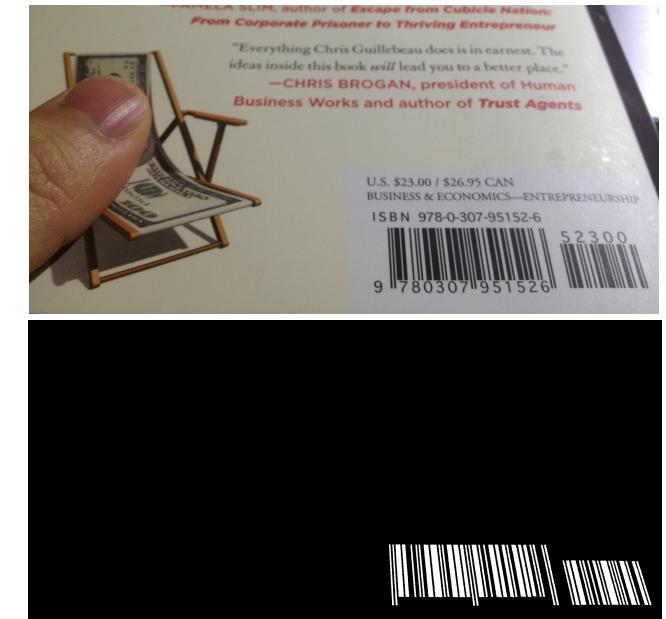
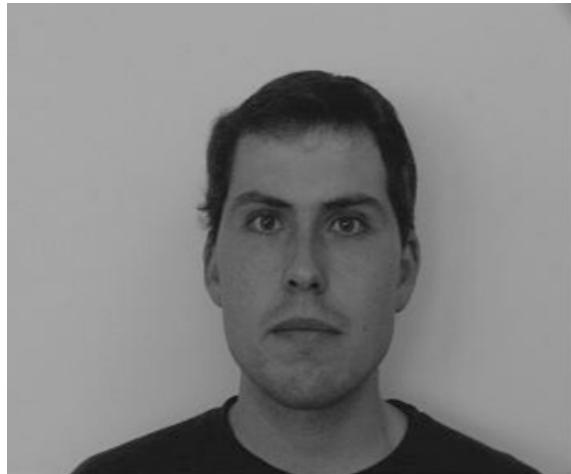


Image Segmentation

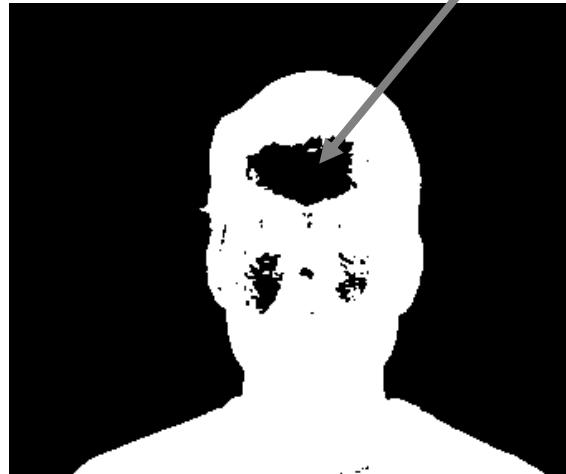
- Gray-level thresholding
- Supervised vs. unsupervised thresholding
- Binarization using Otsu's method
- Locally adaptive thresholding
- Maximally stable extremal regions
- Color-based segmentation
- Region labeling and counting
- Region moments



Gray-level thresholding

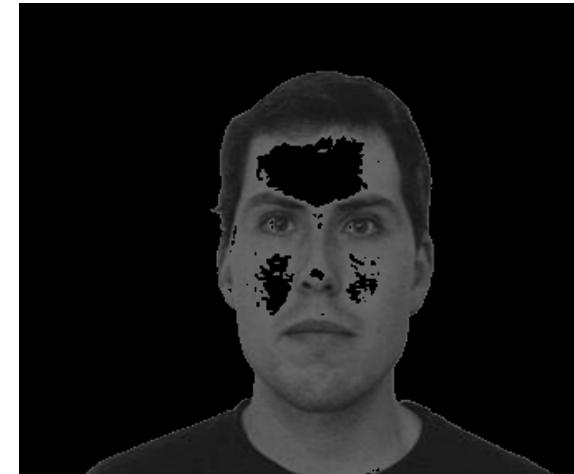


Original image
Peter f [x,y]



Thresholded
Peter m [x,y]

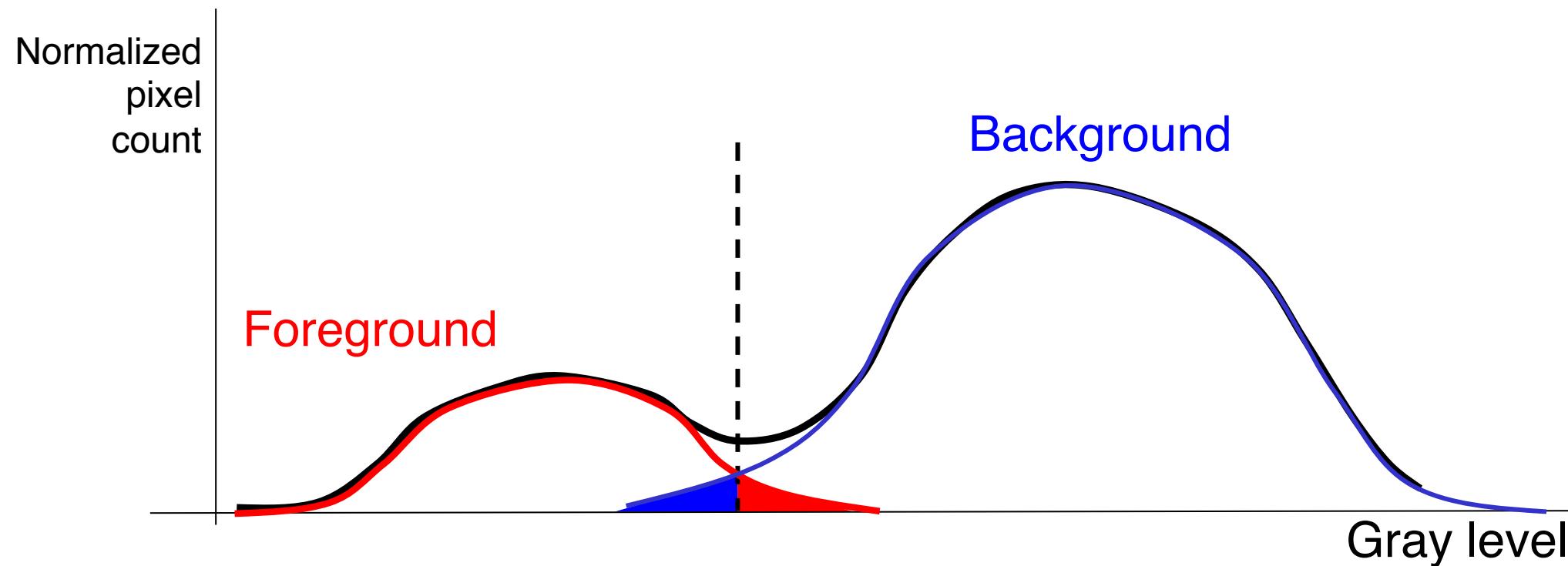
How can holes be filled?



$$f[x,y] \cdot m[x,y]$$



How to choose the threshold?



Unsupervised thresholding

- Idea: find threshold T that minimizes *within-class variance* of both foreground and background (same as k-means)

$$\sigma_{\text{within}}^2(T) = \frac{N_{\text{Fgrnd}}(T)}{N} \sigma_{\text{Fgrnd}}^2(T) + \frac{N_{\text{Bgrnd}}(T)}{N} \sigma_{\text{Bgrnd}}^2(T)$$

- Equivalently, maximize *between-class variance*

$$\begin{aligned}\sigma_{\text{between}}^2(T) &= \sigma^2 - \sigma_{\text{within}}^2(T) \\ &= \left(\frac{1}{N} \sum_{x,y} f^2[x,y] - \mu^2 \right) - \frac{N_{\text{Fgrd}}}{N} \left(\frac{1}{N_{\text{Fgrd}}} \sum_{x,y \in \text{Fgrnd}} f^2[x,y] - \mu_{\text{Fgrnd}}^2 \right) - \frac{N_{\text{Bgrnd}}}{N} \left(\frac{1}{N_{\text{Bgrnd}}} \sum_{x,y \in \text{Bgrnd}} f^2[x,y] - \mu_{\text{Bgrnd}}^2 \right) \\ &= -\mu^2 + \frac{N_{\text{Fgrnd}}}{N} \mu_{\text{Fgrnd}}^2 + \frac{N_{\text{Bgrnd}}}{N} \mu_{\text{Bgrnd}}^2 = \frac{N_{\text{Fgrnd}}}{N} (\mu_{\text{Fgrnd}} - \mu)^2 + \frac{N_{\text{Bgrnd}}}{N} (\mu_{\text{Bgrnd}} - \mu)^2 \\ &= \frac{N_{\text{Fgrnd}}(T) \cdot N_{\text{Bgrnd}}(T)}{N^2} (\mu_{\text{Fgrnd}}(T) - \mu_{\text{Bgrnd}}(T))^2\end{aligned}$$

[Otsu, 1979]

Unsupervised thresholding (cont.)

- Algorithm: Search for threshold T to maximize

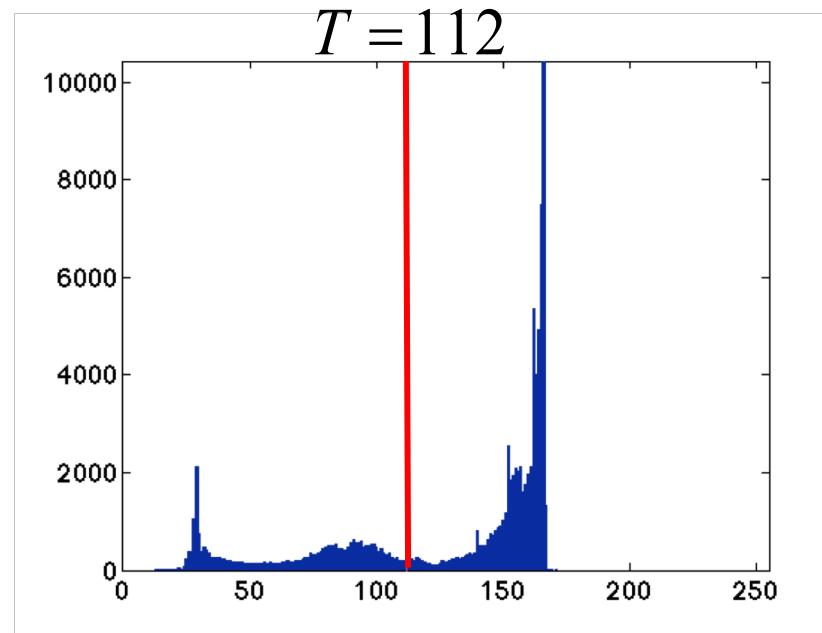
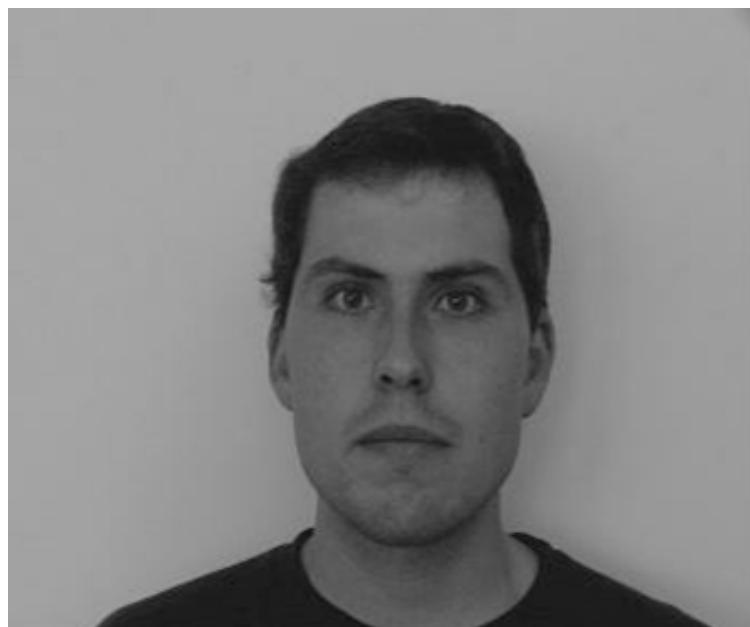
$$\sigma_{between}^2(T) = \frac{N_{Fgrnd}(T) \cdot N_{Bgrnd}(T)}{N^2} (\mu_{Fgrnd}(T) - \mu_{Bgrnd}(T))^2$$

