-123

### Why Selected?

- Generalized approach on how to use graph cuts to minimize a variety of energy functions
  - One application is **segmentation** among others (i.e. stereo, image restoration, motion)
- Binary label segmentation of Spine CTs based off of implementation of theory in paper

# Paper Background

Computer vision problems can be naturally formulated into energy minimization:

$$E(f) = E_{smooth}(f) + E_{data}(f).$$

For a labeling  $f$

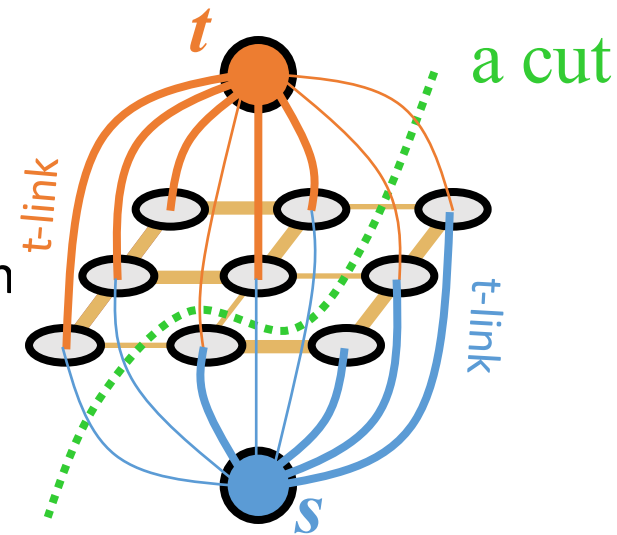
$E_{smooth}(f)$  - Quantifies the similarity of neighboring pixels based on measurables (i.e. intensity)

$E_{data}(f)$  - Quantifies how labeling compares to observed data / priors

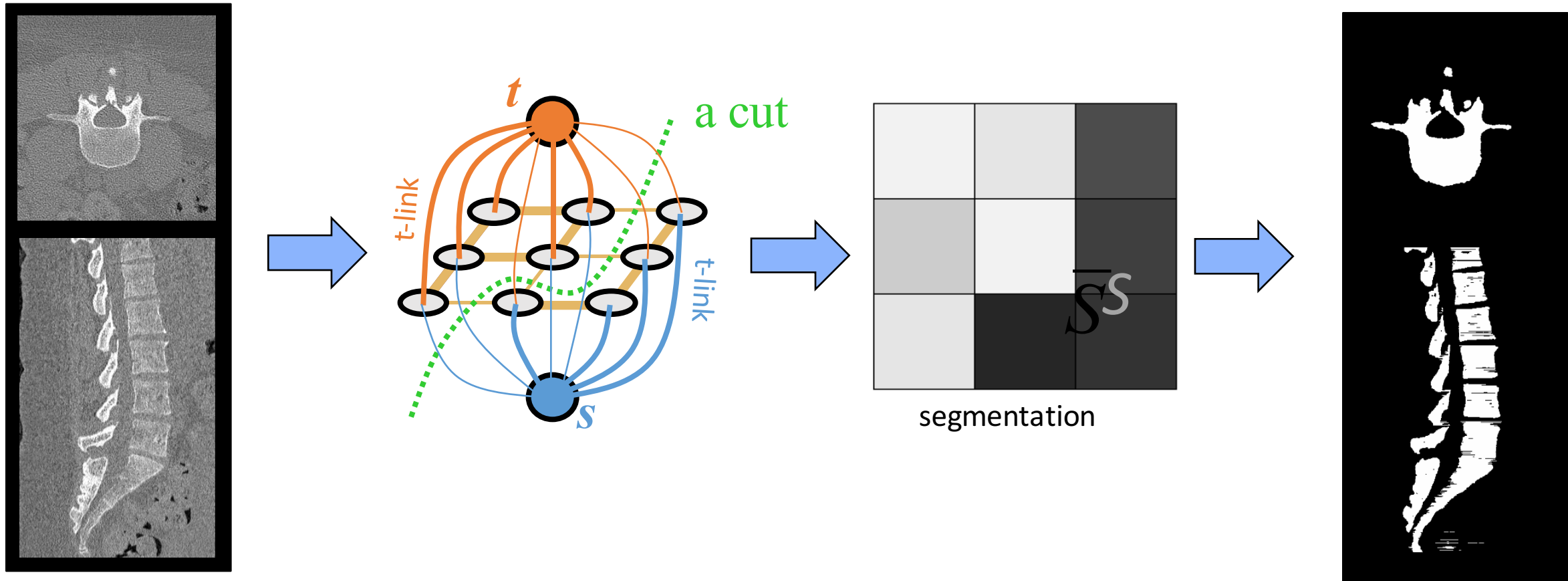
Determining the global minima is often difficult due to computational costs, many local minima, and large possible label space

