



Object Selection

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- III. Problem statement
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Image selection

- An image is a set of sub-images that sometimes referred to as regions-of-interest, ROIs, or simply regions.
- One of the problem in image processing is image selection
 - how to cut out or select an area for later specific image processing operations.

Interactive single-image segmentation

Interactive single-image segmentation (image cutout or foreground/background separation), one of the typical case in region selection problem, is to select the object (e.g. human, flower, etc.) from the background that based on samples provided by the user.

Image segmentation from Lazy Snapping paper





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Literature review

- Greig et al, 1989: the first using min-cut max-flow algorithm to optimize certain energy function in vision.
- Boykov and Jolly, 2001: basing on the work of Greig, finding optimal segmentation which satisfies hard constraints imposed by user and soft constraints combining both region and boundary properties.
- Li, Tang, Sun and Shum, 2004: improving the method of Boykov and Jolly, working on super-pixel with an extra boundary-editing step.
- Rother, Kolgomorov and Blake, 2004: the iterated version of Boykov and Jolly's works, using color and contrast information with border matting for optimize the boundary.

Examples

Lazy Snapping













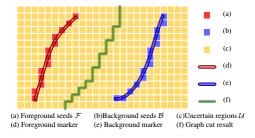
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Problem statement

Suppose we have an input i mage N and some sets of pixels:

- Foreground set $\mathcal{F} = \{f_1, f_2, f_3, ...\}$: set of all pixels that are sample for the object.
- Background set $\mathcal{B} = \{b_1, b_2, b_3, ...\}$: set of all pixels that are sample for the background.
- Uncertain set\(\mu = \mathcal{N} (\mathcal{F} \cup \beta)\): set of all pixels that
 are not in the both fore/background set.

How to figure out all pixels belong to the object in the image and separate them from the background?



Binary images: foreground, background

- A binary image is an image in which each pixel belongs to one of only two possible discrete logical value: 1 or 0. In our problem:
 - The logical value 1 is known as "object".
 - The logical value 0 is known as "not object".
- We define the set of pixels which logical value is 1/0 as the temp foreground/background pixel.

Binary labelling problem

For all image pixels, we need to assign a unique label

$$x_i \in \{foreground (=1), background (=0)\}$$

- If a pixel is in the foreground/background set, the label of it is 1/0.
- If a pixel is not in the foreground and background set, the temporary label of it is "uncertain".

How to find a way to label all pixels in the image so that all pixels belong to object we want to select have same label, and so do to the another pixel?

Binary labelling problem - Constraint

Data constraint

Prior constraint

If a pixel has it colors similar to at Pixels that belong to the object least one pixel belong to tend to group together, and so do foreground seeds, it is more likely with pixels that belong to to get foreground label, and so do background. with background seeds.

Binary labelling problem

Minimize the energy function (Greig et al., 1989)

$$E(L) = \sum_{p} D_{p}(L_{p}) + \lambda * \sum_{p,q \in N} |L_{p} - L_{q}| * g(C_{i,j})$$

Where λ know as a balancing parameter between data constraint and the prior constraint:

- The larger lambda, the less discontinuities in the optimal labeling L.
- The smaller lambda, the more optimal labeling L.

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Energy function

Let A is a {"object", "background"} binary vector of pixels that defines a segmentation

$$E(A) = \lambda \cdot R(A) + B(A) ,$$

where

$$R(A) = \sum_{p \in P} R_p(A_p)$$

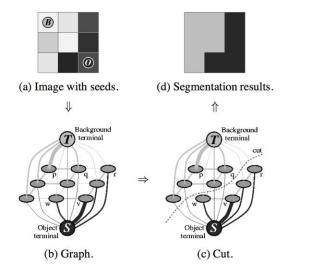
$$B\left(A\right) = \sum_{\{p,q\} \in \mathcal{N}} B_{\{p,q\}} \cdot \delta\left(A_p, A_q\right)$$

and

$$\delta(A_p, A_q) = \begin{cases} 1 & \text{if } A_p \neq A_q \\ 0 & \text{otherwise.} \end{cases}$$

Graph cut construction

A simple segmentation example for a 3x3 image.



Energy function (cont.)

edge	weight (cost)	for
$\{p,q\}$	$B_{\{p,q\}}$	$\{p,q\}\in\mathcal{N}$
$\{p,S\}$	$\lambda \cdot R_p$ ("background")	$p \in \mathcal{P}, p \notin \mathcal{O} \cup \mathcal{B}$
	K	$p \in \mathcal{O}$
	0	$p \in \mathcal{B}$
$\{p,T\}$	$\lambda \cdot R_p$ ("object")	$p \in \mathcal{P}, p \notin \mathcal{O} \cup \mathcal{B}$
	0	$p \in \mathcal{O}$
	K	$p \in \mathcal{B}$

where

$$K = 1 + \max_{p \in \mathcal{P}} \sum_{q: \{p,q\} \in \mathcal{N}} B_{\{p,q\}}.$$

Detailed implementation

• Negative log-likelihood of intensity for regional term

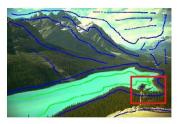
$$R_p$$
 ("object") = $-\ln \Pr(I_p | \mathcal{O})$
 R_p ("background") = $-\ln \Pr(I_p | \mathcal{B})$