- Useful recursion for sweeping T across histogram:

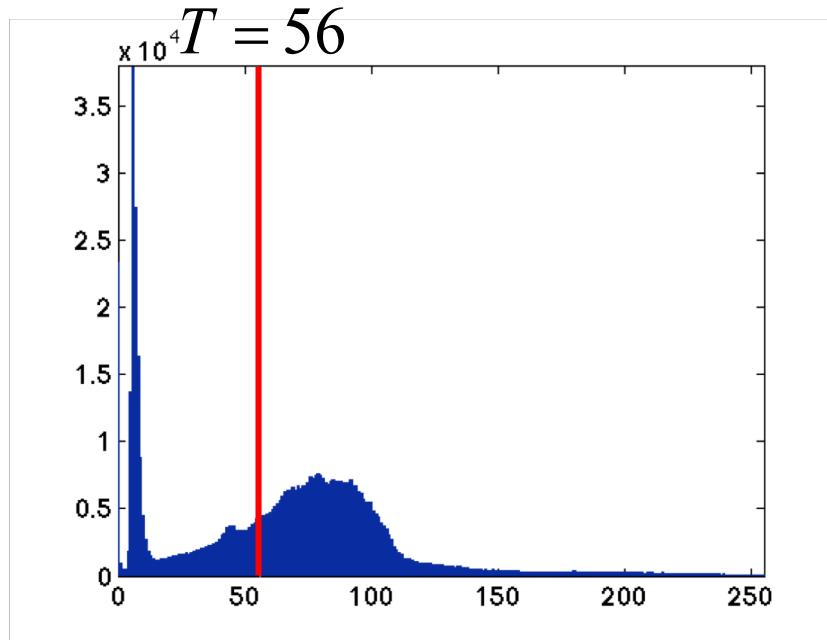
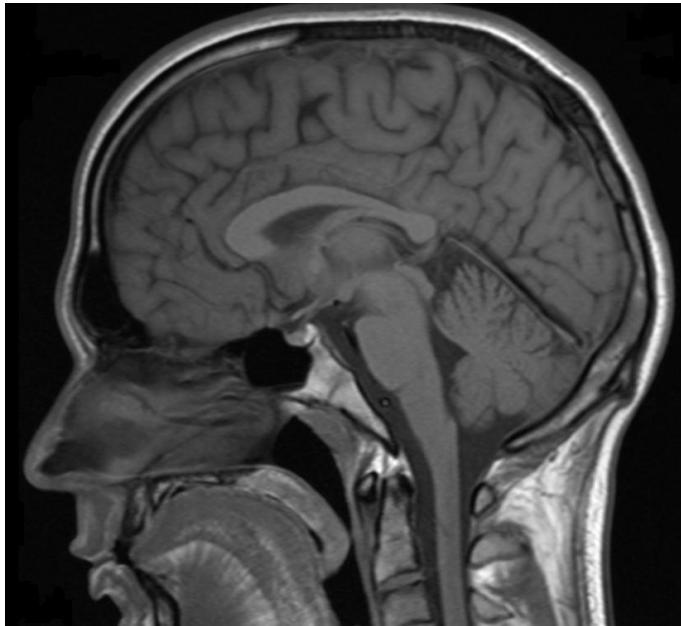
$$\begin{aligned} N_{Fgrnd}(T+1) &= N_{Fgrnd}(T) + n_T \\ N_{Bgrnd}(T+1) &= N_{Bgrnd}(T) - n_T \\ \mu_{Fgrnd}(T+1) &= \frac{\mu_{Fgrnd}(T)N_{Fgrnd}(T) + n_T T}{N_{Fgrnd}(T+1)} \\ \mu_{Bgrnd}(T+1) &= \frac{\mu_{Bgrnd}(T)N_{Bgrnd}(T) - n_T T}{N_{Fgrnd}(T+1)} \end{aligned}$$

[Otsu, 1979]

Unsupervised thresholding (cont.)



Unsupervised thresholding (cont.)



Unsupervised thresholding (cont.)

The Stanford Daily

Tuesday, September 18, 2012 ♦ 13



FOOTBALL

The winding road ahead

By SAM FISHER
FOOTBALL EDITOR

Andrew Luck may be gone, but with his replacement won over, USC, the Stanford Cardinal put itself in position to achieve beyond the path paved by number 12. You heard right though they didn't have much left to do, this 2012 Stanford team showed that it's capable of playing at a national championship level.

Though Stanford survived one of its toughest tests in the games that it has to play this season, the road to Miami 2013 is not walk in the park. The toughest challenges remain on the schedule: four games against Notre Dame, Oregon and UCLA, all of whom are currently ranked in the top 20. The next two games at Wisconsin and then home against Arizona are no pushovers either. And as Stanford has had its top-ranked opponents in years past, any team on the Cardinal's schedule has the potential for a magical run.

Ford Stanford's current vantage point, there are three paths the rest of the season could take. Door Number One leads to The Promised Land, a berth in the BCS National Championship Game. In all likelihood, because Stanford's star names will name the L1 in the D-line, the Cardinal will be sent out to earn a trip to South Beach, including wins at No. 3 Oregon and a potential rematch against USC for the Pac-12 title.

about Andrew Luck.

Josh Mauro: The back-up defense end saw most of his action at nose tackle in the second half, where he completely took over the ballgame, forcing two sacks. The back-up center, Cyrus Hobbs, all had to provide the key pressure up the middle from the defensive line to keep Barkley running. The rest of the D-line played great in support, but Mauro went above and beyond the call of duty to help out.

Please see AWARDS, page 15

Stanford defensive lineman Josh Mauro put the pressure on USC's Matt Barkley. Mauro was relentless in the second half as Stanford's defense completely shut down Barkley and his touted wide receivers.

Handing out the USC game balls

By SAM FISHER
FOOTBALL EDITOR

Stephan Taylor: It all starts and ends with Stephan's workhorse. Taylor was everywhere you looked, and for most against USC. He provided the big plays with a game-tying touchdown up the middle from the defensive line to keep Barkley running. The rest of the D-line played great in support, but Mauro went above and beyond the call of duty to help out.

Please see AWARDS, page 15

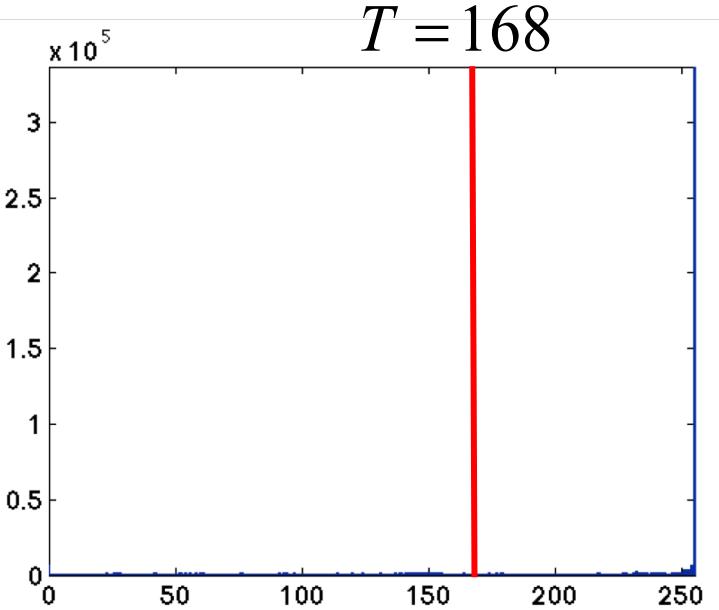
Josh Mauro: The back-up defense end saw most of his action at nose tackle in the second half, where he completely took over the ballgame, forcing two sacks. The back-up center, Cyrus Hobbs, all had to provide the key pressure up the middle from the defensive line to keep Barkley running. The rest of the D-line played great in support, but Mauro went above and beyond the call of duty to help out.

Contact Sam Fisher at sfisher@stanford.edu

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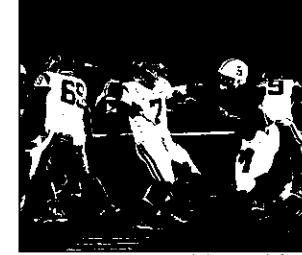
Please see AWARDS, page 15



$T = 168$

The Stanford Daily

Tuesday, September 18, 2012 ♦ 13



FOOTBALL

The winding road ahead

By SAM FISHER
FOOTBALL EDITOR

Andrew Luck may be gone, but with Saturday night's win over LSU, the Stanford Cardinal put itself in position to play at a higher level consistently. From the 12-yard scramble on good field-and-10 on, Nunes was good enough to take the lead with his win over the second-ranked Trojans. However, if the Card regresses to San Jose State's level of consistency, then it is primed to be upset a few times. It might not even take that bad of a performance, as Stanford has been in a semi-solid position in the AP Top 25, including road games at No. 3 Oregon, No. 10 Penn State and No. 19 UCLA. If Stanford loses more than two games, it will in all likelihood end up in a second-tier bowl game for the first time since 2008. In 2010, when Stanford lost a close game to Oklahoma in the Sun Bowl, there is obviously tremendous incentive as to where the rest of the season heads, but it's truly remarkable for Stanford to be in the position it is in now. No Toby Gerhart, no Andrew Luck, and no Andrew Luck; just Josh Nunes, Stephan Taylor, a rabid defense and a whole lot of guys showing a lot of heart. The superstar names might be gone, but the talent left behind is rising to the top, making Door Number One not so crazy to think about.

Handing out the USC game balls

By SAM FISHER
FOOTBALL EDITOR

Josh Mauro: The back-up defense end saw most of his action at nose tackle in the second half, where he completely took over the ballgame, forcing two sacks. The back-up center, Cyrus Hobbs, all had to provide the key pressure up the middle from the defensive line to keep Barkley running. The rest of the D-line played great in support, but Mauro went above and beyond the call of duty to help out.

Please see AWARDS, page 15

For Stanford to even think about returning to the site of its 2011 Orange Bowl beat down of Virginia Tech, Josh Nunes will have to build on his fourth-quarter success against USC to play at a higher level consistently.

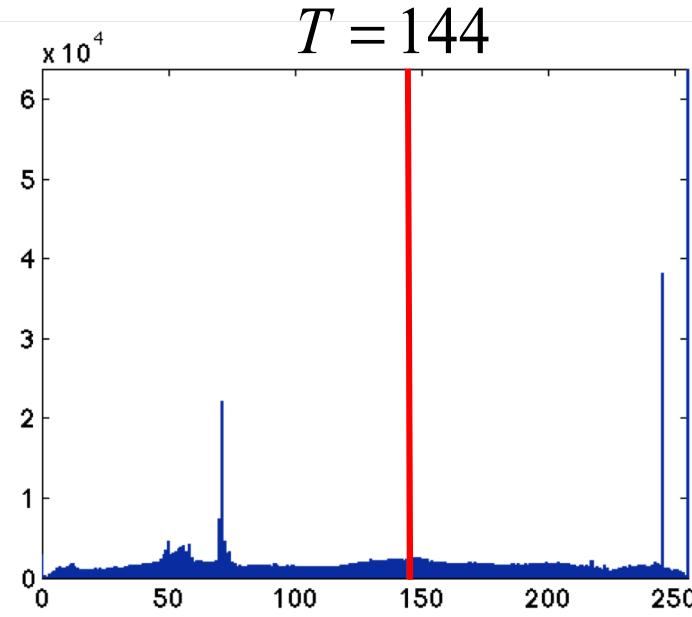
Door Number Three is the disappointment, the setback, the wasted opportunity. Stanford has had a semi-solid position with its win over the second-ranked Trojans. However, if the Card regresses to San Jose State's level of consistency, then it is primed to be upset a few times. It might not even take that bad of a performance, as Stanford has been in a semi-solid position in the AP Top 25, including road games at No. 3 Oregon, No. 10 Penn State and No. 19 UCLA. If Stanford loses more than two games, it will in all likelihood end up in a second-tier bowl game for the first time since 2008. In 2010, when Stanford lost a close game to Oklahoma in the Sun Bowl,

There is obviously tremendous incentive as to where the rest of the season heads, but it's truly remarkable for Stanford to be in the position it is in now. No Toby Gerhart, no Andrew Luck, and no Andrew Luck; just Josh Nunes, Stephan Taylor, a rabid defense and a whole lot of guys showing a lot of heart. The superstar names might be gone, but the talent left behind is rising to the top, making Door Number One not so crazy to think about.

