Joint Optimization of Segmentation and Color Clustering

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Binary Segmentation

$$E(S,\theta) = E_a(S,\theta) + \lambda_S|\partial S|$$

Appearance term:

$$E_a(S,\theta) = \sum_p -\ln \Pr(I_p|\theta_{s_p})$$

Smoothness term:

$$|\partial S| = \sum_{pq} w_{pq}[s_p \neq s_q]$$

θ - Appearance models:

- Gaussian mixture models
- Histograms of pre-processed color binning:
  - full histogram
  - uniform color quantization
  - color clustering

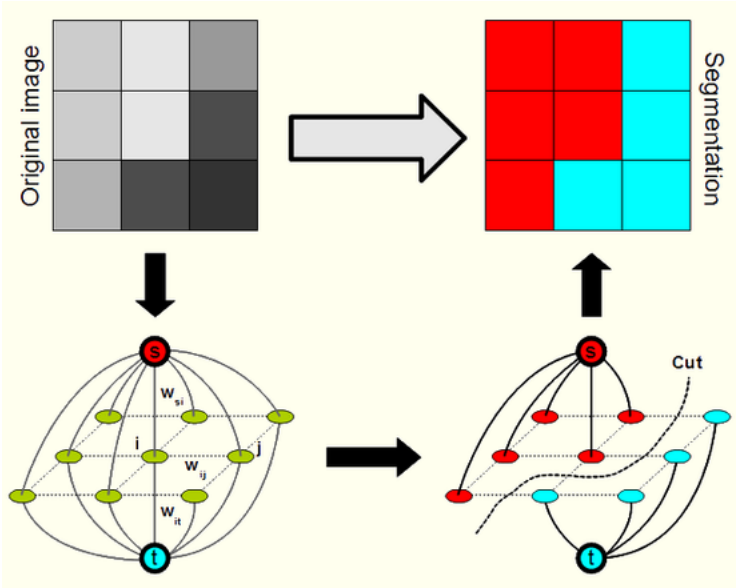
Energy optimization

θ initialization:

Bounding box

Seeds

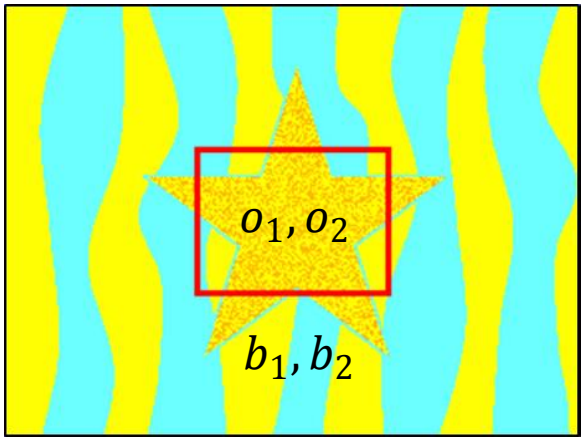
Optimization with fixed θ : Graph Cut



Block coordinate descent:

- Over S: Graph Cut
- Over θ: Histogram counts

Example

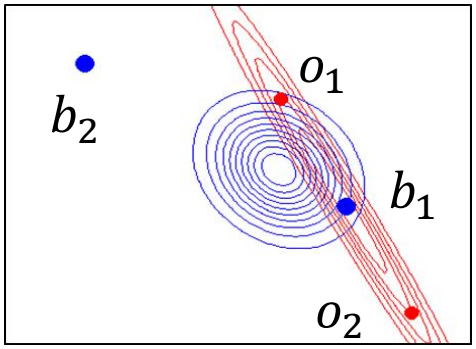


o_1 o_2 foreground

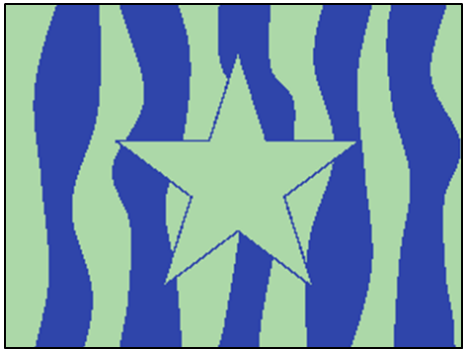
b_1 b_2 background

b_1 is closer to foreground colors!

