Higher Order Conditional Random Field for Multi-Label Interactive Image Segmentation

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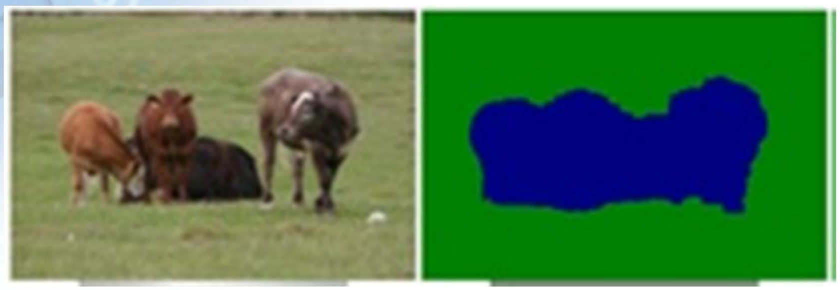
Content

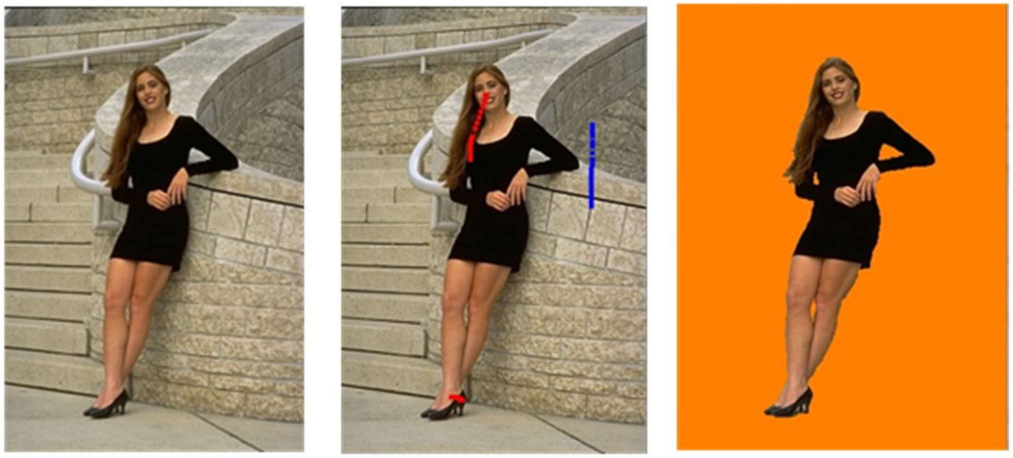
Introduction

Image Segmentation:

- Unsupervised Image Segmentation



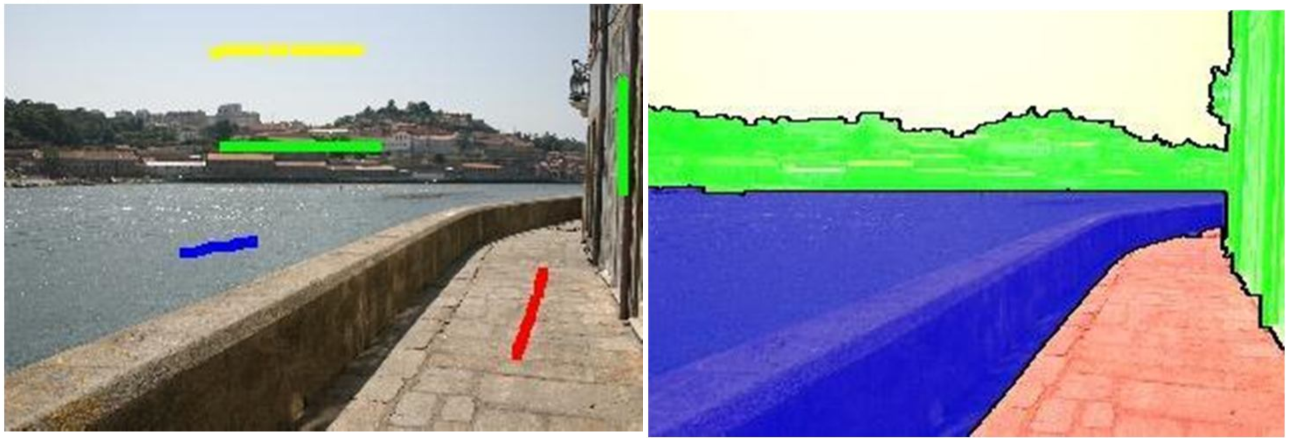
- Supervised (Interactive) Image Segmentation
  - ✓ Binary Label
  - ✓ Multi Label



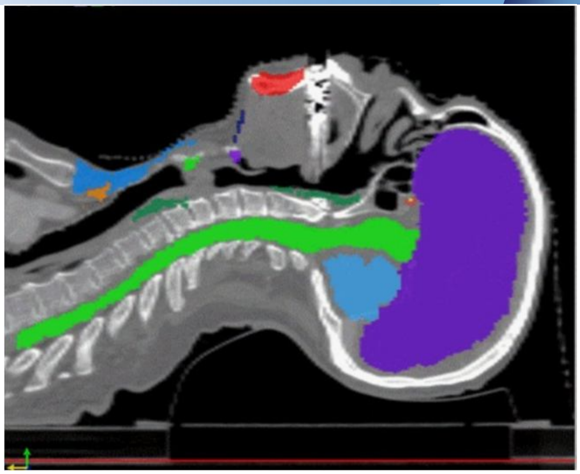
Introduction

Image Segmentation:

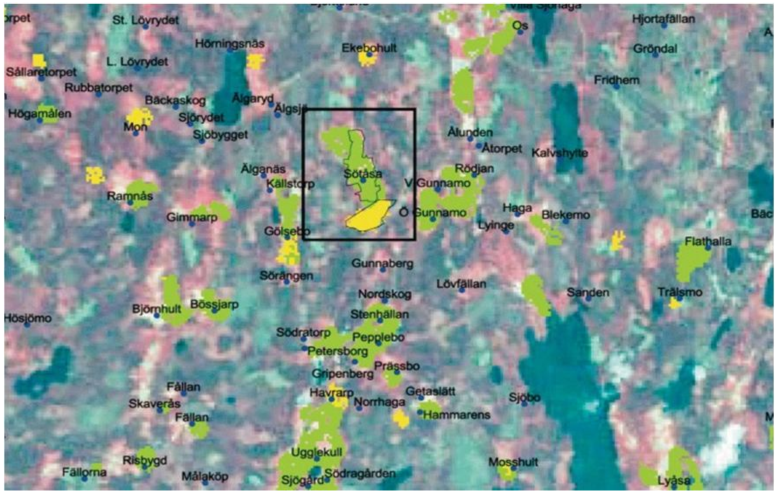
- Unsupervised Image Segmentation
- Supervised (Interactive) Image Segmentation
  - ✓ Binary Label
  - ✓ **Multi Label**



Application

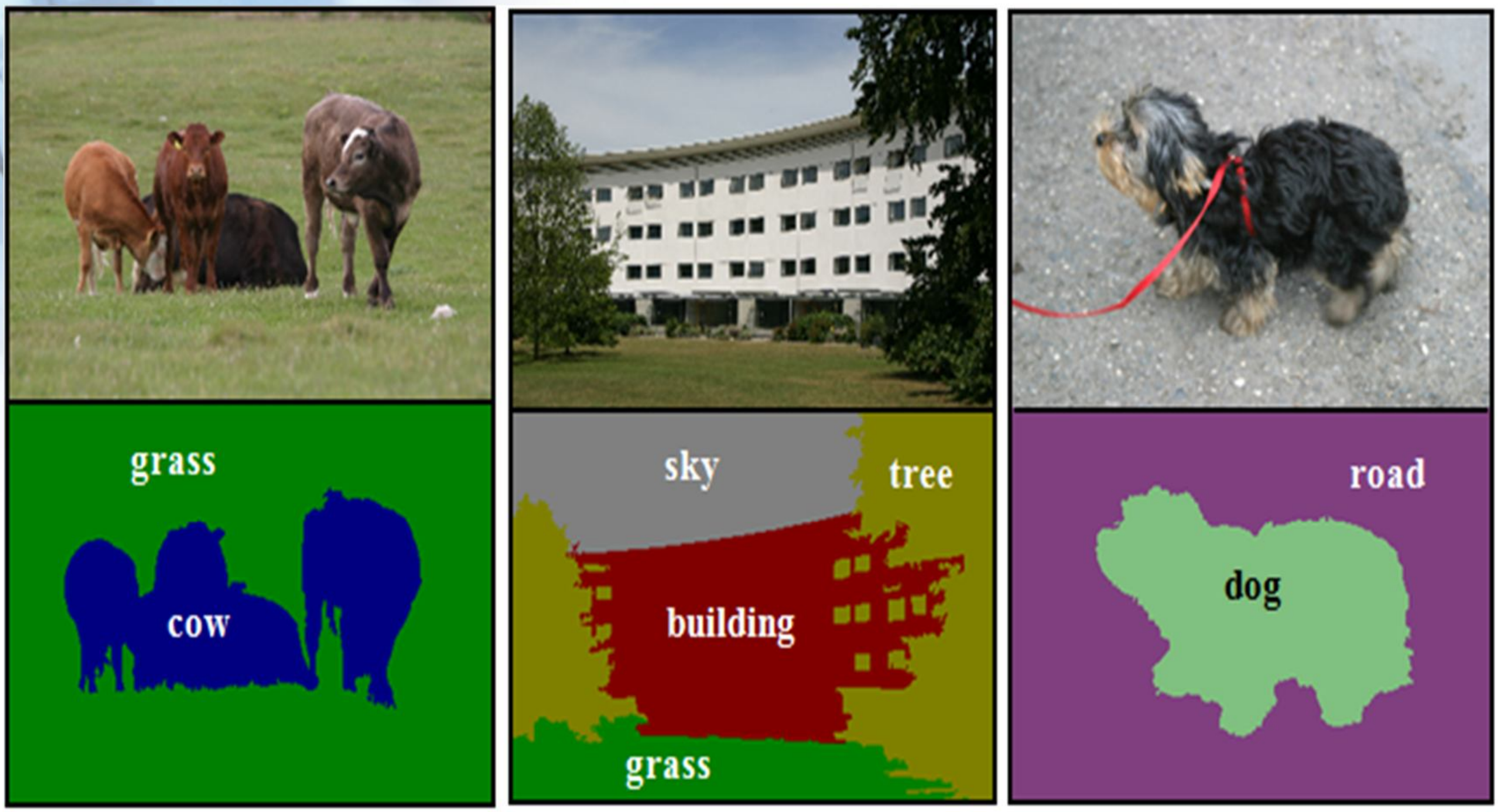


- ❖ **Medical Imaging**
- ❖ **Locate objects in satellite images (roads, forests, etc.)**