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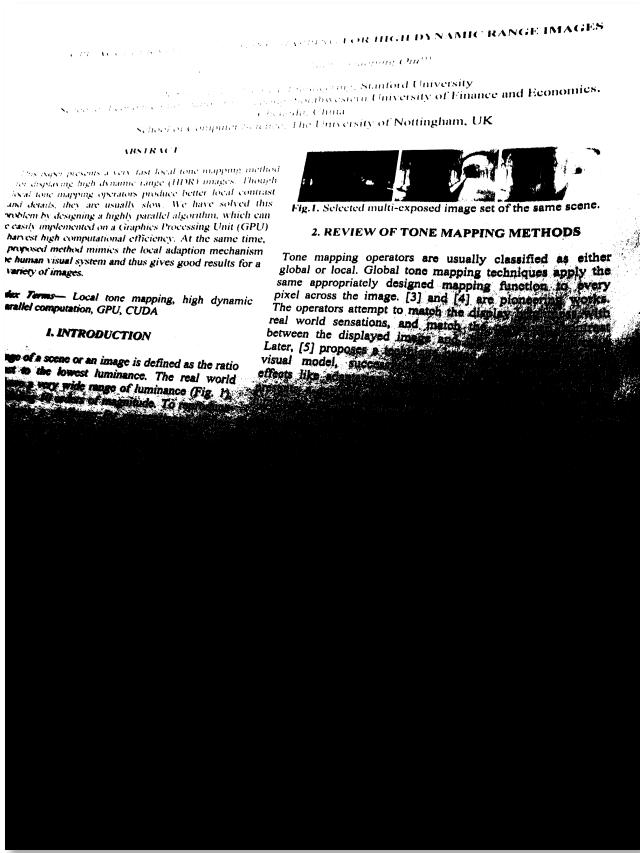
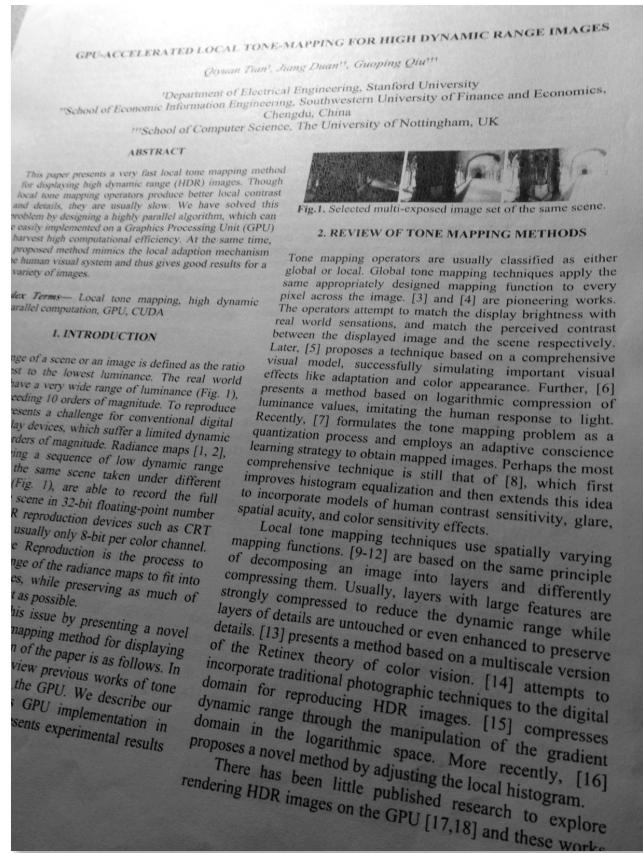


Unsupervised thresholding (cont.)



Sometimes, a global threshold does not work

Original image

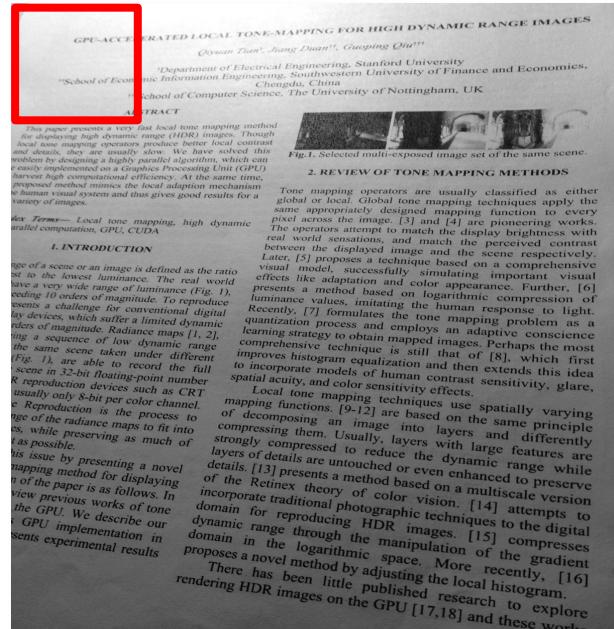


Thresholded with Otsu's Method

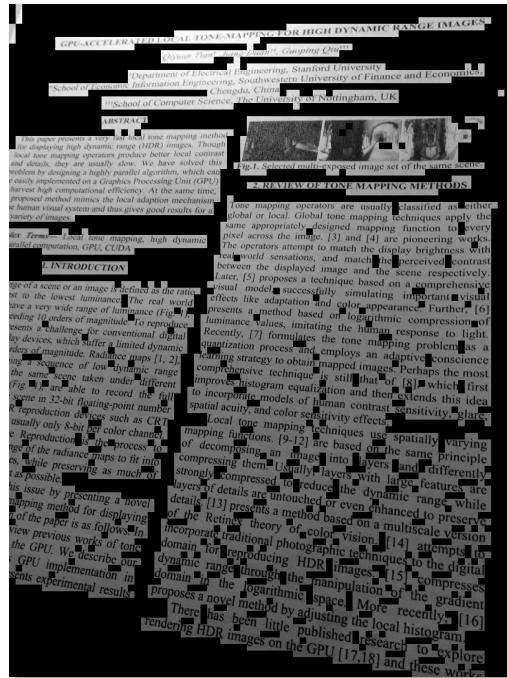


Locally adaptive thresholding

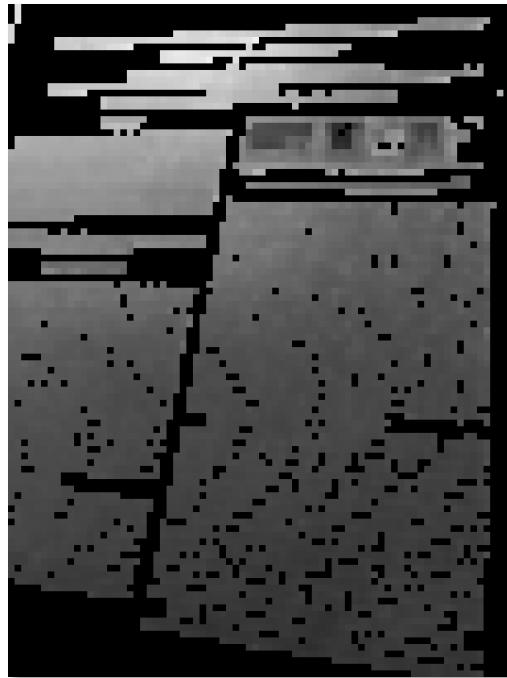
- Slide a window over the image
- For each window position, decide whether to perform thresholding
 - Thresholding should not be performed in uniform areas
 - Use variance or other suitable criterion
- Non-uniform areas: apply Otsu's method (based on local histogram)
- Uniform areas: classify the entire area as foreground or background based on mean value



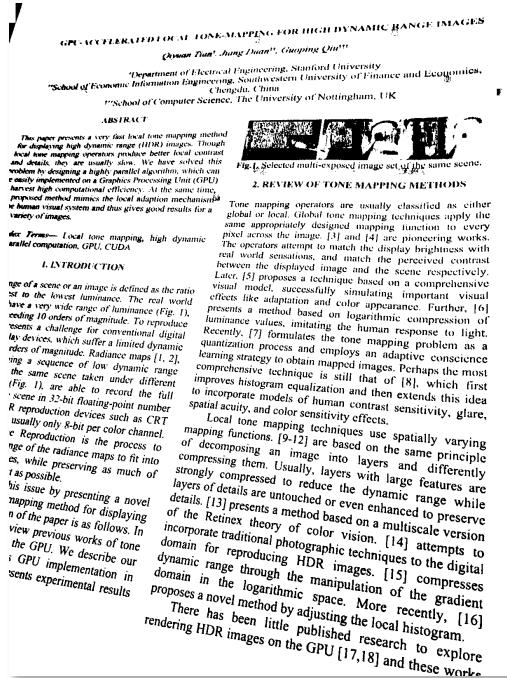
Locally adaptive thresholding (example)



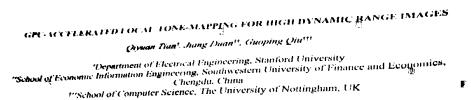
Non-uniform areas



Local threshold values



Locally thresholded result



2. REVIEW OF TONE MAPPING METHODS

Tone mapping operators are usually classified as either global or local. Global tone mapping techniques apply the same appropriate compression function to every pixel across the image. [3] and [4] are pioneering work. The operators attempt to match the display brightness with real world sensations, and match the perceived contrast between the displayed image and the scene respectively. Later, [5] proposes a technique based on an adaptive visual model, successfully simulating important visual effects like adaptation and color appearance. Further, [6] presents a challenge for conventional digital cameras, which suffer a limited dynamic range of magnitude. Radiance maps [1, 2], propose a sequence of images over the same scene taken under different lighting conditions. Perhaps the most comprehensive technique is still that of [8], which first performs histogram equalization and then extends this idea to incorporate models of human contrast sensitivity, glare, spatial acuity, and color sensitivity effects.

Local tone mapping techniques use spatially varying mapping functions. [9-12] are based on the same principle of decomposing an image into layers and differently compressing them. Usually, layers with large features are strongly compressed to reduce the dynamic range while layers of details are untouched or even enhanced to preserve details. [13] presents a method based on a multiscale version of the Retinex theory of color vision. [14] attempts to incorporate traditional photographic techniques to the digital domain for reproducing HDR images. [15] compresses the dynamic range through the manipulation of the gradient domain in the logarithmic space. More recently, [16] proposes a novel method by adjusting the local histogram rendering HDR images on the GPU [17,18] and these works

have been little published research to explore



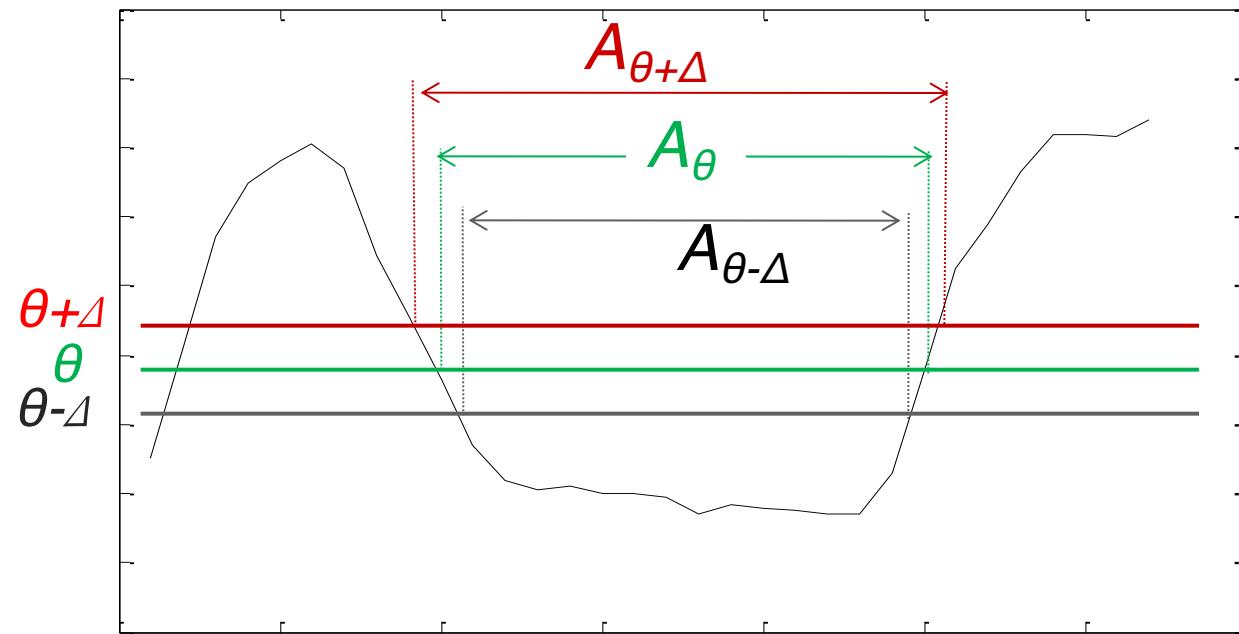
Maximally stable extremal regions

- Extremal region: any connected region in an image with all pixel values above (or below) a threshold
- Observations:
 - Nested extremal regions result when the threshold is successively raised (or lowered).
 - The nested extremal regions form a “component tree.”
- Key idea: choose thresholds θ such that the resulting bright (or dark) extremal regions are nearly constant when these thresholds are perturbed by $+/-\Delta$