• Ad hoc function for boundary term

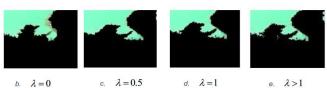
$$B_{\{p,q\}} \propto \exp\left(-\frac{\left(I_p - I_q\right)^2}{2\sigma^2}\right) \cdot \frac{1}{dist(p,q)}.$$

• Max-flow algorithm provided by Boykov and Kolgomorov (2001)

Sample result and comment



a. Image with seeds and selected red regions for zooming in in results



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Silent Lazy Snapping model A Input image b. Object marking c. Presegmentation d. Final segmentation e. Output Composition

Step 1: Sample definition



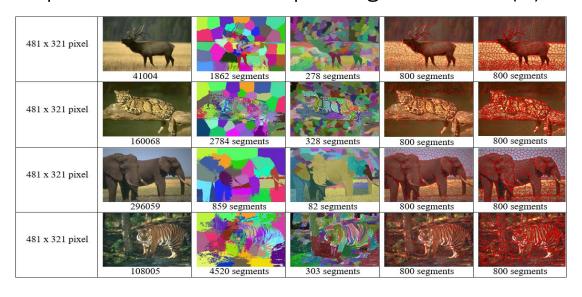
Step 2: Pre-segmentation



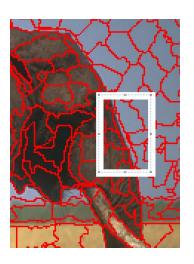
Experimental result on pre-segmentation (1)

Table 6. Results of different segmentation methods SEEDs Superpixels method SEEDs Revised Image Size Original Image K-means method Watershed method Mean Pixels 481 x 321 pixel 800 segments 124084 600 segments 481 x 321 pixel 800 segments 351 segments 800 segments 189011 1194 segments 321 x 481 pixel

Experimental result on pre-segmentation (2)

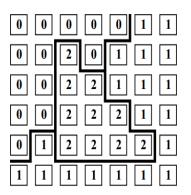


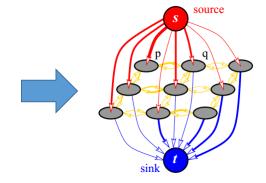
Experimental result on pre-segmentation (3)



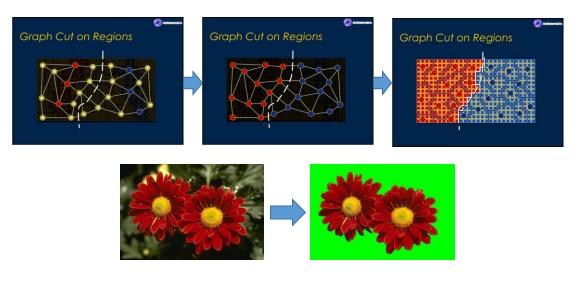


Step 3: Graph initialization





Step 4: Graph cut and final segmentation



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Limitation 1: Pixel loss in thin area

189080 with samples



Final segmentation



Limitation 2: Unsmooth boundary

Dancing_Emily with samples



Final segmentation



Limitation 3: Poor performance when foreground and background have similar color distribution

Vango with samples



Final segmentation

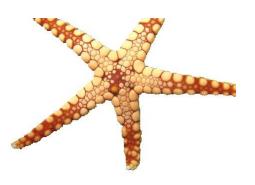


Berkeley dataset – 12003.jpg

Interactive Graph Cut



Silent Lazy Snapping



Berkeley dataset – 35070.jpg

Interactive Graph Cut

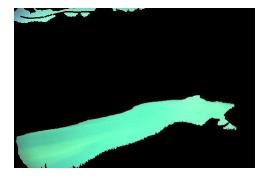


Silent Lazy Snapping



Berkeley dataset – 176035.jpg

Interactive Graph Cut



Silent Lazy Snapping



Berkeley dataset – 187029.jpg

Interactive Graph Cut

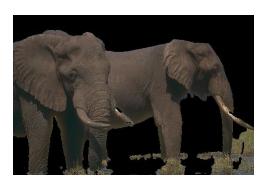


Silent Lazy Snapping

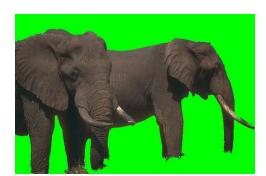


Berkeley dataset – 207056.jpg

Interactive Graph Cut



Silent Lazy Snapping



Khoi's dataset – 5.jpg

Original Image



Interactive Graph Cut



Khoi's dataset – 6.jpg

Original Image



Interactive Graph Cut



Khoi's dataset – 7.jpg

Original Image



Interactive Graph Cut

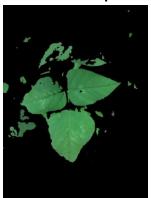


Khoi's dataset – 8.jpg

Original Image



Interactive Graph Cut



Khoi's dataset – 9.jpg

Original Image



Interactive Graph Cut



Nam's dataset – Cat.jpg

Original Image



Silent Lazy Snapping



Nam's dataset – TrangAn.jpg

Original Image



Silent Lazy Snapping



Nam's dataset – Nam_2.jpg

Original Image



Silent Lazy Snapping



Nam's dataset – WSpaper.jpg

Original Image



Silent Lazy Snapping



Nam's dataset – Emily_child.jpg

Original Image



Silent Lazy Snapping



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Future works

Graph Cut for Image Segmentation

- Try several other feature descriptor (such as HOG, etc.) for achieving the better results
- Add GUI options for easier experimenting

Lazy Snapping

- Add boundary editing function
- Add some filter

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THANK YOU FOR LISTENING!