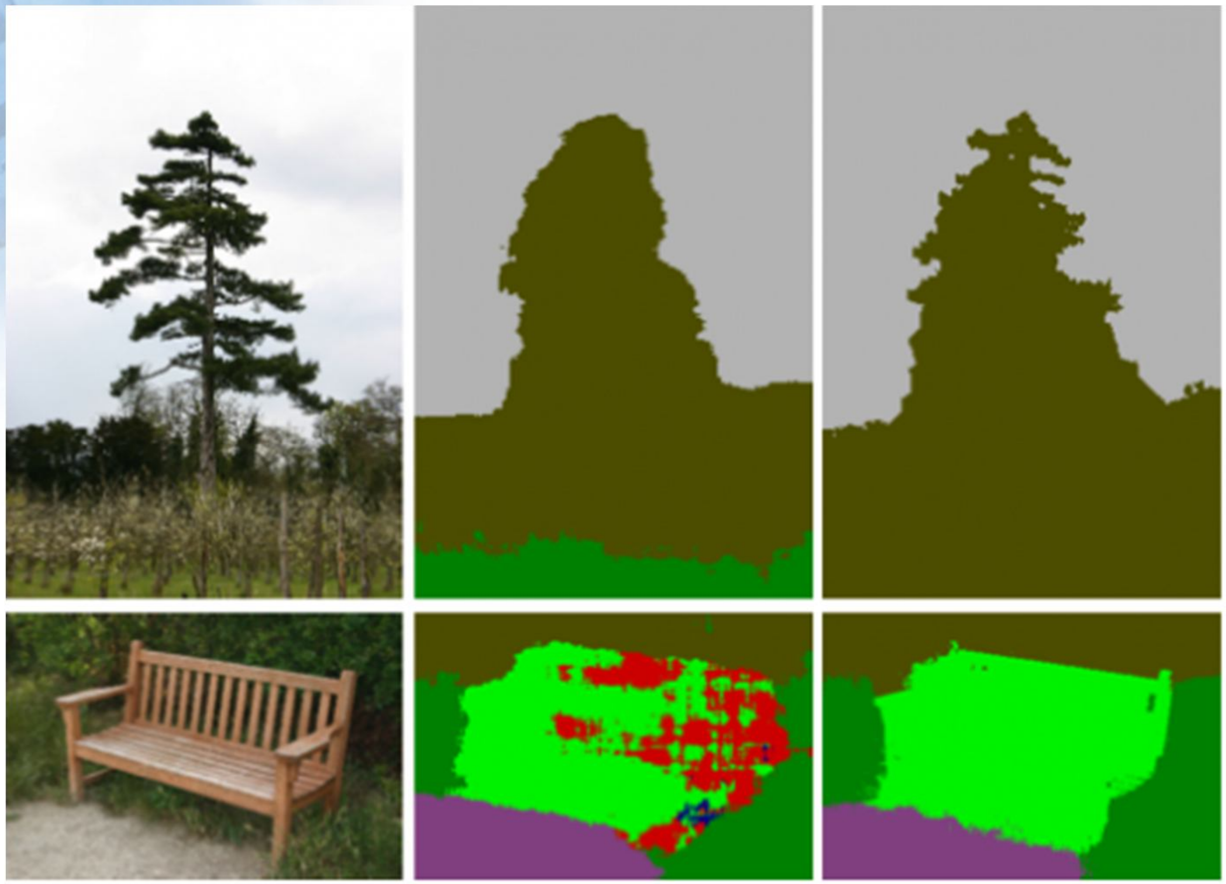
- ❖ **Photo Editing**

Application Image Segmentation
Image Understanding



object class	building	grass	tree	cow	sheep	sky	airplane	water	face	car
bicycle	flower	sign	bird	book	chair	road	cat	dog	body	boat

Example of Unsupervised Image Segmentation



Challenges of Unsupervised Image Segmentation

- Training Data Set : required
  how many data set is enough?
  {horse, tree, human, car, grass…}

- How to deal with unknown Object ?

Interactive Image Segmentation

Multi Label Interactive Image Segmentation

Conditional Random Field (CRF)

- CRF was introduced by Lafferty in 2001, Natural Language Processing issues.

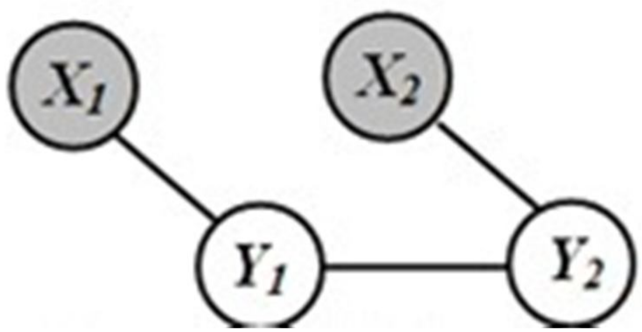
- General form:

$$p(\boldsymbol{Y} = \boldsymbol{y} | X = \boldsymbol{x}) = \frac{1}{Z(\boldsymbol{x})} \exp\left\{-\sum_{c} \psi_c(\boldsymbol{y}_c, \boldsymbol{x})\right\}$$

where ***Y*** :label

X : observation

- Graphical Model



Ordinary CRF Energy Function

$$E(x) = \sum_{p \in \mathcal{P}} \Psi_p(x_p) + \sum_{p \in V, q \in N_j} \Psi_{pq}$$

Unary Cost

Neighboring Cost

Higher Order CRF Energy Function

$$E(x) = \sum_{p \in \mathcal{P}} \Psi_p(x_p) + \sum_{p \in V, q \in N_j} \Psi_{pq} + \sum_{c \in S} \Psi_c(x_c)$$