→ “***maximally stable***” ***extremal regions (MSER)***

[Matas, Chum, Urba, Pajdla, 2002]

MSERs: illustration



$$\text{Local minimum of } \left| \frac{A_{\theta-\Delta} - A_{\theta+\Delta}}{A_\theta} \right| \rightarrow \text{MSER}$$

[Matas, Chum, Urba, Pajdla, 2002]

Level sets of an image

1	1	1	1	1	1	1	1	1	1	1	5	4	4	8
1	7	6	4	2	2	3	3	3	3	1	5	4	4	8
1	7	6	4	2	2	3	3	3	3	1	5	4	4	8
1	7	6	4	2	2	3	3	3	3	1	5	4	4	8
1	7	6	4	2	2	5	5	5	5	1	5	4	4	8
1	6	6	4	2	2	5	5	5	6	1	5	4	4	4
1	6	6	4	2	2	6	6	6	6	1	5	5	5	5
1	4	4	4	2	2	6	6	6	6	1	5	5	5	5
1	1	1	1	1	2	6	1	1	1	1	2	2	2	2
1	8	8	5	1	2	6	1	7	7	1	2	2	2	2
1	8	8	5	1	1	1	1	7	7	1	1	1	1	2
1	8	8	5	5	5	3	3	7	7	1	1	1	1	2
1	8	8	5	5	3	3	3	7	7	7	1	1	1	1
1	8	8	5	5	3	3	3	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

$$f[x, y]$$

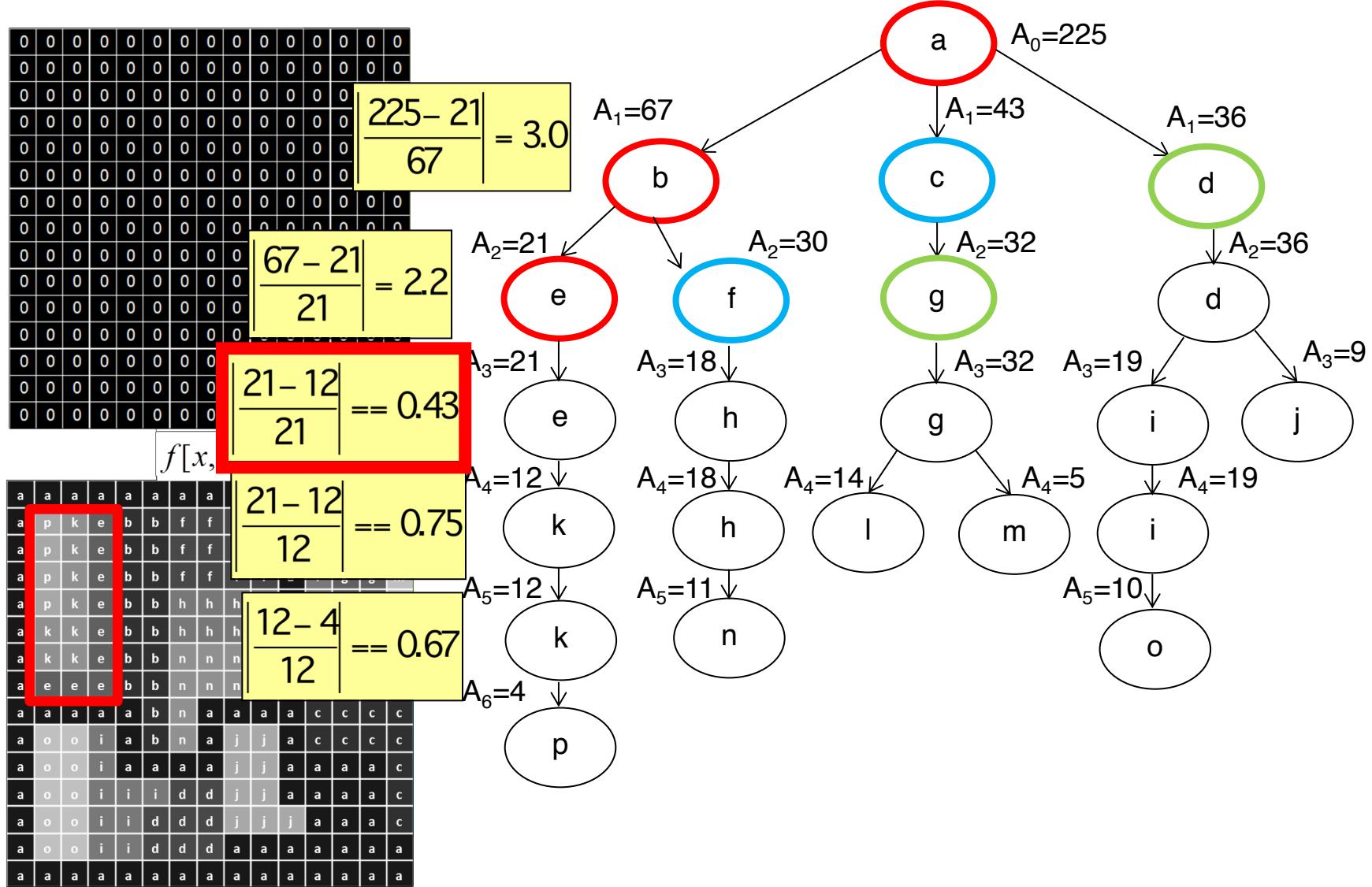
Image

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

$$f[x, y] > 8$$

Level Set

Component tree of an image



Local minima of sequence

$$\left| \frac{A_{\theta-\Delta} - A_{\theta+\Delta}}{A_\theta} \right|$$

$\theta = \Delta, \Delta + 1, \dots \rightarrow \text{MSERs}$

MSER: examples



Dark MSERs, $\Delta=15$



Original image



Bright MSERs, $\Delta=15$

MSER: examples



Dark MSERs, $\Delta=15$

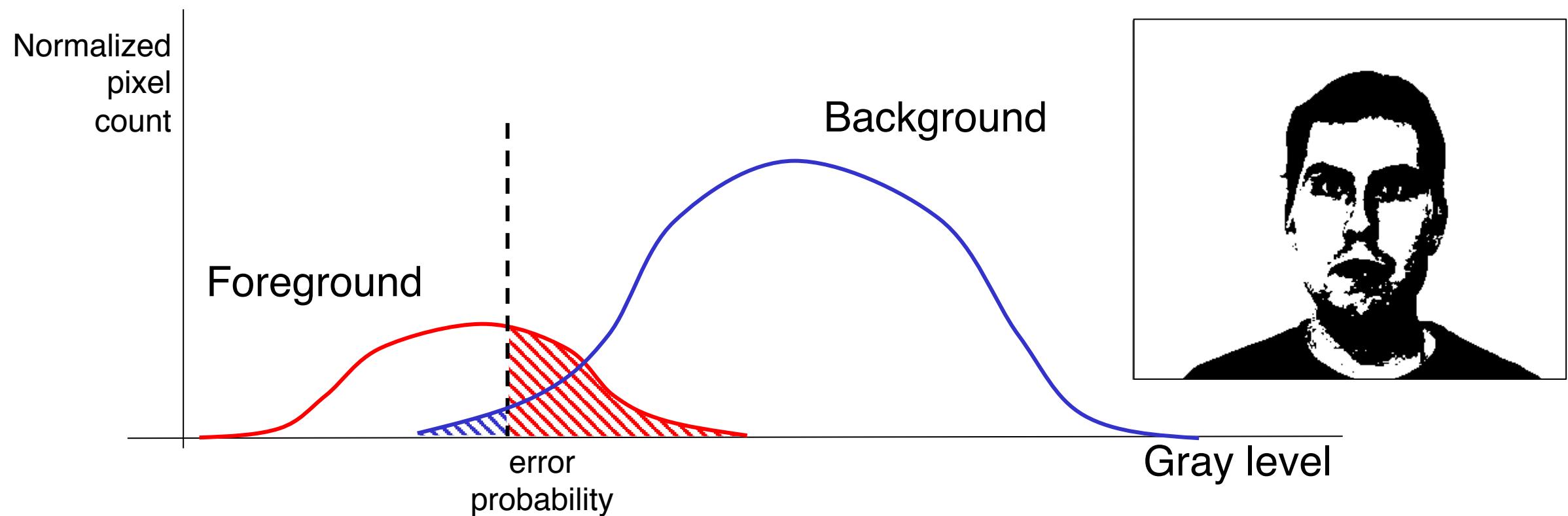


Original image

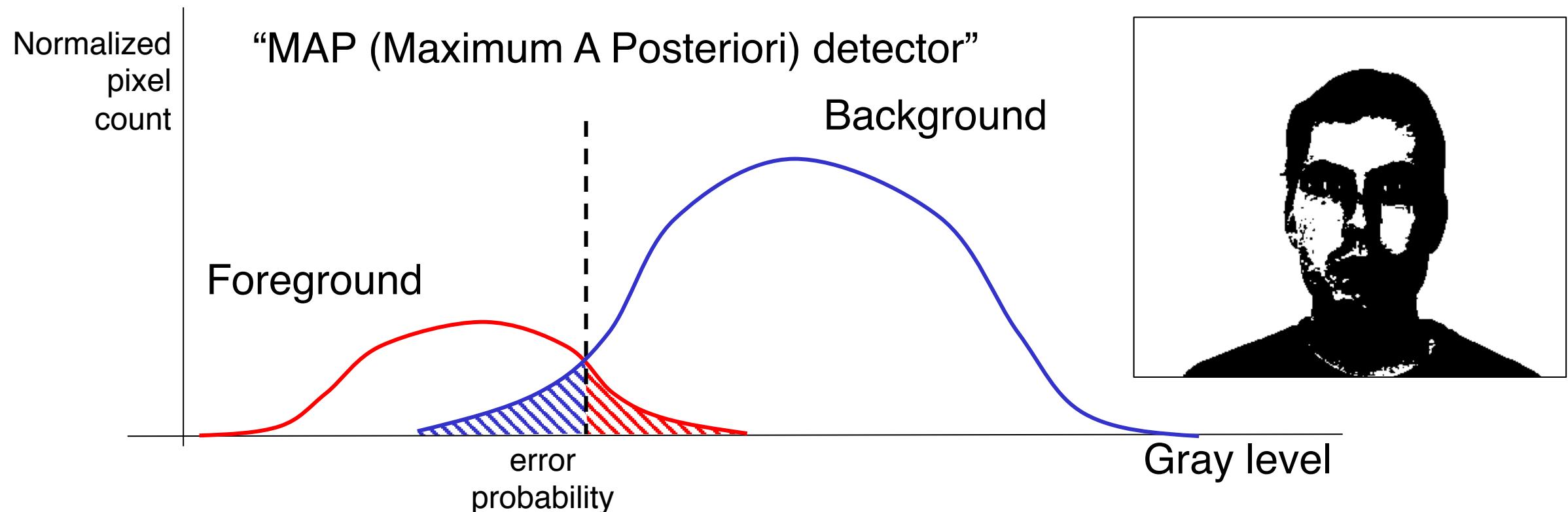


Bright MSERs, $\Delta=15$

Supervised thresholding



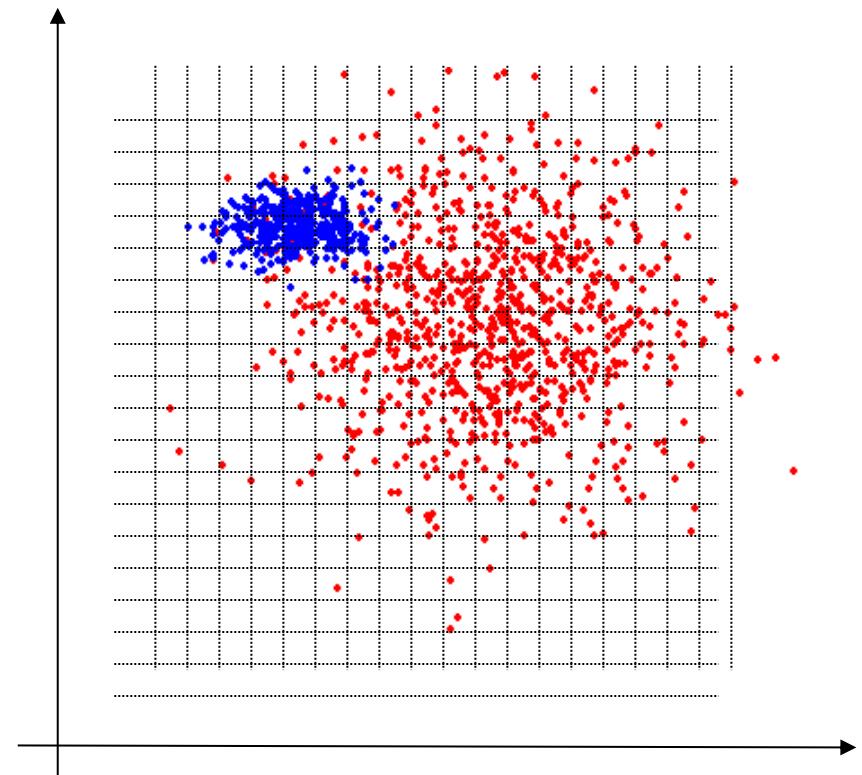
Supervised thresholding



If errors $\text{BG} \rightarrow \text{FG}$ and $\text{FG} \rightarrow \text{BG}$ are associated with different costs:
“Bayes minimum risk detector” is optimal.