# Paper Goals

- How does one minimize an energy function in a quick and computationally efficient manner?
- Previous Method: Simulated annealing
  - Can approach the global minimum of arbitrary energy function
  - **Standard Moves** – can only do single pixel changes at each iteration
    - Exponential in time
- Explored Methods: Graph Cuts
  - $\alpha$ - $\beta$  swaps
  - $\alpha$ -expansion
  - **Large moves** – many pixels' labels can change at each iteration
  - For binary labelling **global minimum** can be reached in **polynomial time**



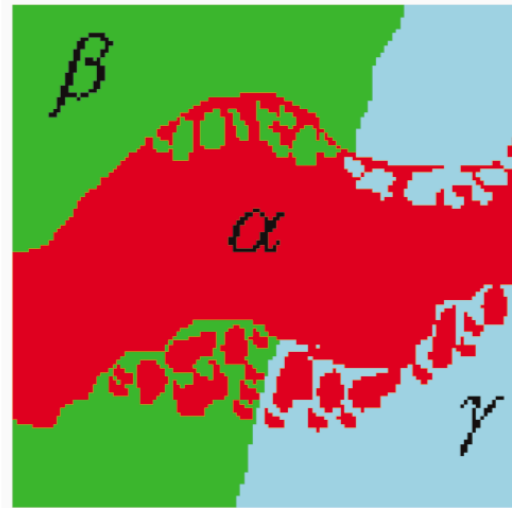
# Max-Flow Min-Cut Explanation (Segmentation Example)



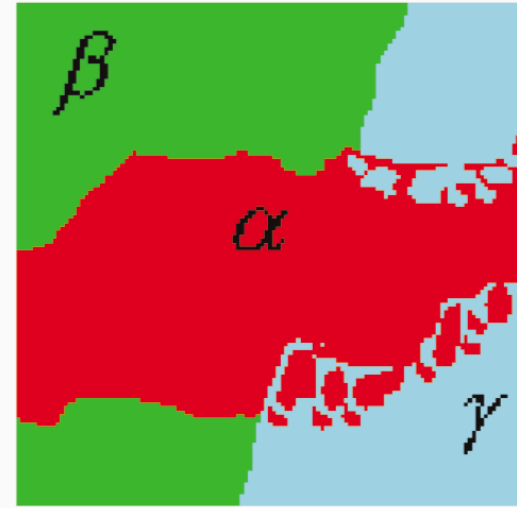
# $\alpha$ - $\beta$ swap

1. Start with an arbitrary labeling  $f$
  2. Set `success := 0`
  3. For each pair of labels  $\{\alpha, \beta\} \subset \mathcal{L}$ 
    - 3.1. Find  $\hat{f} = \operatorname{argmin} E(f')$  among  $f'$  within one  $\alpha$ - $\beta$  swap of  $f$  (Section 3)
    - 3.2. If  $E(\hat{f}) < E(f)$ , set  $f := \hat{f}$  and `success := 1`
  4. If `success = 1` goto 2
  5. Return  $f$
- 

