AI (B) - Computer Vision Part

Pixel Operations, Histogram, Thresholding

version-watch&understand

Learning Outcomes

Be able to understand the basics of point operators
Be able to compute histograms, optimal threshold for a given image by
programming

Be able to design and apply simple background extraction algorithms.

Contents

- **□Pixel Processing**
- ☐ Histogram and Normalization
- □Intensity Thresholding
- **□**Background Extraction

Reading



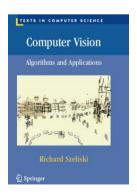
FP: Parts of 7 & 8:

Books from library



Relevant HIPR2 worksheets

http://homepages.inf.ed.ac.uk/rbf/HIPR2/wksheets.htm



RS: Parts of 3

http://szeliski.org/Book/drafts/SzeliskiBook_20100903_draft.pdf

Pixel Processing: Basics

Negate (Invert)

```
Formula: O(i, j) = Max - I(i, j)
Max = 255
Pseudo Code: for (p=0; p<nPixels; p++)
image[p] = MAXVAL - image[p];
```

Examples





Original Image

Inverted Image

Contrast Scaling

Scale a selected grey-scale range [low, high] to fill the available range [0,MAXVAL]

$$O(i,j) = egin{cases} MAXVAL, & I(i,j) >= H \ rac{I(i,j)-L}{H-L}*MAXVAL, & L < I(i,j) < H \ 0, & I(i,j) <= L \end{cases}$$

```
Pseudo code: for (p=0; p<nPixels; p++)
  if (image[p] >= low && image[p] <= high)
      image[p] =
          (image[p] - low) * MAXVAL / (high-low);
else if (image[p] < low) image[p] = 0;
  else image[p] = MAXVAL;</pre>
```

Image Arithmetic

addition, subtraction, multiplication, division

Example: averaging two images

```
for (p=0; p<nPixels; p++)
{
  imageout[p] = image1[p] + image2[p];
  imageout[p] = imageout[p] / 2;
}</pre>
```

怎么解决overflow的问题????????

when the new value after adding is beyond the 255

Potential for overflow!

Hazard of Overflow/Underflow

```
If pixels are bytes, 200 + 100 = ???
Wraparound?
```

Stay at maximum?

Control it:

Step1: make pixel storage larger (double int)

Step2: add images

Step3: scale to original range (single int)

Step4: convert image back to original storage type

or use float or double!

D-I-Y

All these functions (and many more) are explained in more detail in HIPR and examples are given with images.

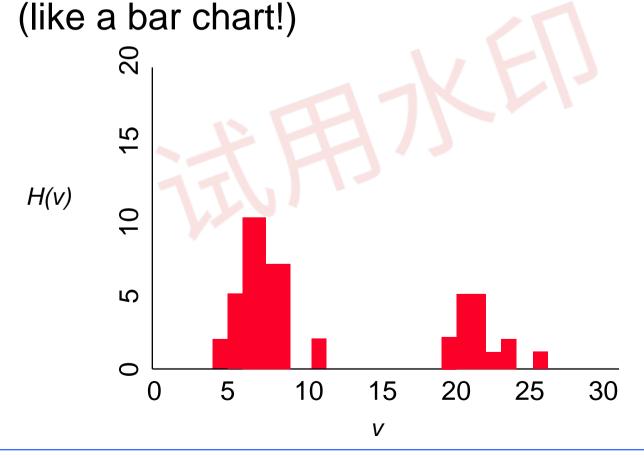
Almost all these functions can be implemented in Paint Shop Pro & most other image packages

Try some DIY in labs!

Intensity Histograms

Grey-level Histogram

Count number of times each grey-level, *v*, occurs in image. Shows *distribution* of values.



Statistics from Histogram

❖Mean:

$$u = \sum_{i=1}^{N} i * h(i)$$

*****Variance:

$$v = \sum_{i=1}^{N} (i - u)^2 * h(i)$$

*Entropy: The information of the histogram. (flatness) entropy= expected information

$$en(h) = -\sum_{i=1}^{N} h(i) \log(h(i))$$

- **❖**Modes: the most frequently happened items, i.e., the intensities
- ! Histogram needs to be normalised first, .i.e.,

$$\sum_{i=1}^{N} h(i) = 1$$

Thresholding

Image intensity thresholding separate pixels into two categories:

- *Larger than or equal a threshold
- Smaller than a threshold

Thresholding creates a binary image, often called binarization, e.g. counting the number of cells in a histological images, number of rice in a visual image.