Multidimensional MAP detector

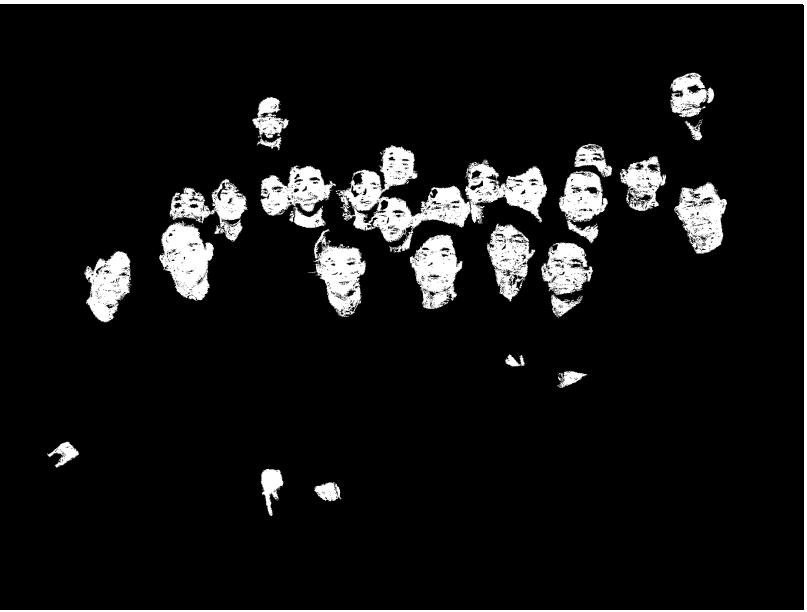
- Training
 - Provide labelled set of training data
 - Subdivide n-dimensional space into small bins
 - Count frequency of occurrence for each bin and class in training set, label bin with most probable class
 - (Propagate class labels to empty bins)
- For test data: identify bin, look up the most probable class



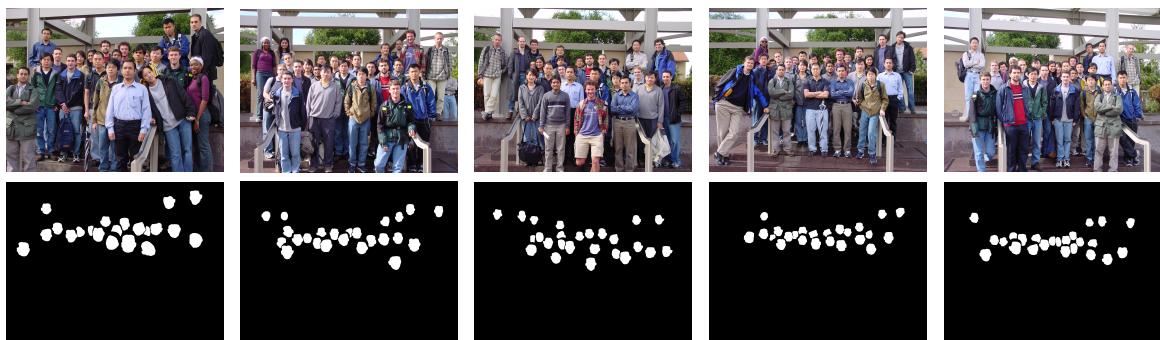
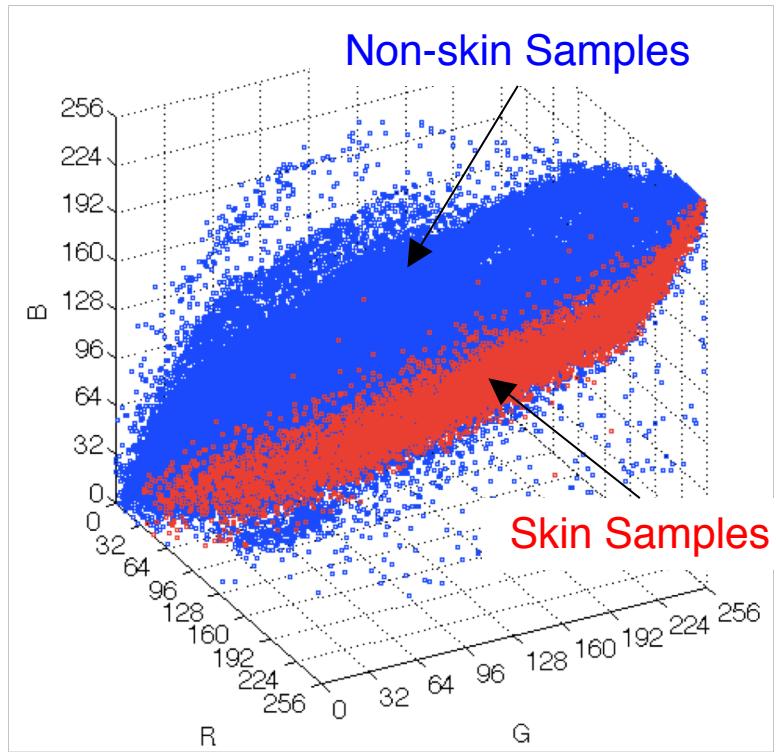
MAP detector in RGB-space



Original image



Skin color detector



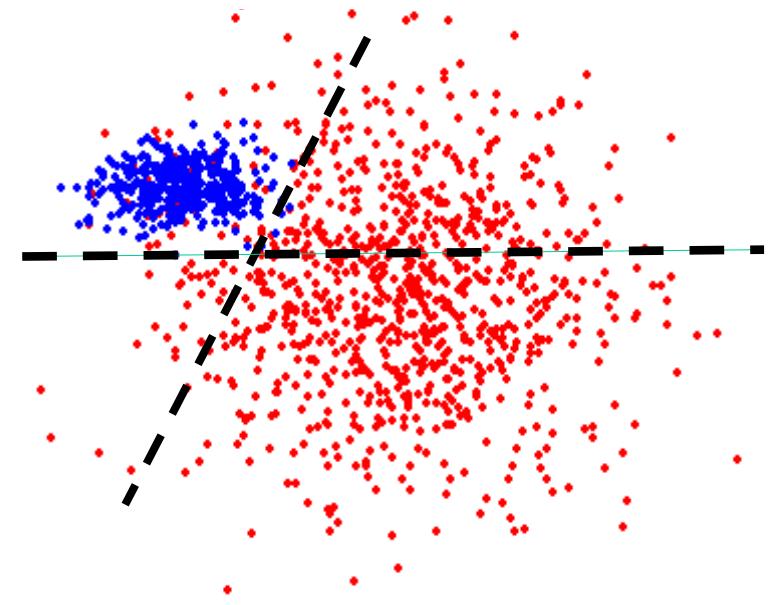
Five training images



Linear discriminant function

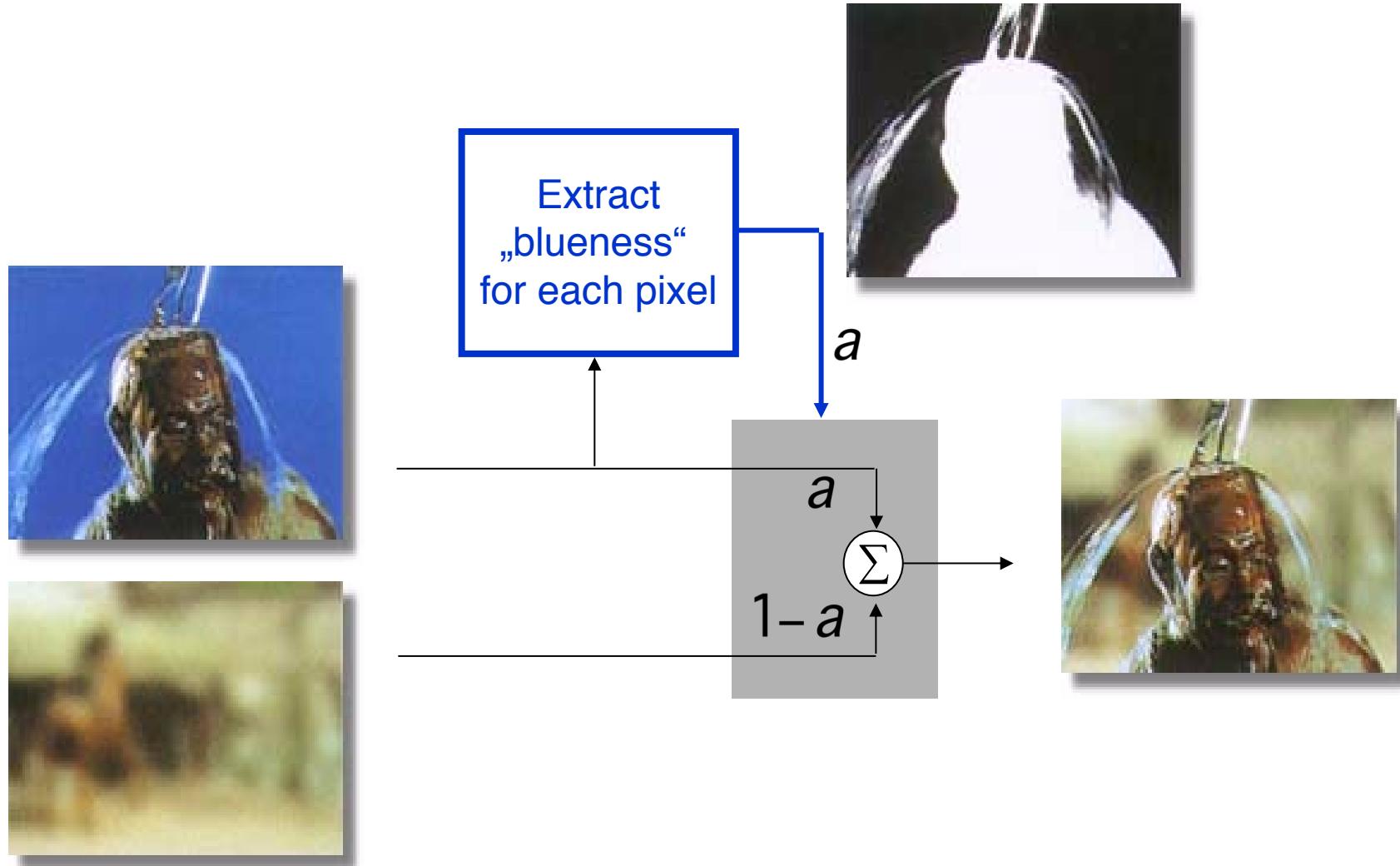
- To segment image with n components $f_i, i=1,2,\dots,n$ into two classes, perform test

$$\sum_i w_i f_i + w_0 \geq 0 ?$$

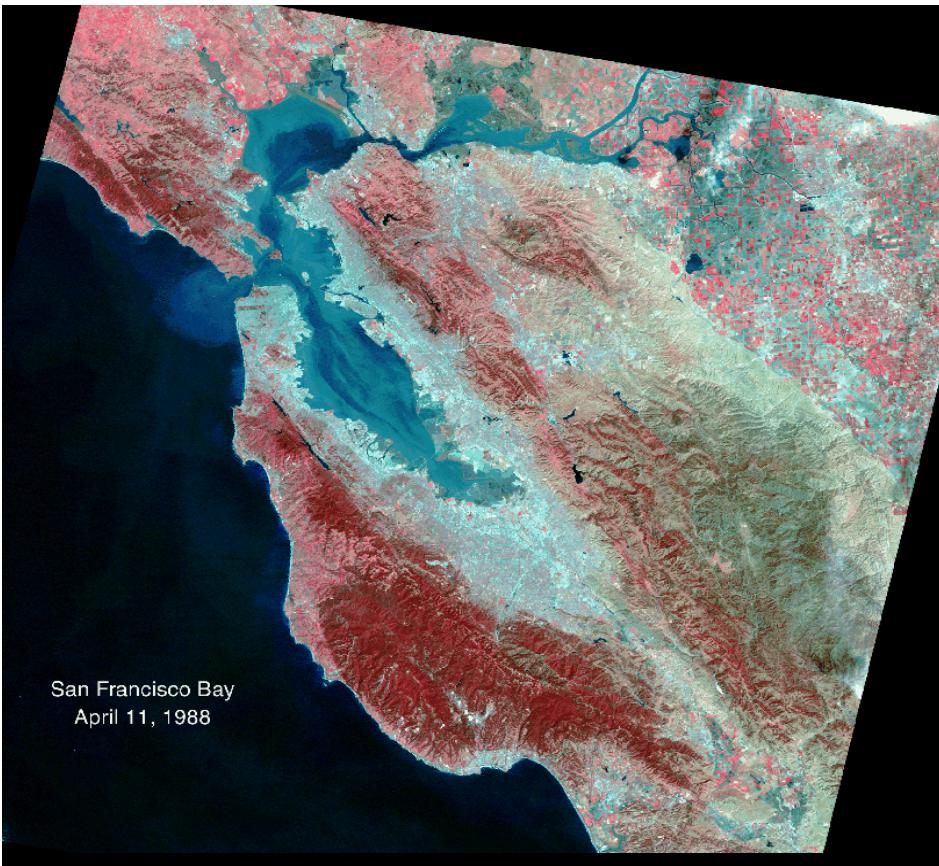


- Categories are separated by hyperplane in n -space
- Numerous techniques to determine weights
 $w_i, i=0,1,2,\dots,n$, see, e.g., [\[Duda, Hart, Stork, 2001\]](#)
- Can be extended to the intersection of several linear discriminant functions
- Can be extended to multiple classes