Unary Cost

Higher Order Cost

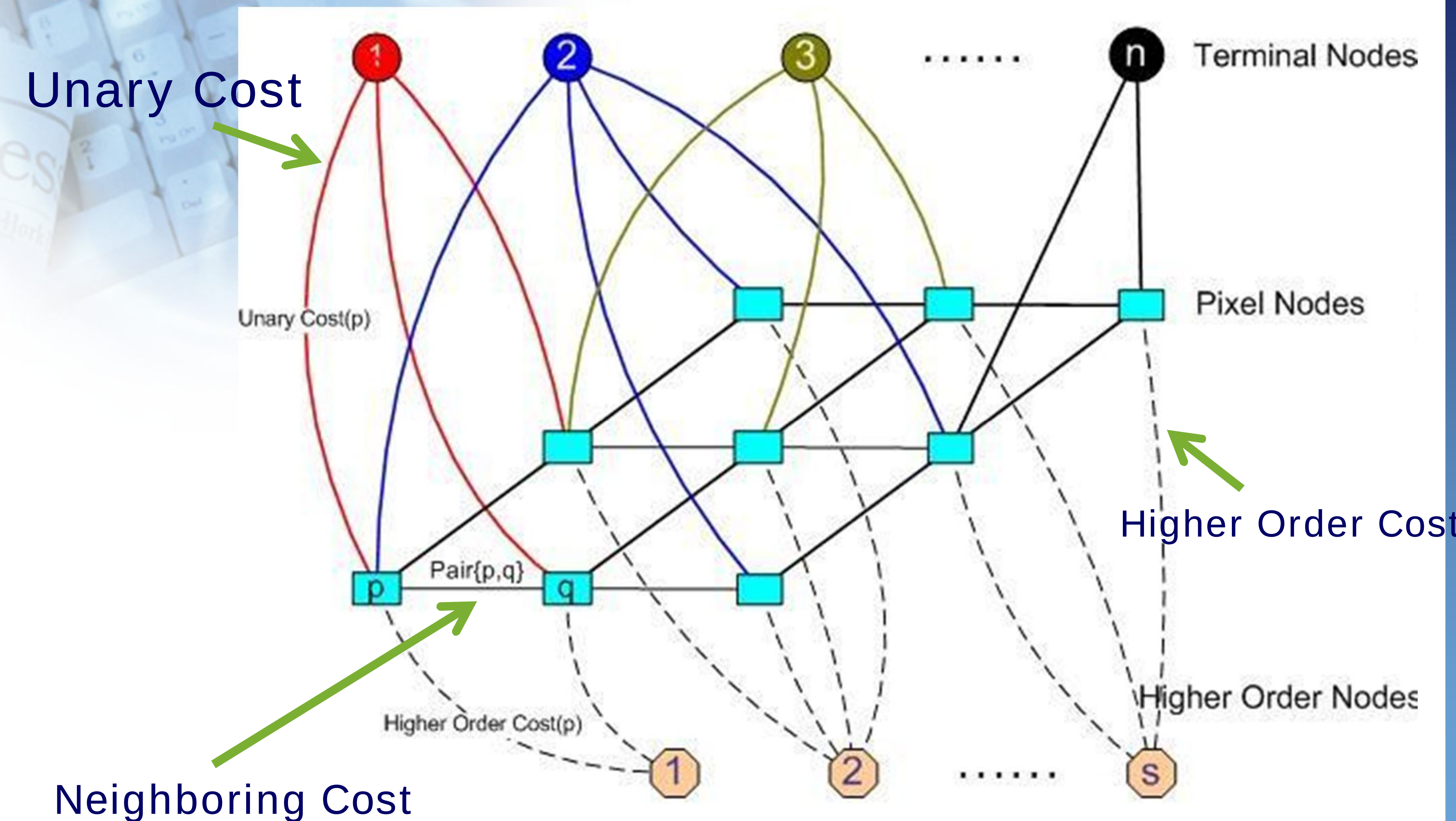
Neighboring Cost

Higher Order CRF Interactive Image Segmentation: 2 steps

- 1. Building up the Higher Order CRF model

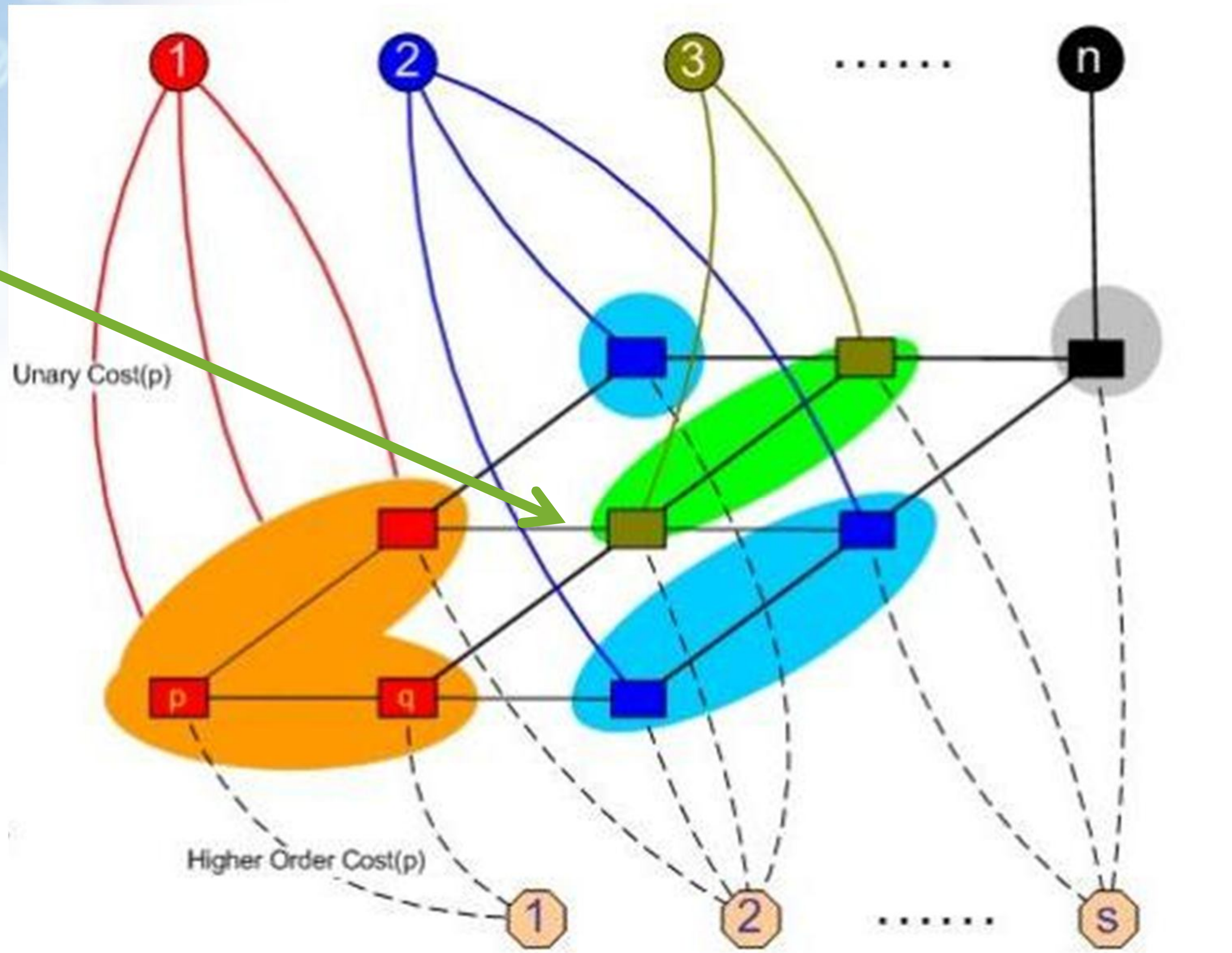
- 2. Energy Minimization

Building up the Higher Order CRF model



Higher Order CRF Model

Energy Minimization Process



1. Unary Cost

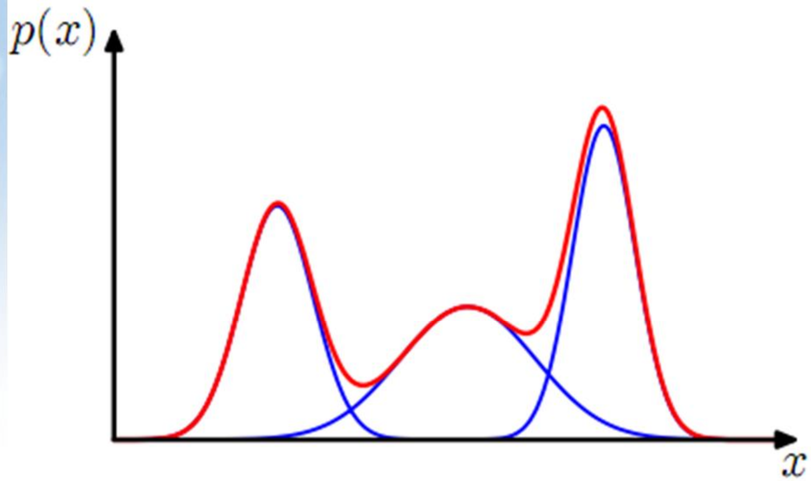
$$E(x) = \sum_{p \in \mathcal{P}} \Psi_p(x_p) + \sum_{p \in V, q \in N_j} \Psi_{pq} + \sum_{c \in S} \Psi_c(x_c)$$