Initial



Final

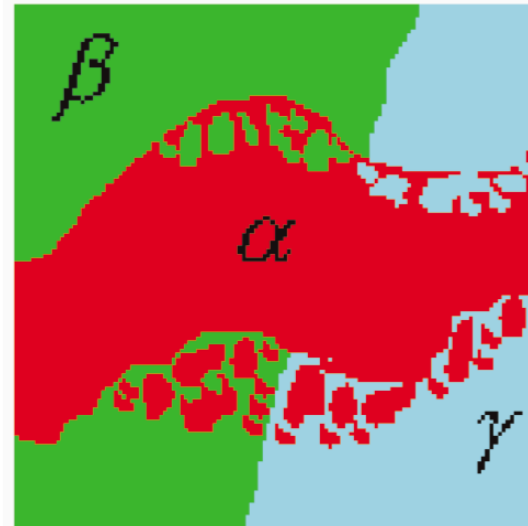




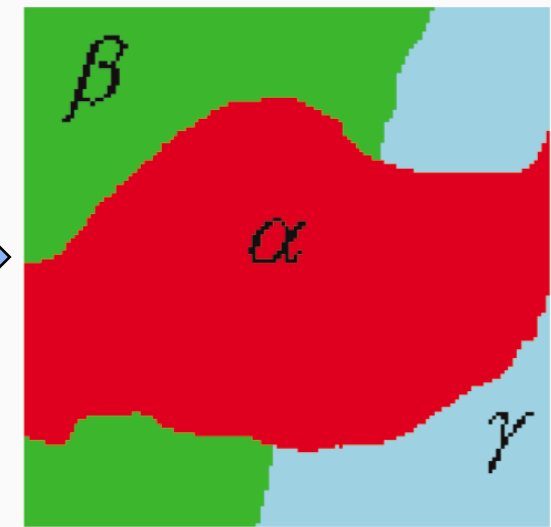
# $\alpha$ - Expansion

1. Start with an arbitrary labeling  $f$
2. Set  $\text{success} := 0$
3. For each label  $\alpha \in \mathcal{L}$ 
  - 3.1. Find  $\hat{f} = \operatorname{argmin} E(f')$  among  $f'$  within one  $\alpha$ -expansion of  $f$  (Section 4)
  - 3.2. If  $E(\hat{f}) < E(f)$ , set  $f := \hat{f}$  and  $\text{success} := 1$
4. If  $\text{success} = 1$  goto 2
5. Return  $f$