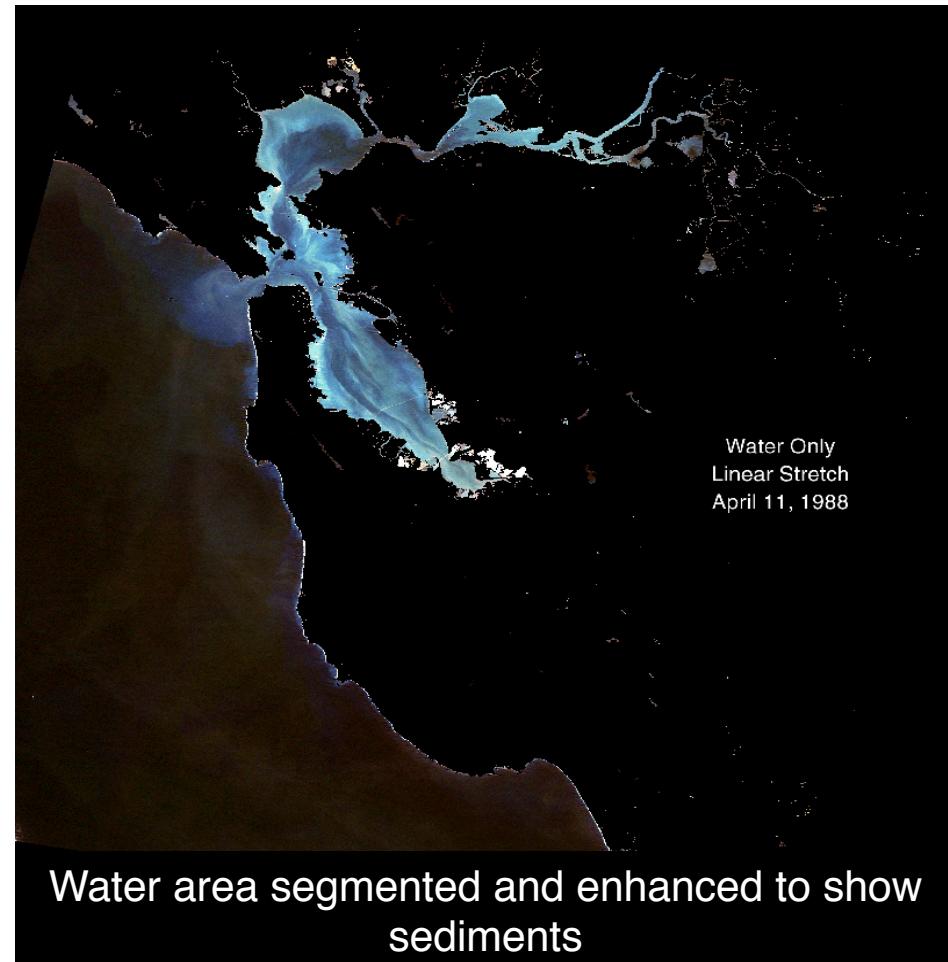
Chroma keying



Landsat image processing



Original Landsat image false color picture out of bands 4,5,6

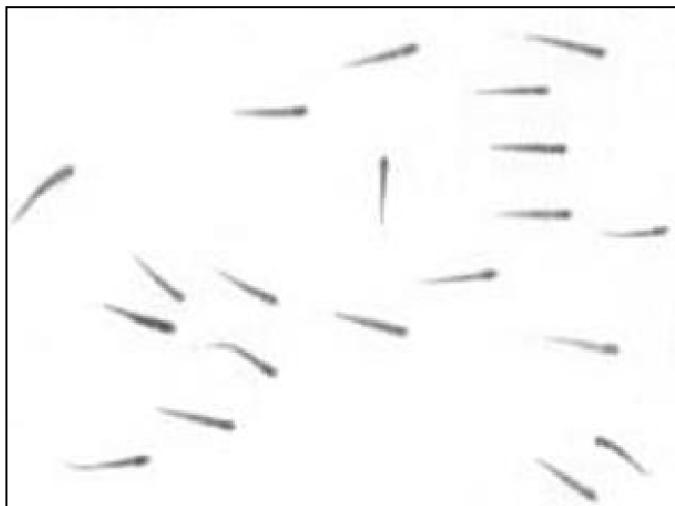


Water area segmented and enhanced to show sediments

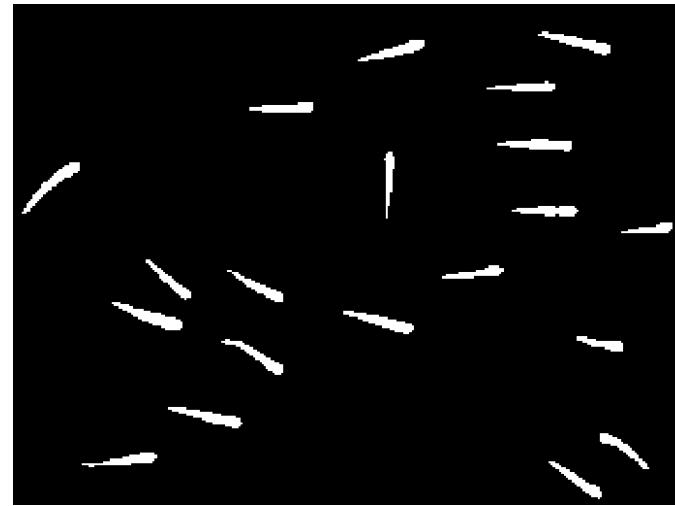
Source: US Geological Survey USGS, <http://sfbay.wr.usgs.gov/>

Region labeling and counting

- How many fish in this picture?



Original *Fish* image



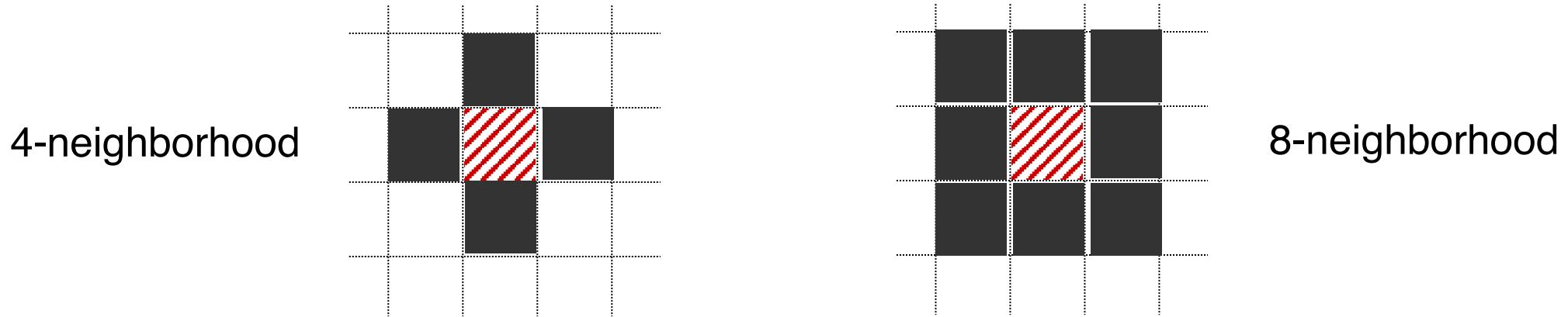
after thresholding

- Which pixels belong to the same object (region labeling)?
- How large is each object (region counting)?



4-connected and 8-connected neighborhoods

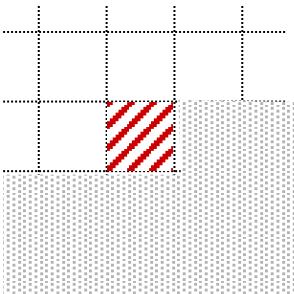
- Definition: a ***region*** is a set of pixels, where each pixel can be reached from any other pixel in the region by a finite number of steps, with each step starting at a pixel and ending in the neighborhood of the pixel.



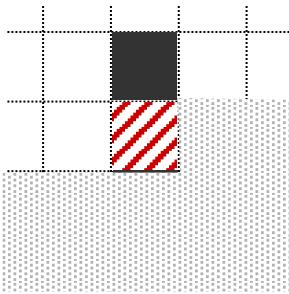
- Typically, either definition leads to the same regions, except when a region is only connected across diagonally adjacent pixels.

Region labeling algorithm (4-neighborhood)

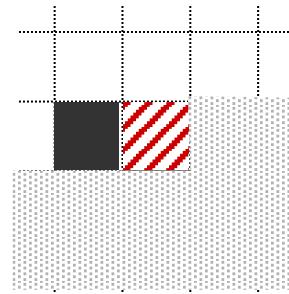
- Loop through all pixels $f[x,y]$, left to right, top to bottom
- If $f[x,y]=0$, do nothing.
- If $f[x,y]=1$, distinguish 4 cases