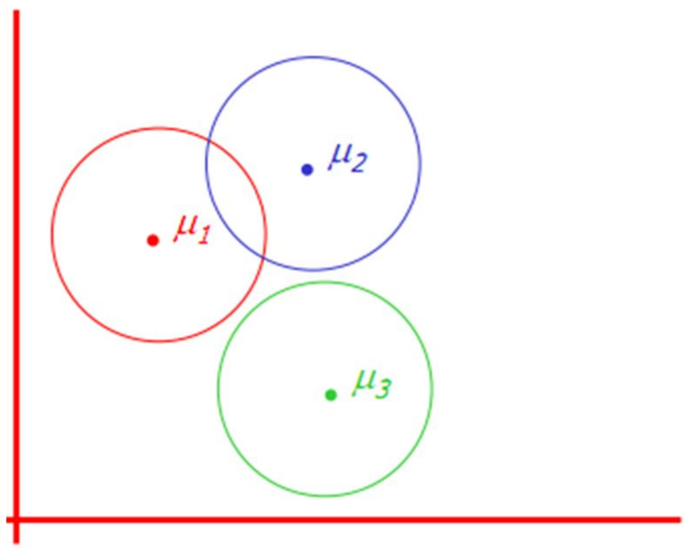
Unary Cost

Color Likelihood Term

$$\Psi_i(x_i) = \sum_{n=1}^{N} p(x_i | obj_n)$$

Gaussian Mixture Model





2. Neighboring Cost

$$E(x) = \sum_{p \in \mathcal{P}} \Psi_p(x_p) + \sum_{p \in V, q \in N_j} \Psi_{pq} + \sum_{c \in S} \Psi_c(x_c)$$

Neighboring Cost

The similarity between two pixels

$$\Psi_{p,q} \propto exp(-\frac{||C_p - C_q||^2}{\sigma^2}).\frac{1}{dist(p,q)}$$