GMM



Fixed binning



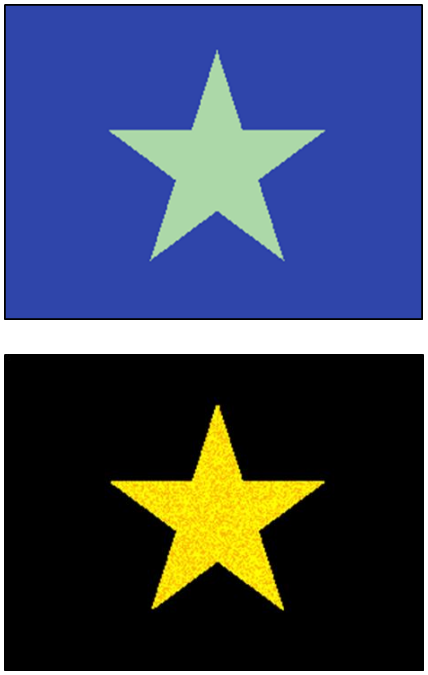
Segmentation

Main Idea

Let's optimize binning and segmentation together!

$$E(S, \theta, \boldsymbol{B}) = E_a(S, \theta, \boldsymbol{B}) + \lambda_C E_c(\boldsymbol{B}) + \lambda_S |\partial S|$$

+ kmeans-based clustering term



Results:

Clustering and Segmentation

Find clustering that minimizes foreground/background overlap

New Energy

$$E(S,\theta,B) = E_a(S,\theta,B) + \lambda_C E_c(B) + \lambda_S|\partial S|$$

$$\sum_S h(n^S) - \sum_B \sum_S h(n_B^S)$$

$$\sum_{p\in P} \left\| I_p - \mu_{B_p} \right\|^2$$

$h(x) = x\log(x)$ n – number of pixels in S or in $B \cap S$

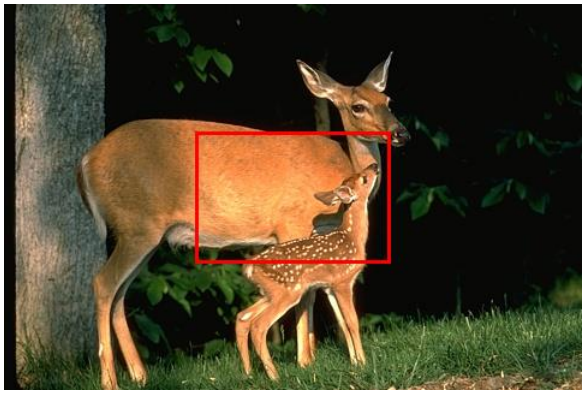
Normalized histograms of B

- Minimizes foreground/ background overlap
- Volume balance
- Prefers less clusters

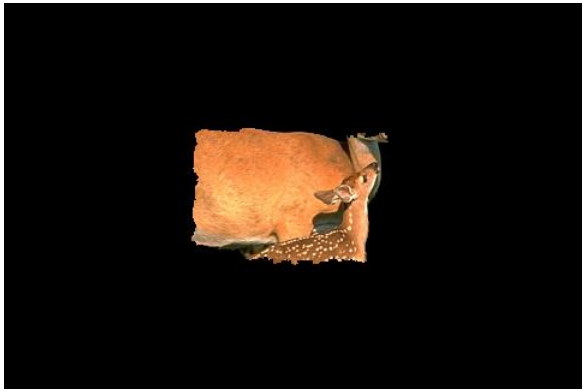
Kmeans energy

- Groups pixels of similar colors
- Prefers more clusters

The tradeoff



Init



Low λ_C

High λ_C

Optimization

Init: box without hard constraints

+ start from 5 different initializations

Over B: $\min_B \; E_a(S, \theta, B) + \lambda_C E_c(B)$

Swap-kmeans

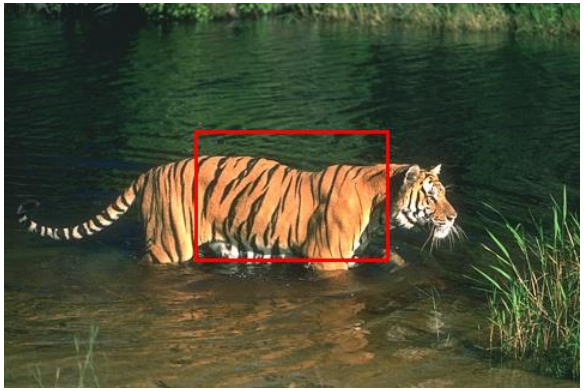
- Cluster assignment - swap algorithm for labeling pixels with cluster indexes
- Usual updating of the means