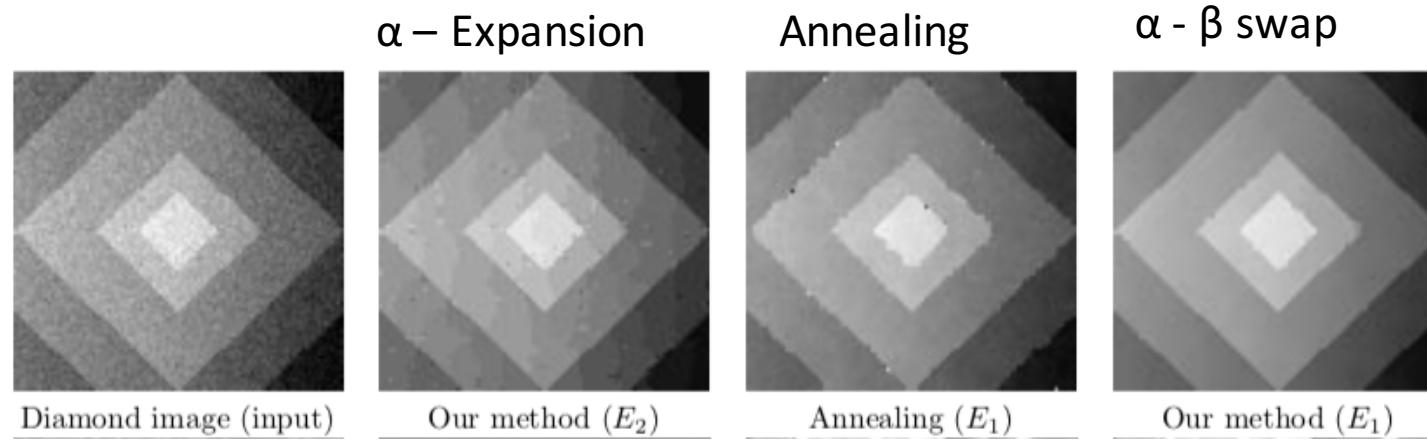
Initial



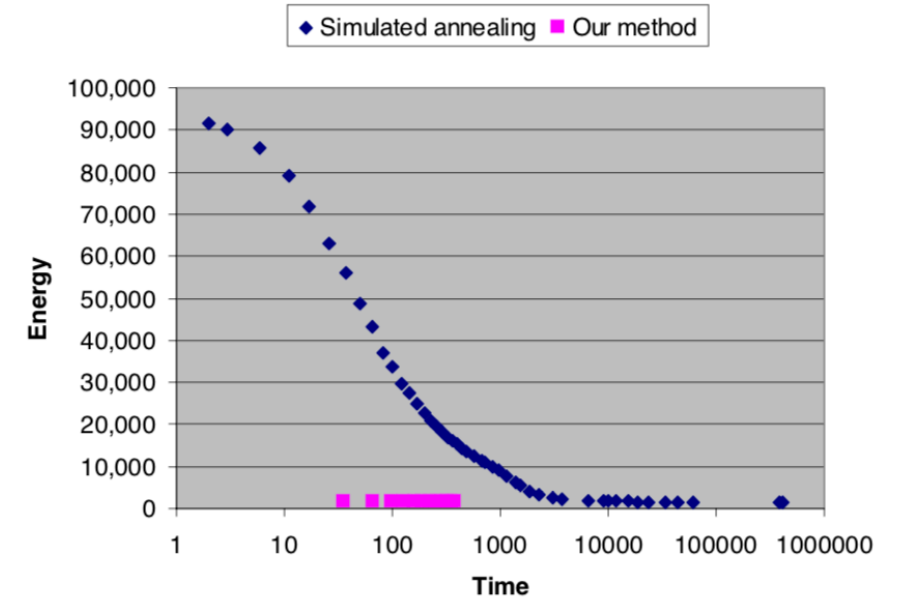
Final



# Experimental Results on Image Restoration



	$E$			$E_{smooth}$		
	Our results	Annealing	Ratio	Our results	Annealing	Ratio
Diamond (image restoration, $E_1$ )						
First cycle ( $t = 36$ )	1,577	55,892	<b>35.5</b>	637	9,658	<b>15.2</b>
Last cycle ( $t = 389$ )	1,472	15,215	<b>10.3</b>	576	8,475	<b>14.7</b>
Best annealing ( $t = 417, 317$ )	—	1,458	—	—	571	—



# Conclusion / Paper Assessment

## Pros

- Generalizable to many computer vision problems (i.e. segmentation, stereo, image restoration, motion)
- Computationally efficient and speedy when compared to the then-current algorithms
- Binary labelling guarantees reaching global minimum
- For multi-labeling with  $\alpha$ -expansion, minima has guaranteed bounds of a factor within global minimum

## Cons

- The Smoothness Functions are limited to pairs of adjacent pixels
- Graph cut methods take a discrete approach

# Reading List

- Boykov, Y., et al. “Fast Approximate Energy Minimization via Graph Cuts.” *Proceedings of the Seventh IEEE International Conference on Computer Vision*, 1999, doi:10.1109/iccv.1999.791245.
- Boykov, Y., et al. “Fast Approximate Energy Minimization via Graph Cuts.” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 11, 2001, pp. 1222–1239., doi:10.1109/34.969114.