3. Higher Order Cost

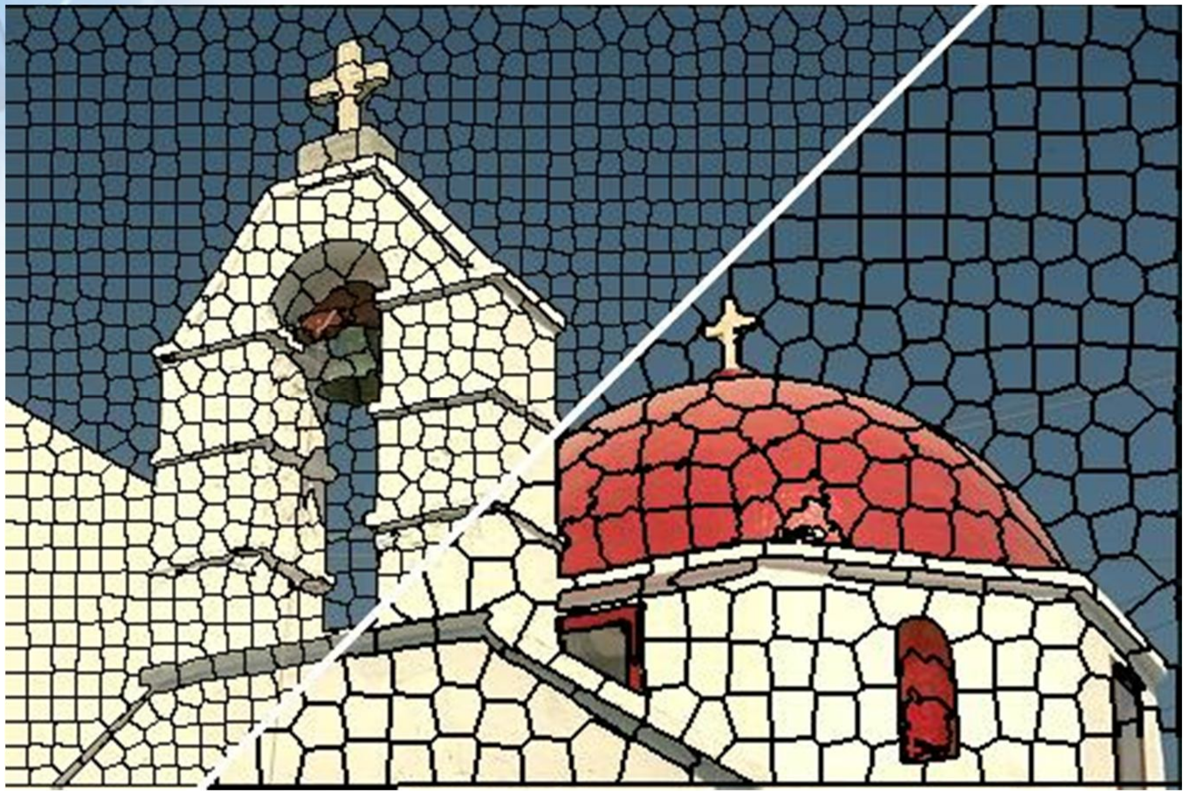
$$E(x) = \sum_{p \in \mathcal{P}} \Psi_p(x_p) + \sum_{p \in V, q \in N_j} \Psi_{pq} + \sum_{c \in S} \Psi_c(x_c)$$

Higher Cost

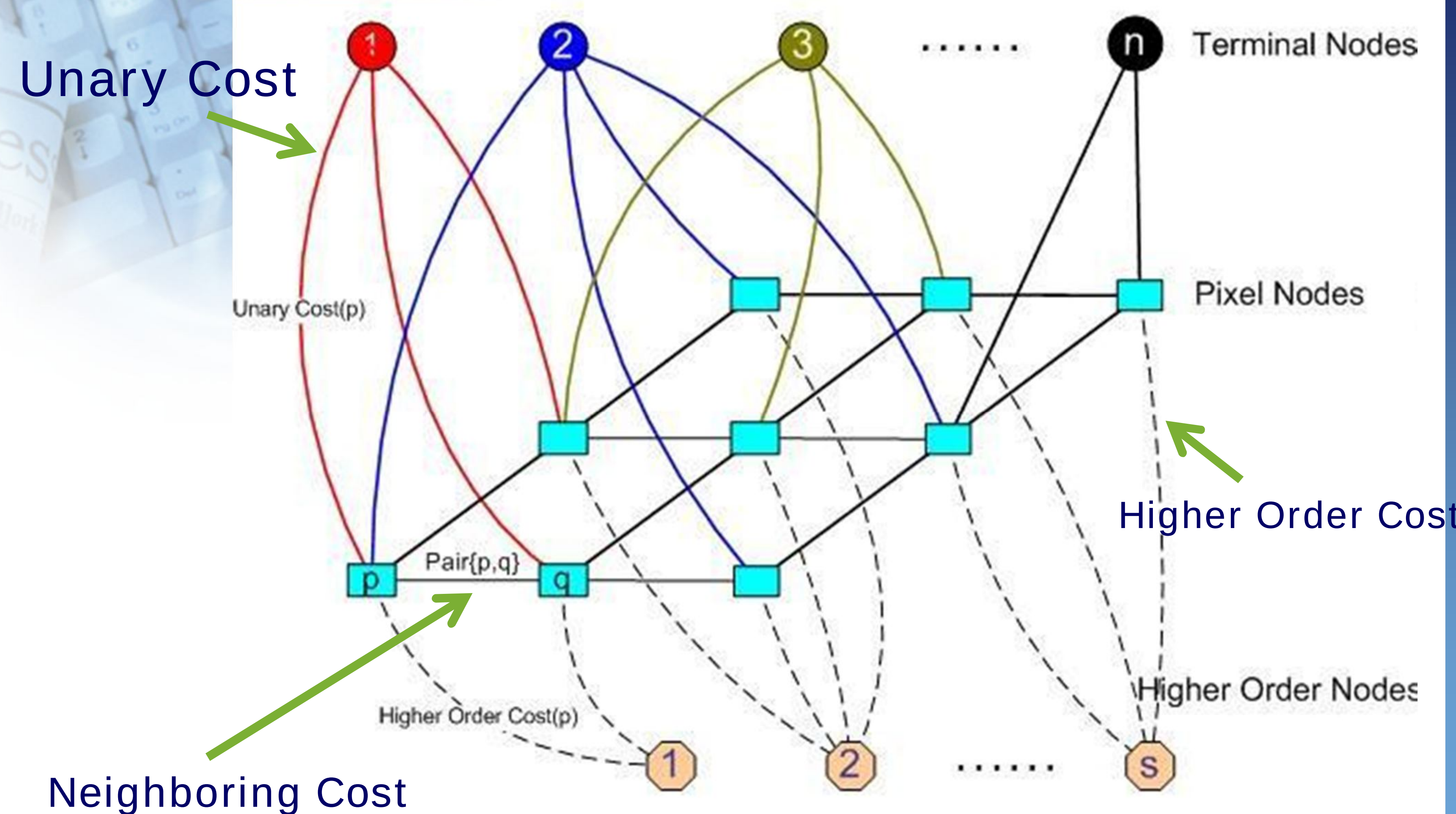
Pre segmented procedure

$$\Psi_c(x_c) = \begin{cases} 0 & if\ x_i = l_k, \forall i \in c \\ \frac{1}{log(|c|)} & otherwise \end{cases}$$