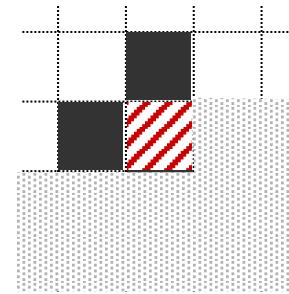
Generate new
region label



Copy label
from above



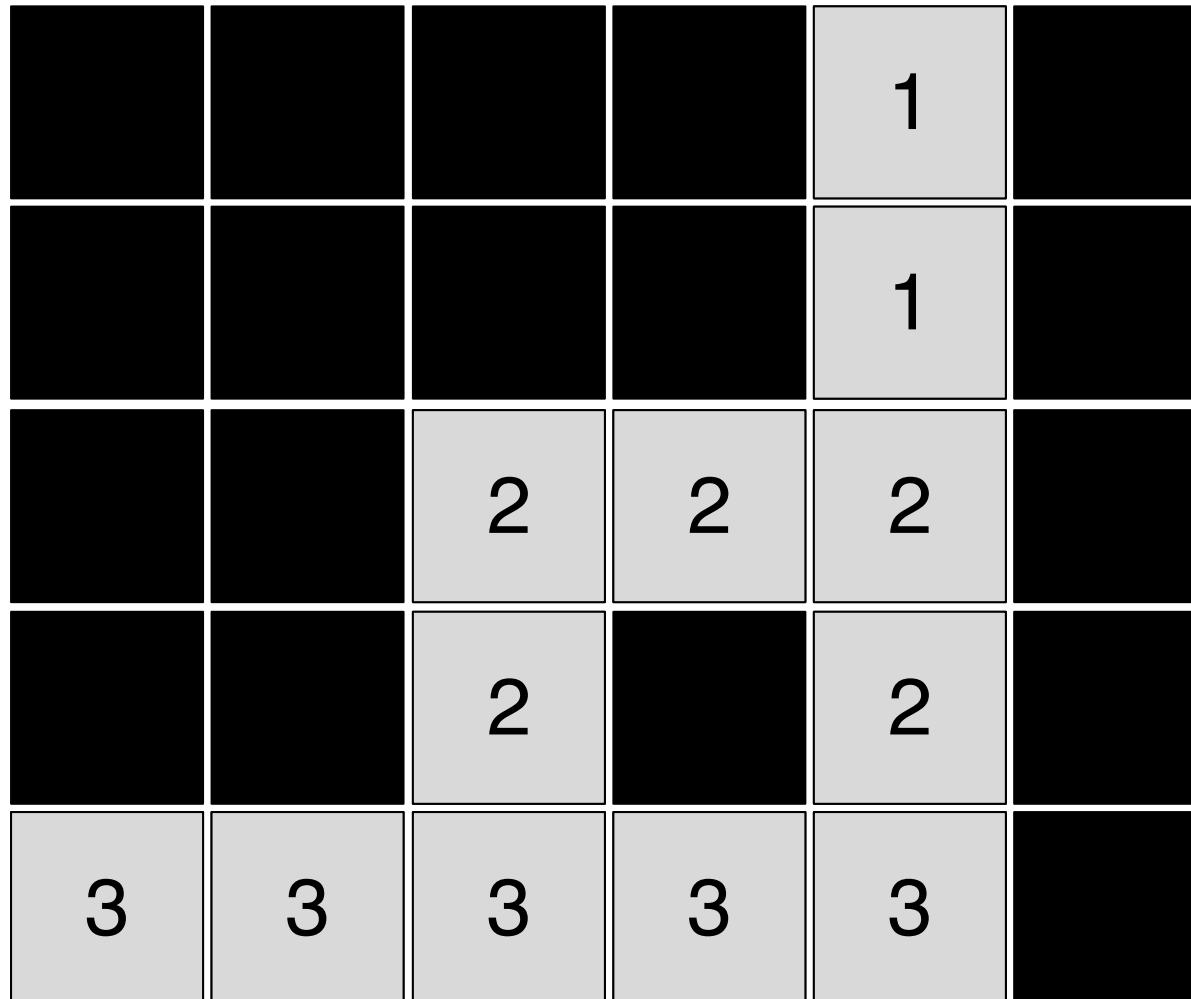
Copy label
from the left



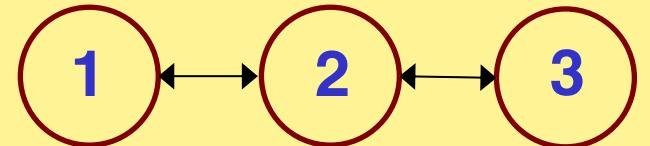
Copy label from the left. If
labels above and to the left are
different, store equivalence.

- Second pass through image to replace equivalent label by the same label.

Region labeling example (4-neighborhood)

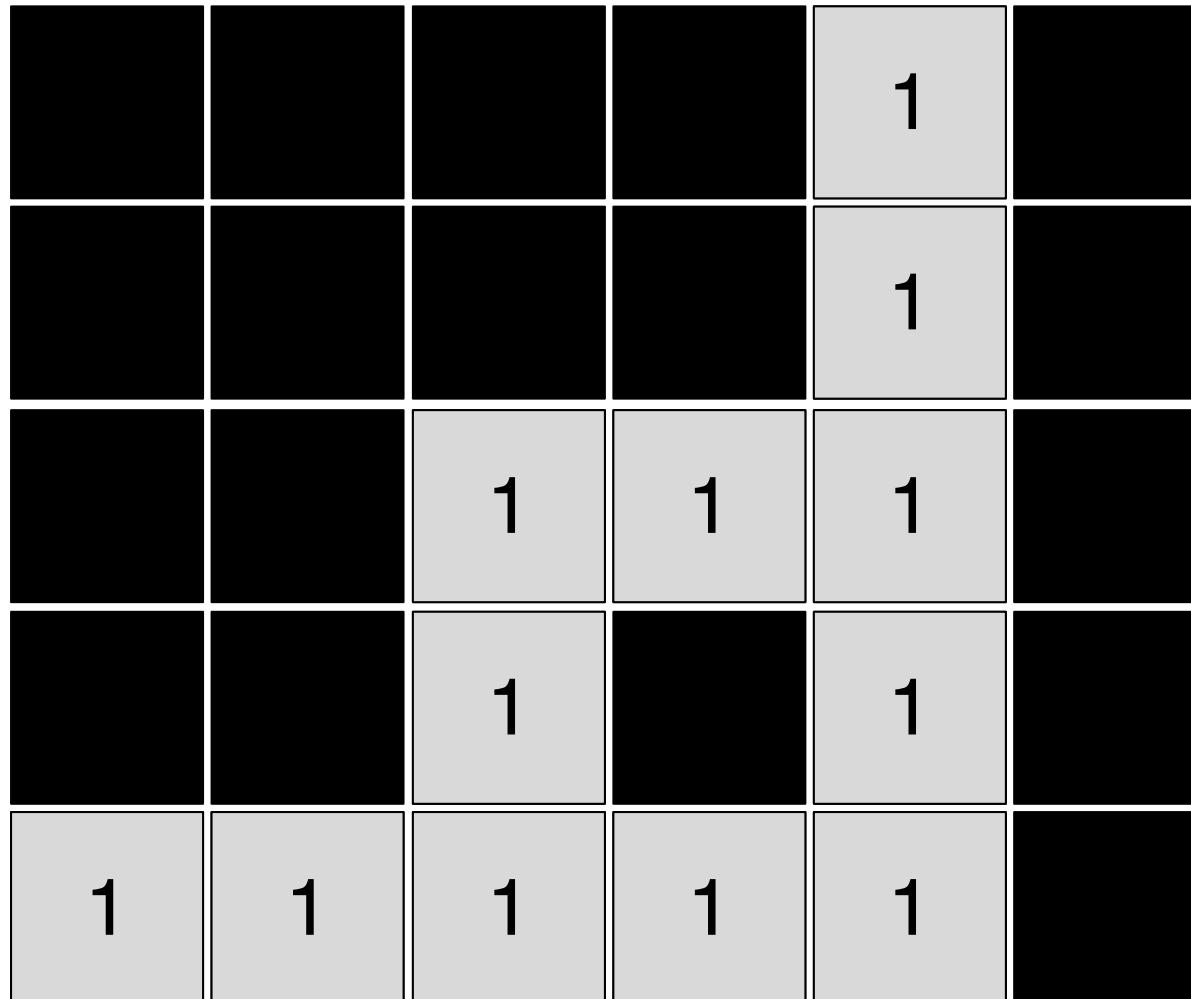


List of Region Labels



All three labels are equivalent, so merge into single label.

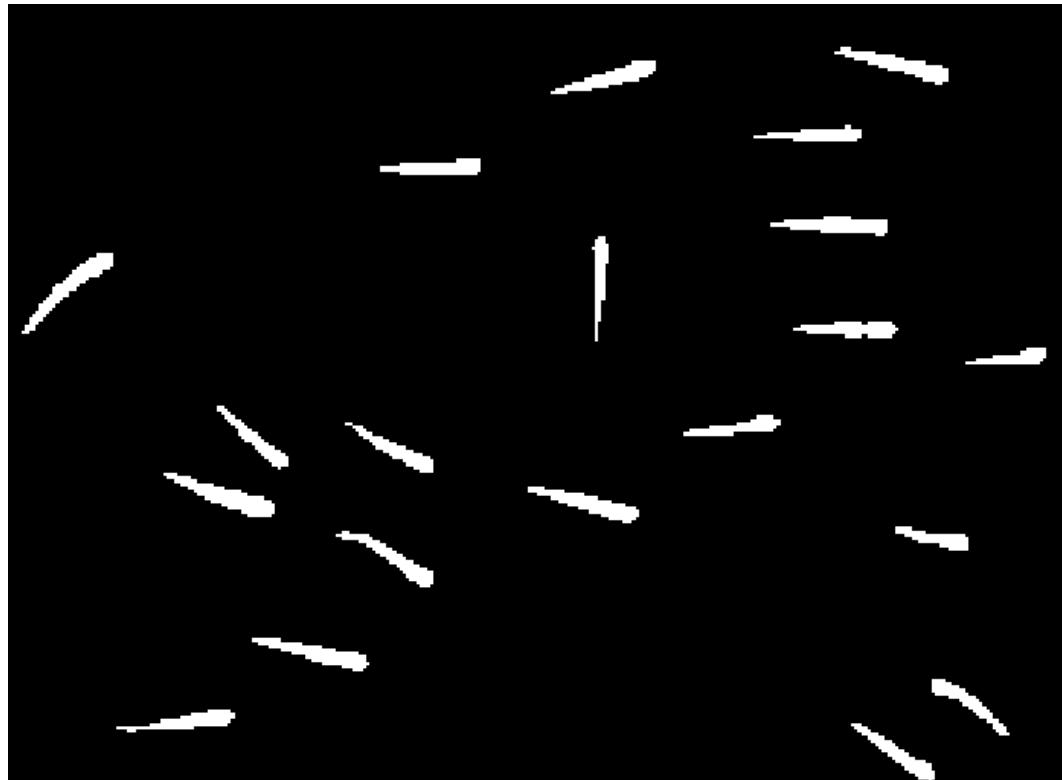
Region labeling example (4-neighborhood)



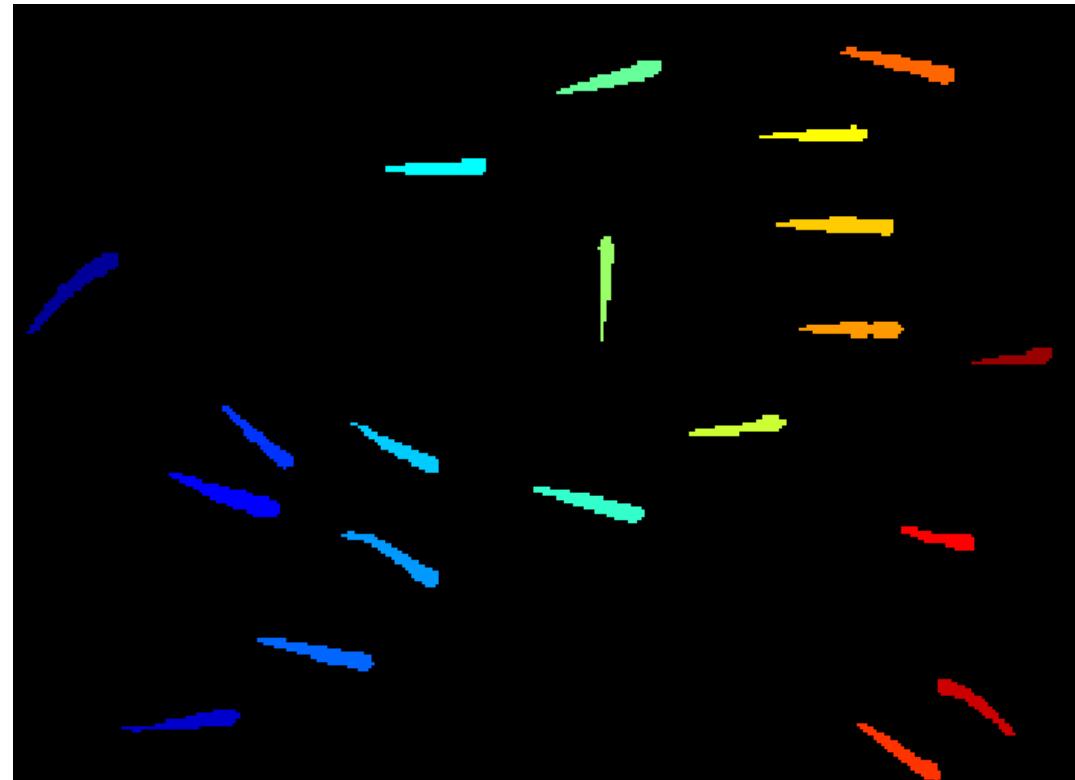
List of Region Labels

1

Example: region labeling



Thresholded image



20 labeled regions



Region counting algorithm

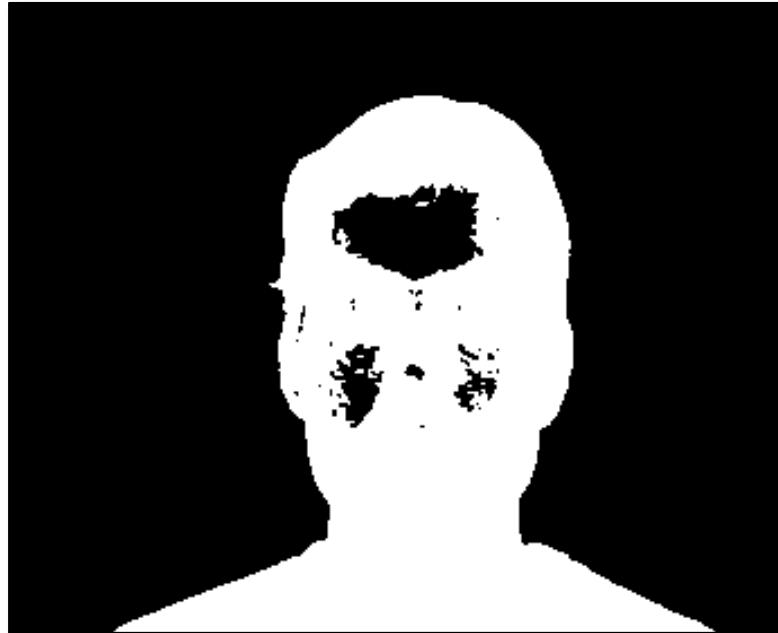
- Measures the size of each region
- Initialize $counter[label]=0$ for all $label$
- Loop through all pixels $f[x,y]$, left to right, top to bottom
 - If $f[x,y]=0$, do nothing.
 - If $f[x,y]=1$, increment $counter[label[x,y]]$