Binary Threshold

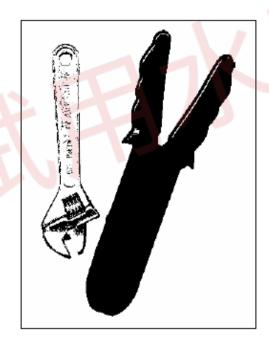
```
Formula B(i, j) = \begin{cases} 0, & I(i, j) >= T \\ 1, & otherwise \end{cases}
```

```
Pseudo Code: for (p=0; p<nPixels; p++)
  if (image[p] < threshold)</pre>
    image[p] = 0;
  else image[p] = MAXVAL;
```

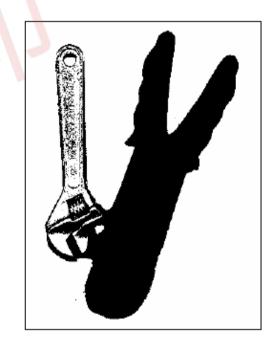
Thresholding Examples

Original





Threshold = 50



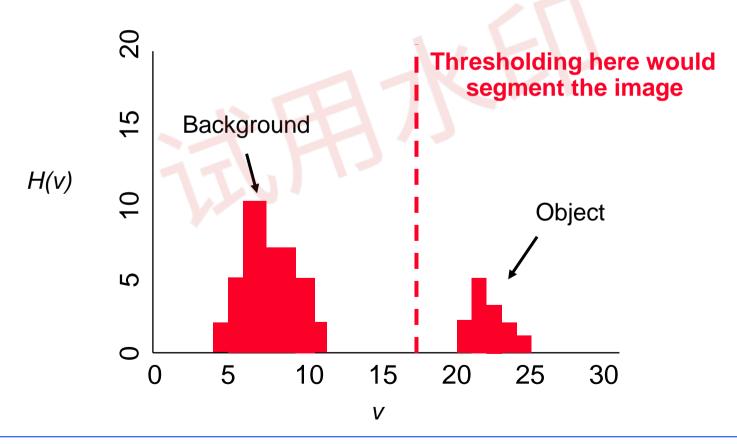
Threshold = 75

Thresholding

Intensity thresholding usually needs to *analyzing* the distribution of the intensity – the histogram

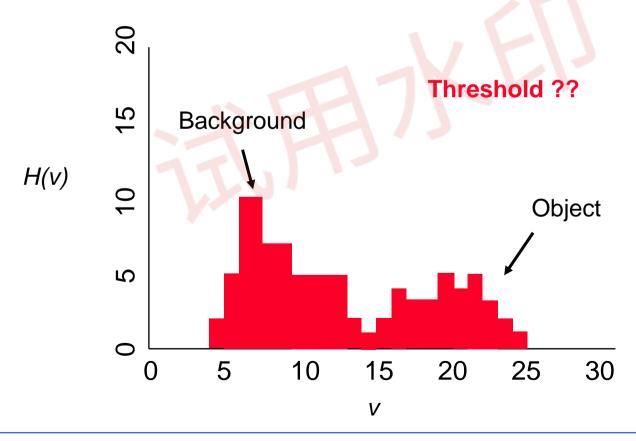
Thresholding: A Bimodal Histogram

e.g. A bright object on a dark background



... but more commonly...

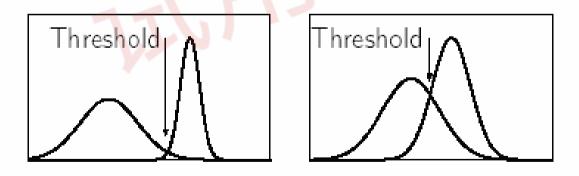
Object and background distributions overlap:



Optimal Thresholding

Histogram shape can be useful in locating the threshold

- However it is not reliable for threshold selection when peaks are not clearly resolved.
- A "flat" object with small intensity variations will give rise to a relatively narrow histogram peak.



Normally works well for Bimodal Histogram

Optimal Thresholding

- -Usually need to specify a criterion function to measure separation between groups
- -- 1) Otsu's method: choose the threshold to minimize the intra-class variance while maximize the inter-class distance (such a criteria is often called Fisher criterion in statistics).
- -2) Approximate Ostu's method: Auto Thresholding

Paper: Nobuyuki Otsu (1979). "A threshold selection method from gray-level histograms".