Superpixel

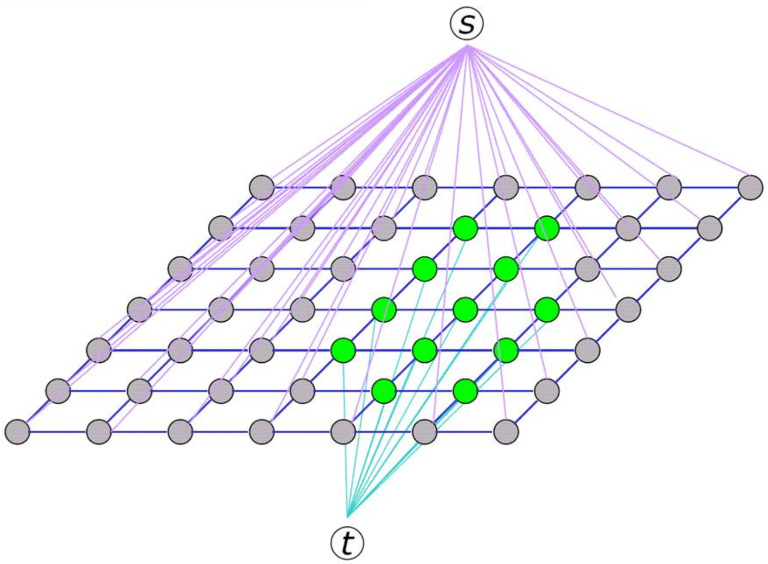


Higher Order CRF Model

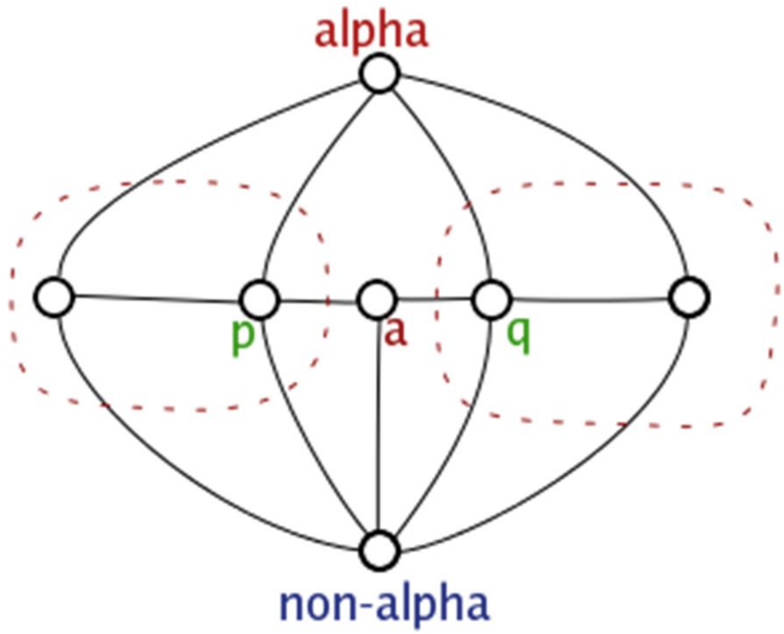


Energy Minimization by Graphcut and Alpha Expansion

$$E(x) = \sum_{p \in \mathcal{P}} \Psi_p(x_p) + \sum_{p \in V, q \in N_j} \Psi_{pq} + \sum_{c \in S} \Psi_c(x_c)$$