Small region removal

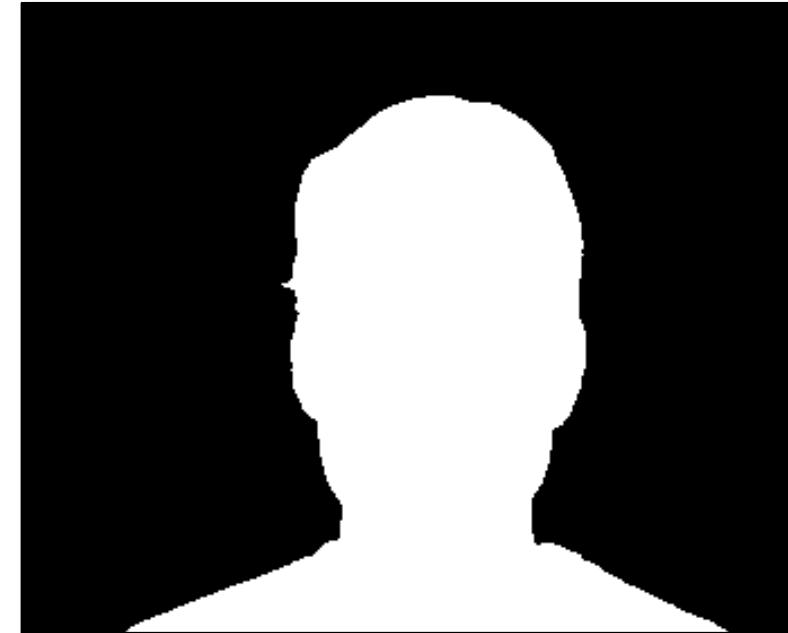
- Loop through all pixels $f[x,y]$, left to right, top to bottom
 - If $f[x,y]=0$, do nothing.
 - If $f[x,y]=1$ and $counter[label[x,y]] < S$, set $f[x,y]=0$
- Removes all regions smaller than S pixels

Hole filling as dual to small region removal

Mask with holes



After NOT operation, (background) region labeling, small region removal, and second NOT operation



Region moments

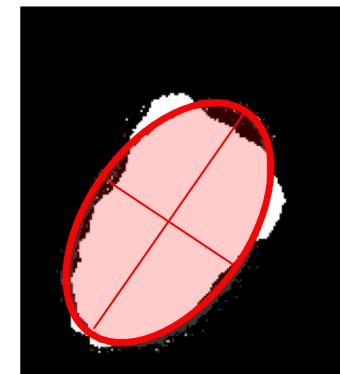
- Raw moments $M_{pq} = \sum_{x,y \in \text{Region}} x^p y^q$

- Central moments

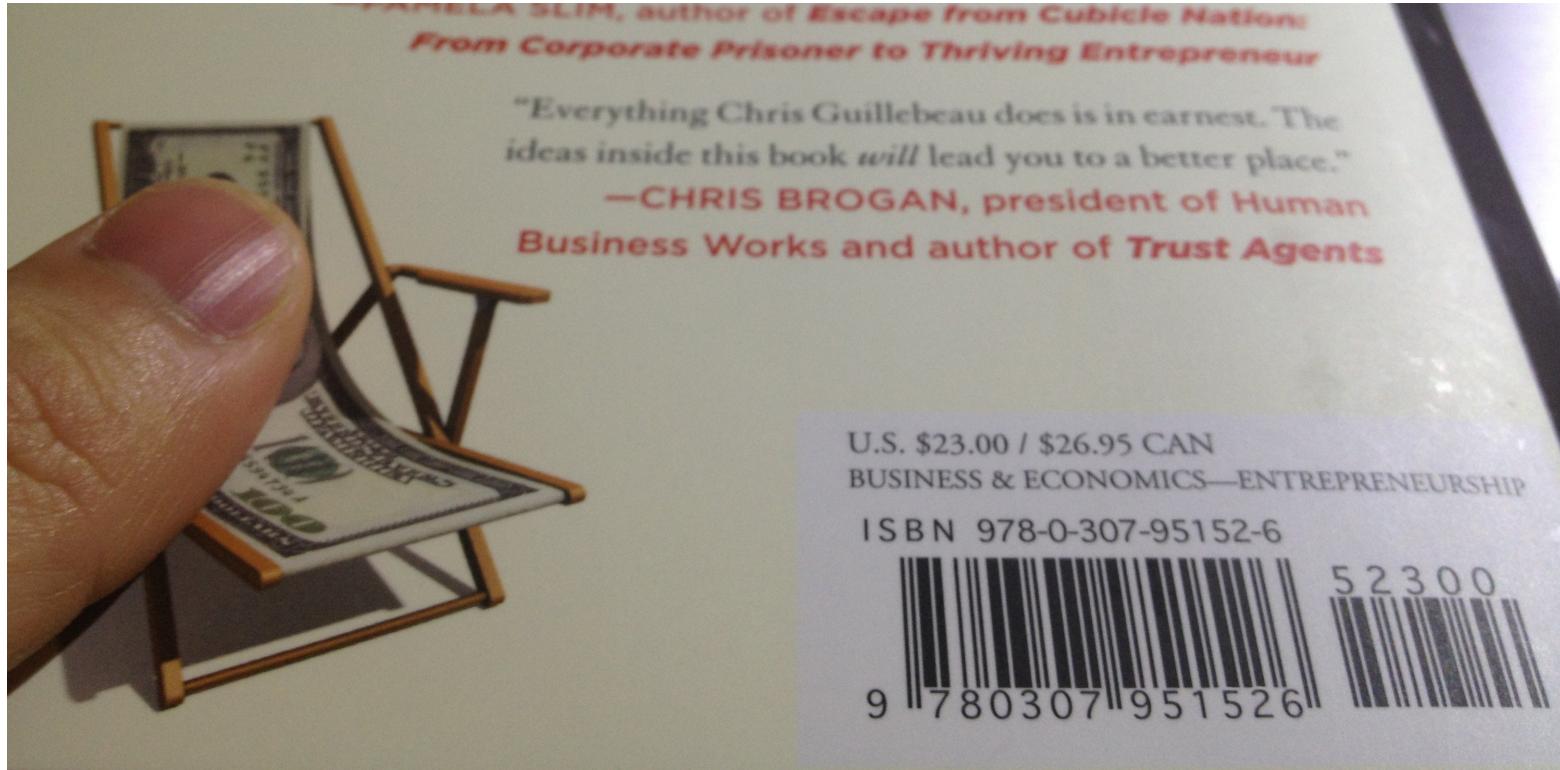
$$\mu_{pq} = \sum_{x,y \in \text{Region}} (x - \bar{x})^p (y - \bar{y})^q \quad \text{with } \bar{x} = \frac{M_{10}}{M_{00}} \text{ and } \bar{y} = \frac{M_{01}}{M_{00}}$$

- Region orientation and eccentricity:
calculate eigenvectors of covariance
matrix

$$\begin{bmatrix} \mu_{20} & \mu_{11} \\ \mu_{11} & \mu_{02} \end{bmatrix}$$



Example: Detecting bar codes

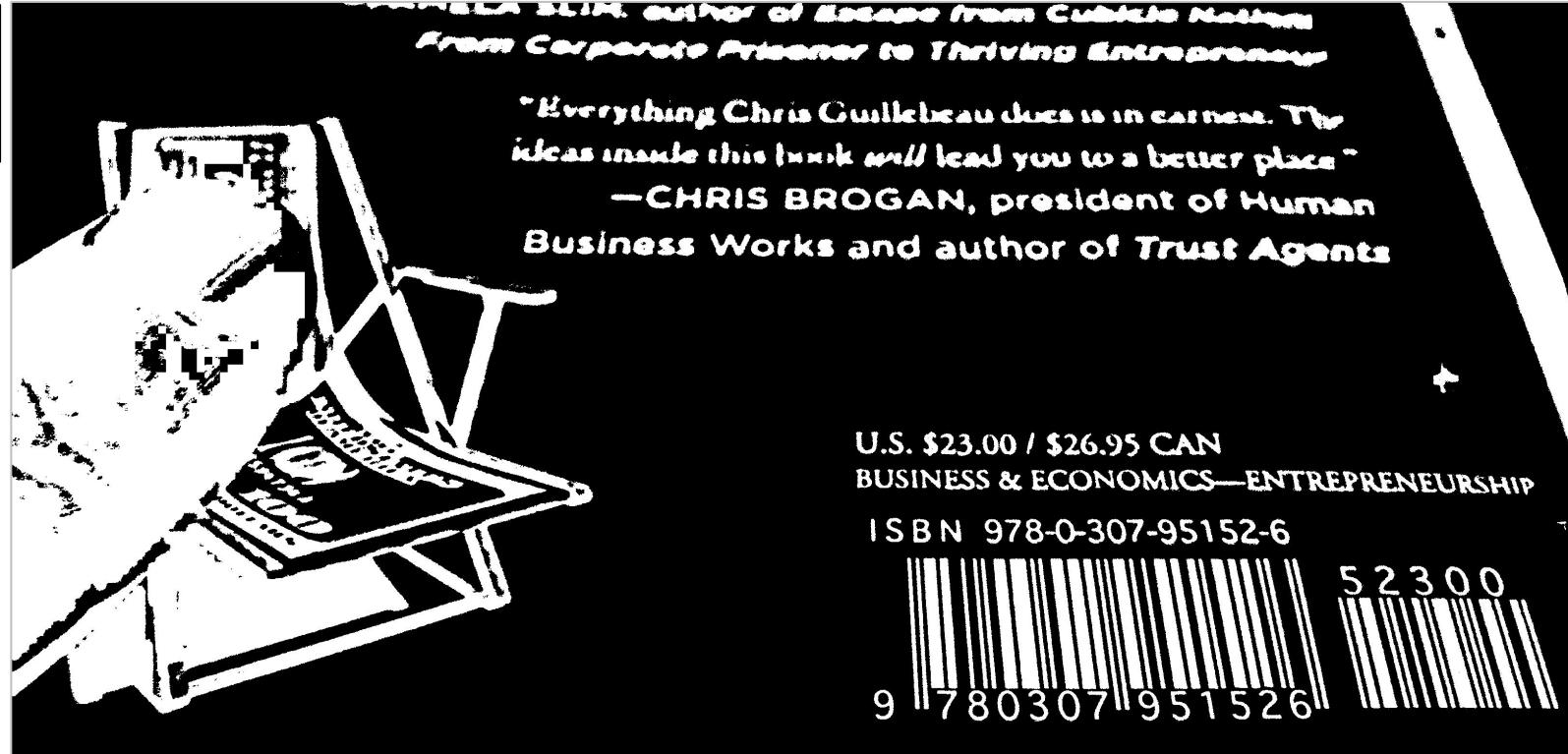


Original Image



Example: Detecting bar codes

Locally adaptive
thresholding



Example: Detecting bar codes

Locally adaptive
thresholding

Filtering by
eccentricity

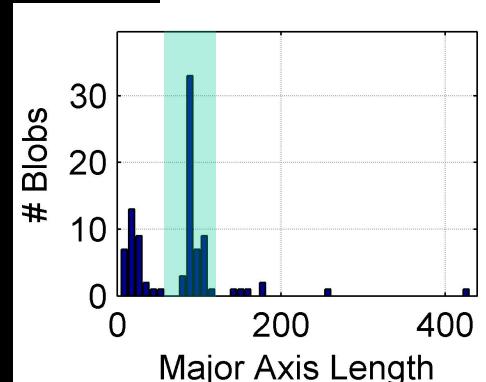


Example: Detecting bar codes

Locally adaptive thresholding

Filtering by eccentricity

Filtering by major axis length



Example: Detecting bar codes

Locally adaptive
thresholding

Filtering by
eccentricity

Filtering by major
axis length

Filtering by
orientation