Over S: $\min_{S,\theta} \; E_a(S, \theta, B) + \lambda_S |\partial S|$

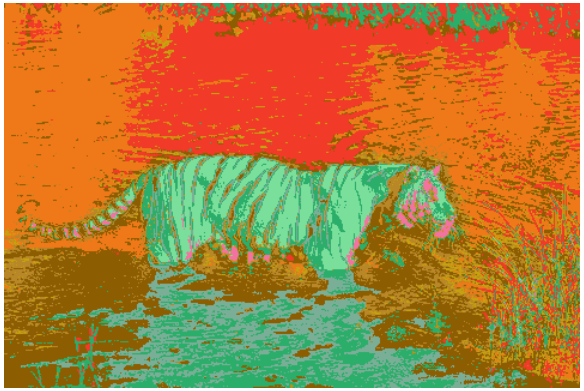
Usual Block Coordinate Descent

- S with graph cut
- Histogram counts

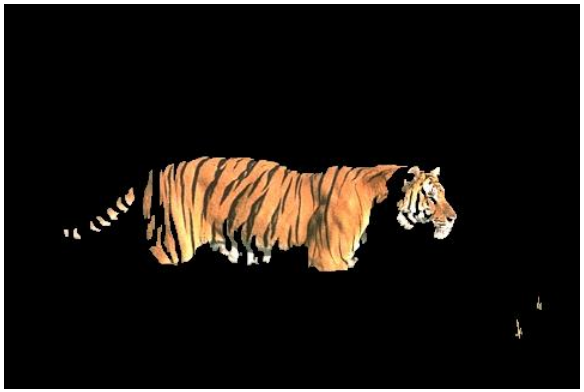
Experiments: example



a) original image with initialization



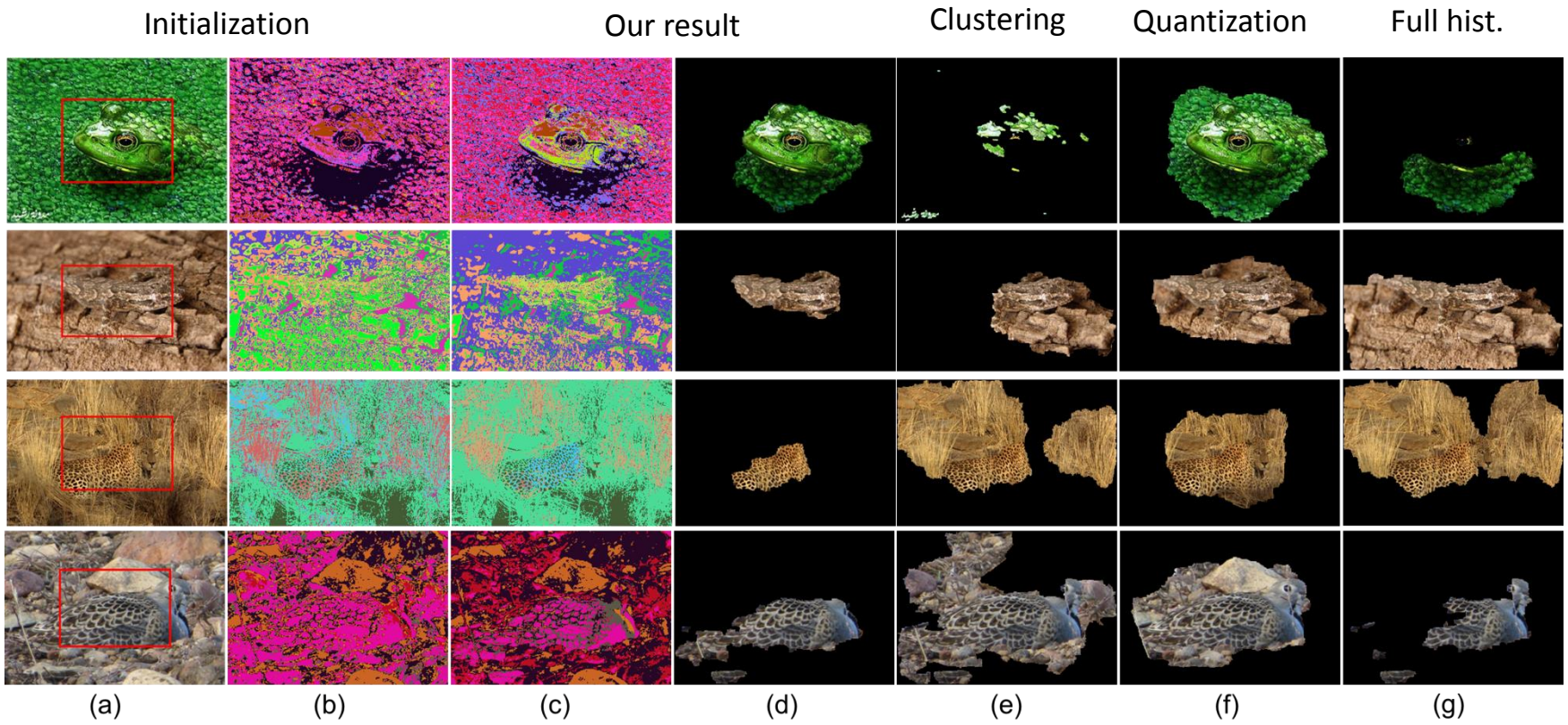
b) initial color clustering



c) final segmentation

d) final color clustering

Experiments: Camouflage Images



Experiments

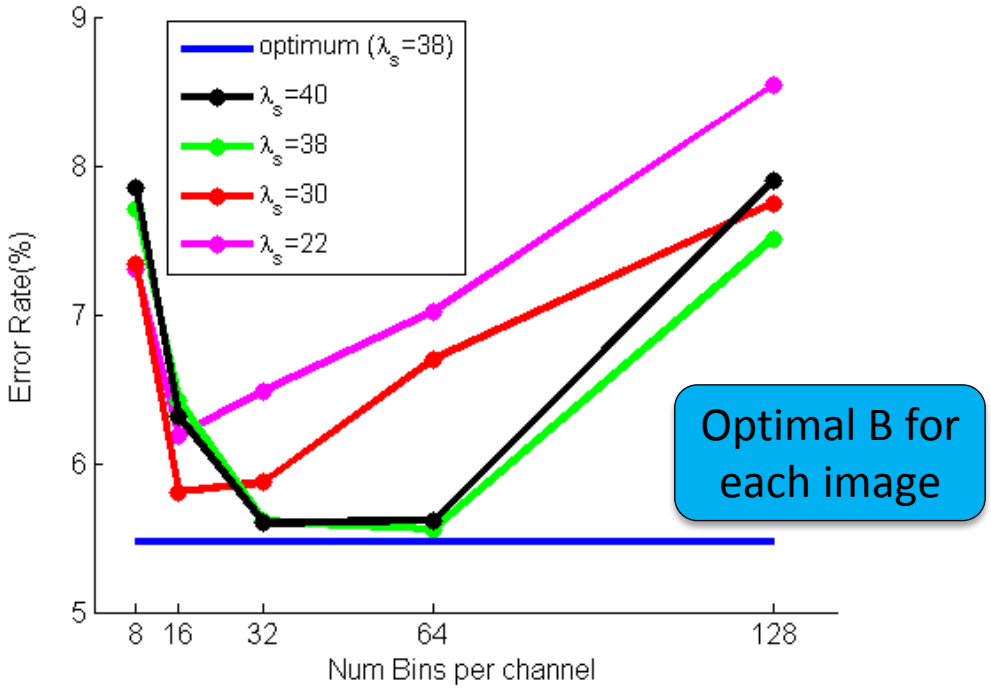
	Interactive (GrabCut)		NonInteractive	
	% pixel err	aver. time (sec)	GrabCut	Achanta
Ours	7.5	10.4	8.0	6.0
GMM	8.9	5.4	9.4	7.5
Full hist.	12.3	3.6	13.8	10.5
Quantization	8.5	4.8	9.3	8.2
Clustering	8.2	7.2	8.8	7.6

FutureWork: Generalized energy

$$H(B) + H(I|B) - MI(S,B) + \lambda_S|\partial S| + \gamma\|B\|_0$$

sparsity

$$E_a(S,\theta,B) + \lambda_C E_c(B)$$



Optimal B for each image

from MDL principles for image compression

λ_S, γ – from scheme

+ better optimization algorithm