Graphcut

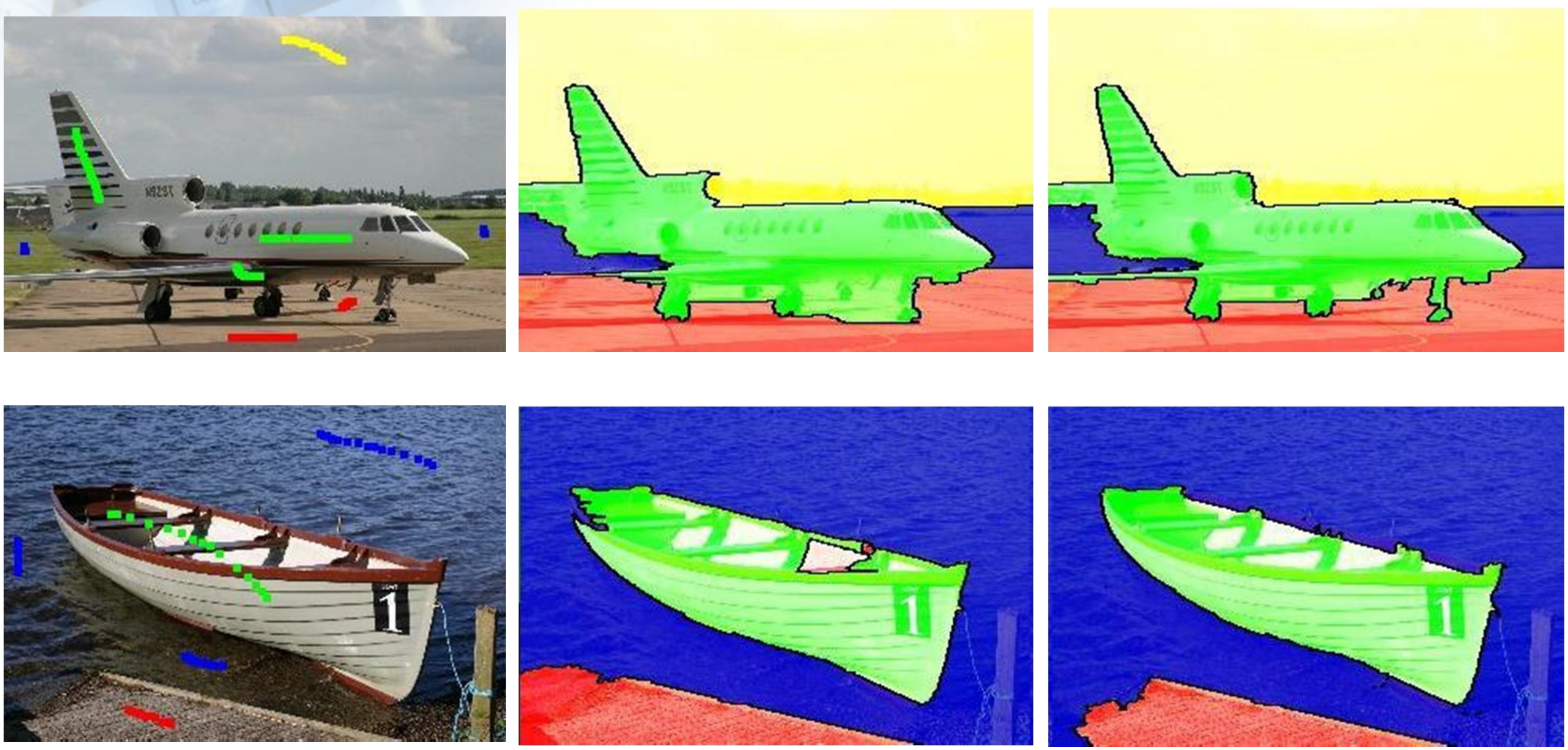


Alpha Expansion

Experiments

Microsoft Research Cambridge MSRC dataset

Scrabbled Image | Ordinary CRF | Higher Order CRF

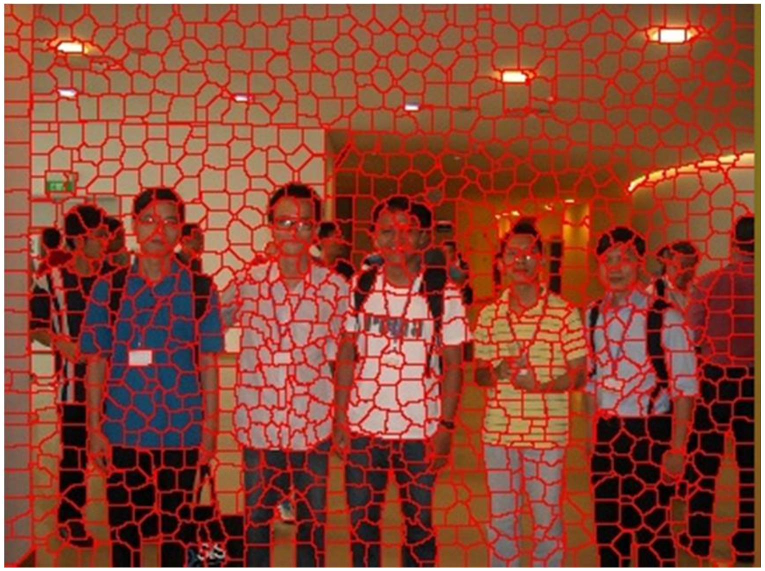


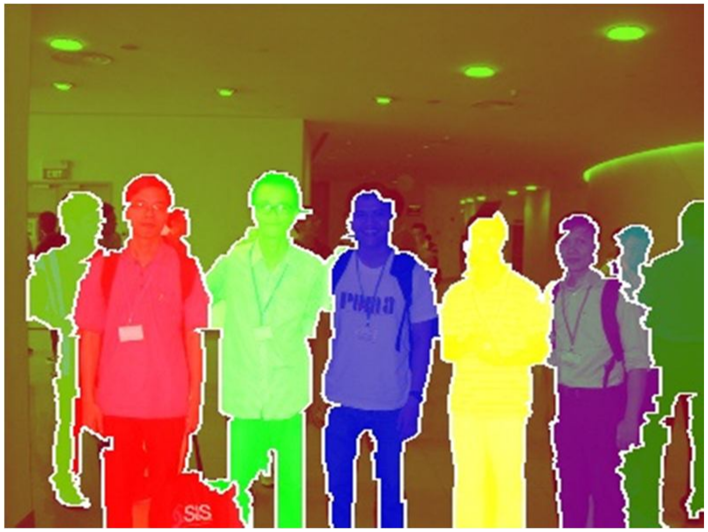
Accuracy Measurement

$$Accuracy = \sum_{i=1}^{N} \frac{True_i}{True_i + False_i}$$

Method	**Accuracy**
Multi-label Interactive CRF	**89.54%**
Multi-label Interactive Higher Order CRF	**92.8%**

Experiments on Arbitrary Image





Demo

Conclusion

- ❖ Developing effectively interactive multi label image segmentation from unsupervised issue.
- ❖ Utilizing higher order CRF model comparable experiments with the original CRF.
- ❖ Computational expensive for large size image.

Reference

- Tien-Vu Nguyen, Trung Tran, Phong Vo, Bac Le, Efficient Image Segmentation Incorporating Photometric and Geometric Information, International Conference on Imaging Engineering (ICIE), Hong Kong, 16 – 18 March, 2011.
- Y. Boykov and M. P. Jolly. Interactive graph cuts for optimal boundary and region segmentation of objects in N-D images. In ICCV, volume 1,pages 105–112, July 2001.
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Thank You !