IEEE Trans. Sys., Man., Cyber. **9** (1): 62–66.

Normally works well for Bimodal Histogram

Otsu's Method

Otsu's thresholding method is based on selecting the lowest point *between* two *classes* (peaks).

Weight and Mean value

Weight:
$$\omega = \sum_{i=0}^{T} P(i)$$
 $P(i) = n_i / N$ N: total pixel number

Weight:
$$\omega = \sum_{i=0}^{T} P(i)$$
 $P(i) = n_i / N$ N: total pixel number

Mean: $\mu = \sum_{i=0}^{T} iP(i)/\omega$ $\mathbf{n_i}$: number of pixels in level I

Analysis of variance (variance=standard deviation²)

Total variance:

$$\partial_t^2 = \sum_{i=0}^T (i - \mu)^2 P(i)$$

Otsu's Method

Inter-classes/between-classes variance (δ_b^2) :

The variation of the mean values for each class from the overall intensity mean of all pixels:

$$\delta_b^2 = \omega_0 (\mu_0 - \mu_t)^2 + \omega_1 (\mu_1 - \mu_t)^2$$
,
Substituting $\mu_t = \omega_0 \mu_0 + \omega_1 \mu_1$, we get:
 $\delta_b^2 = \omega_0 \omega_1 (\mu_1 - \mu_0)^2$

 ω_{0} , ω_{1} , μ_{0} , μ_{1} stands for the weights and mean values of two classes, respectively.

Otsu's Method

Pseudo Code:

- 1. Initialize a threshold, normally the starting value (e.g.,0) Loop -- Repeat:
- 2. Separate the pixels into two clusters based the threshold
- 3. Computer the mean value of each cluster
- 4. Square the difference between the means
- 5. Multiply the number of pixels on one cluster times the number in the other (the between-class variance) for that threshold
- 6. Until the every possible threshold being tested (e.g., till 254).
- 7. Select the threshold that having the largest between class variance

Otsu's Method- Matlab

```
I = imread('coins.png');
level = graythresh(I);
BW = im2bw(I,level);
figure, imshow(BW)
```

Reading: Nobuyuki Otsu (1979). "A threshold selection method from gray-level histograms". *IEEE Trans. Sys., Man., Cyber.* **9** (1): 62–66.

The pdf is available from the VLE!

Auto Thresholding – Approximate to Otsu's Method

Objective: Minimizing the intra-class/within-class variance (= max inter-class variance).

Ostu's method: exhaustive search

Alternatives – approximate search:

- 1. Select an initial estimate of the threshold *T*. A good initial value is the average intensity of the image.
- 3. Calculate the mean grey values μ_1 ind μ_2 of the partitions, R1, R2.
- 2. Partition the image into two groups, R1, R2, using the threshold T.
- 4. Select a new threshold:

$$T = \frac{1}{2}(\mu_1 + \mu_2)$$

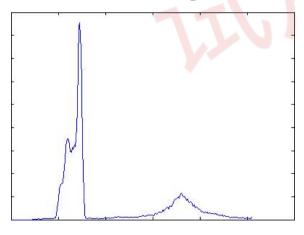
5. Repeat steps 2-4 until the mean values μ_1 nd μ_2 in successive iterations do not change.

Note: this is essentially a 1-D k-means algorithm. You will learn the general k-means in later lectures

Examples



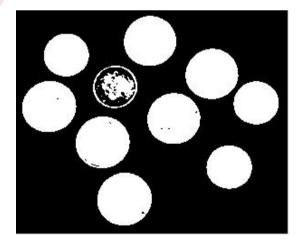
Coins Image



Histogram



Threshold at 50



Optimal Threshold

Change Detection and Background Extraction

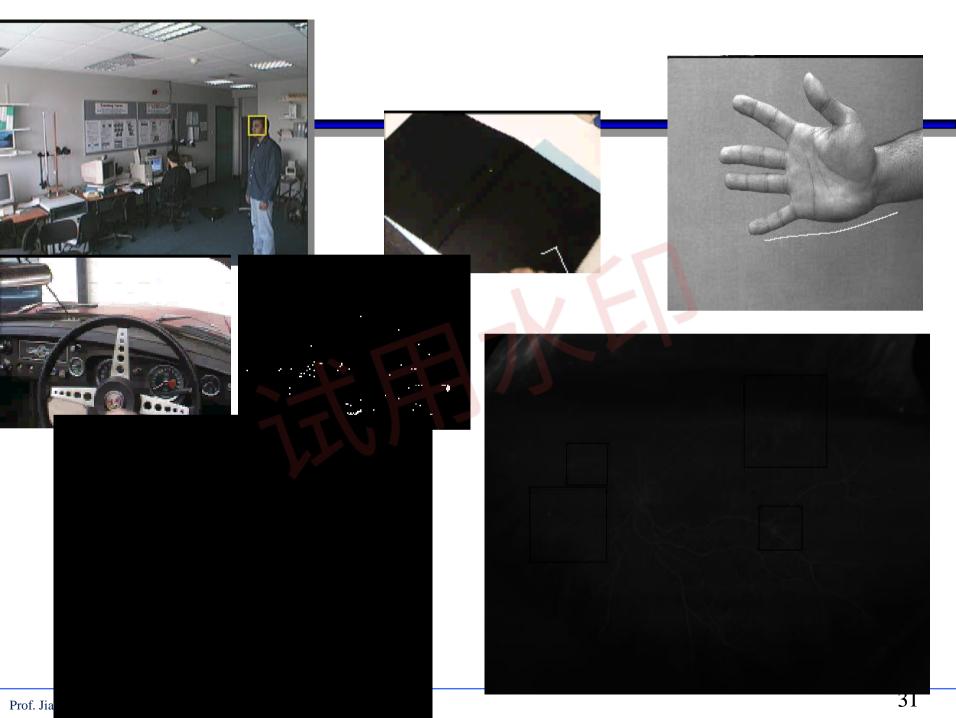
Motivation: Situational Awareness

- Having a complete understanding of an environment
- Acquiring knowledge of what events happened when:
 - Is the event a common event?
 - Did a daily event not happened today?
 - Is something abnormal happening?
 - Is the event dangerous?
- Events that likely can include people and vehicles, happening anytime day or night

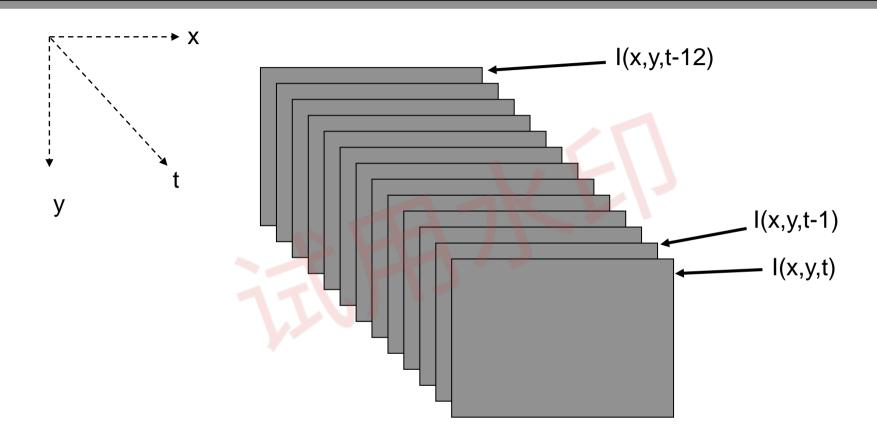
Image Sequences

- * A typical frame-rate: 25Hz
- Notation:
 - An intensity image: I(x,y)
 - An image acquired at time t: I(x,y,t)
 - An image sequence:

$$I(x,y,0), I(x,y,1) ... I(x,y,t-1), I(x,y,t)$$



Space-time



- Think of sequence as occupying a block of 'space-time'
- Time is divided into frames like space is divided into pixels

Change Detection: Temporal Difference

* Absolute difference between subsequent images:

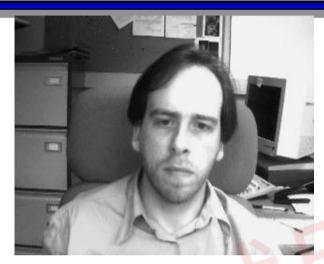
$$D(x, y, t) = |I(x, y, t) - I(x, y, t - 1)|$$

Could threshold to give binary change detection image:

$$B(x, y, t) = 1 \text{ if } D(x, y, t) \ge \tau$$

$$B(x, y, t) = 0 \text{ if } D(x, y, t) < \tau$$

I(t-1) I(t)





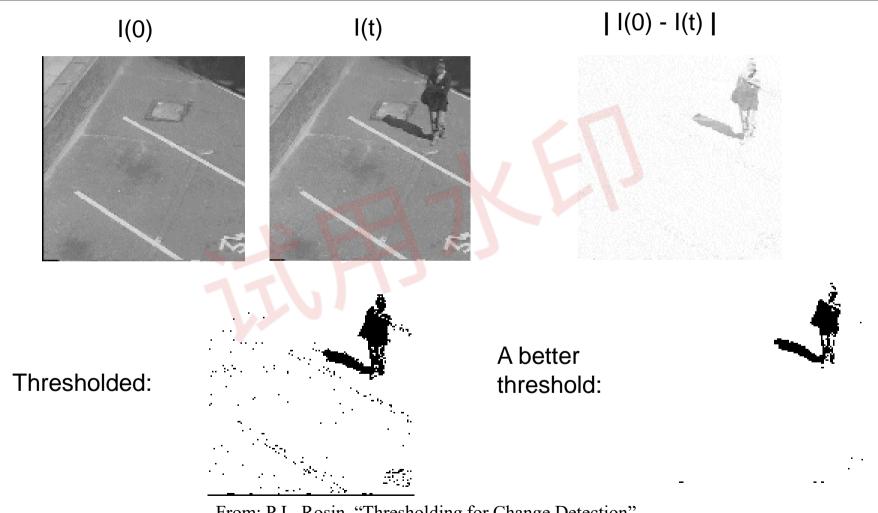
B(t)

D(t)



Poor choice of threshold τ

Frame Differencing



From: P.L. Rosin, "Thresholding for Change Detection" http://www.dai.ed.ac.uk/CVonline/LOCAL_COPIES/ROSIN2/thresh.html

Background Subtraction

- Detects change in homogenous regions provided different from background
- But background image needs updating

Image differencing: pros & cons

Pros:

- Fast and simple
- Useful for focusing visual attention

Cons:

- How to set thresholds? (see Rosin's article)
- Detects any change
 - ⇒moving objects
 - ⇒illumination change
 - ⇒moving shadows
 - ⇒camera motion
 - ⇒camera noise (filtering can overcome this)

Background Modelling

- Simple Frame Difference against a background non adaptive
- Moving Average lower-level adaptation
- Online Gaussian (not covered, requires further reading)

Background Subtraction-Not Adaptive

- Simple Frame Difference against a known background
 - Simple, and easy to implement
 - Not robust
 - Applicable when a camera is fixed, background fixed
 - Can not handle illumination changes well, especially in outdoor scenarios, e.g, sunlight, cloudy, day/night, slight movement of tree leaves.
 - the need for manual initialization. Without re-initialization, errors in the background accumulate over time, making this method useful only in highlysupervised, short-term tracking applications without significant changes in the scene.
- Math Model for foreground extraction
 - $B(x,y) = mean_t(v(x,y,t))$
 - f(x,y,t) = abs(v(x,y,t)-B(x,y)), and then setting threshold for f

Moving Average- Adaptive

- Moving average filtering
 - Current background equals to the mean of previous n frames.
 - Algorithms (pseudo code)
 - Initialise the value of a background estimate B, for each frame F
 - Update the background estimate by computing

$$B(n+1) = (w_a F + \sum_i w(i)B(n-i)) / w_c$$

for a choice of w_a , w(i) and $w_c = w_a + \sum w(i)$

Or:
$$B(n+1) = \sum_{i} w(i)F(n-i)$$

- * Substract the background estimate from the frame, and report the value of each pixel where the magnitude of the difference is greater than some threshold
- end
 - Could handle a certain level of background changes and Illumination changes (ref: Chapter 14, Computer Vision: a Modern Approach, Forsyth and

Ponce)

Background Extraction Demo

- Using GMM method
 - Gaussian Mixture
 - Landmark Paper: Adaptive background mixture models for real-time tracking. Chris Stauffer. W.E.L Grimson, CVPR 2008
 - Watch Video Now

Further Reading

Further Reading

- Chris Stauffer and W.E.L Grimson, <u>Adaptive background mixture models for real-time</u> <u>tracking</u>, CVPR08 (landmark paper)
- Zoran Zivkovic and van der Heijden, <u>Efficient adaptive density estimation per image</u> <u>pixel for the task of background subtraction</u>, <u>Pattern Recognition Letter</u> 2005 (Good technique paper)

Computer Vision

Pixel Operations, Histogram, Thresholding

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Be able to compute histograms, optimal threshold for a given image by
programming

Be able to design and apply simple background extraction algorithms.