

## BE244 - Lecture Outline - January 28, 2009

Image Enhancement - Spatial Domain:

- Basics Spatial filtering
- Neighborhood operations
- Spatial convolution
- Border Issues
- Mean, Median Spatial Filters
- Calculation Examples
- Other order statistic filter: midpoint filter
- First Second-order derivatives (review)
- Laplacian
- Unsharp Masking

Image Segmentation - Thresholding Basics


## Contrast Mapping

An image has a max value of 12000 . Its minimum is -3200 .
Display it using values $0-255$.
Give equation needed to rescale it appropriately.

$$
\begin{aligned}
& y=[(x-\min ) /(\max -\min )] * 255 \\
& \text { Or, } \\
& y=[(x+3200) / 15200] * 255
\end{aligned}
$$

| Mean Spatial Filter (2) |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Example: <br> Vertical edge | 0 | 0 | 9 | 9 | 9 | Filtered using a $3 \times 3$ mean filter |  |  |
|  | 0 | 0 | 9 | 9 | 9 |  |  |  |
|  | 0 | 0 | 9 | 18 | 9 | 1/9 | 1/9 | 1/9 |
|  | 0 | 0 | 9 | 9 | 9 | $1 / 9$ <br> $1 / 9$ | 1/9 |  |
|  | 0 | 0 | 9 | 9 | 9 |  |  |  |
| 0 | 0 | 9 | 9 | 9 |  | Issues with borders.... |  |  |
| 0 | 3 | 7 | 10 | 9 |  |  |  |  |
| 0 | 3 | 7 | 10 | 9 |  |  |  |  |
| 0 | 3 | 7 | 10 | 9 |  |  |  |  |
| 0 | 0 | 9 | 9 | 9 |  |  |  |  |



## Smoothing Spatial Filter: Mean Filter

- Used for removal (or reduction) of small (irrelevant) details in image
- Every pixel replaced by average of its neighbors
- "Low-pass filter": removes high spatial frequencies reduces noise in image best for removing gaussian noise


Filtered using a $3 \times 3$ mean filter | $1 / 9$ | $1 / 9$ | $1 / 9$ |
| :--- | :--- | :--- |
| $1 / 9$ | $1 / 9$ | $1 / 9$ |
| $1 / 9$ | $1 / 9$ | $1 / 9$ |$\quad \square$

## Spatial Filtering: Summary

Neighborhood process, scanning all image

$$
\Rightarrow \text { computationally intensive. }
$$

Mask size or shape: any, but arbitrary shapes will play role in result (i.e. Math. Morphology).
Typically: small square/rectangular 2D array, odd number of elements (eg $3 \times 3,5 \times 5$ neighborhoods) to ease programming, centered at pixel being filtered.


| Mean Spatial Filter (1) |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Example: Vertical edge | 0 | 0 | 9 | 9 | 9 | Filtered using a $3 \times 3$ mean filter: |  |  |
|  | 0 | 0 | 9 | 9 | 9 |  |  |  |
|  | 0 | 0 | 9 | 18 | 9 | 1/9 | 1/9 | 1/9 |
|  | 0 | 0 | 9 | 9 | 9 | $1 / 9$ | $1 / 9$ | 1/9 |
|  | 0 | 0 | 9 | 9 | 9 |  |  |  |
|  | 0 | 0 | 9 | 9 | 9 | 10 |  |  |
|  | 0 | ? | ? | ? | 9 |  |  |  |
|  | 0 | ? | ? | ? | 9 |  |  |  |
|  | 0 | ? | ? | ? | 9 |  |  |  |
|  | 0 | 0 | 9 | 9 | 9 |  |  |  |


| Spatial Filtering: Border Issues |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Issues at borders using HxH masks on NxM image: <br> - First (H-1)/2 rows and columns not filtered <br> - Last (H-1)/2 rows and columns not filtered |  |  |  |  |  |  |
| Example with 3x3 mask: 1 st and last rows + columns of original image are not filtered. | - | - | - | - | - |  |
|  | - | x | X | X | - |  |
|  | - | x | x | X | - |  |
|  | - | x | x | x | - |  |
|  |  | - | - | - | - |  |
| $\square 2$ main approaches |  |  |  |  |  |  |

## Spatial Filtering: Border Issues (2)

2 main approaches to deal with border issues when spatial filtering:

1. Leave all borders unfiltered (easiest)

- Common solution
- Most information is located at center of image, not border.

2. Replicate bordering pixels, before and after image, to define and use HxH neighbors around all pixels of the image

- More computing complexity


$0 \longleftarrow$| 0 | 0 | 0 | 9 | 9 | 9 | 9 |
| :---: | :---: | :---: | :---: | :--- | :--- | :--- |
| 0 | 0 | 0 | 9 | 9 | 9 | 9 |
| 0 | 0 | 0 | 9 | 9 | 9 | 9 |
| 0 | 0 | 0 | 9 | 18 | 9 | 9 |
| 0 | 0 | 0 | 9 | 9 | 9 | 9 |
| 0 | 0 | 0 | 9 | 9 | 9 | 9 |
| 0 | 2 | 0 | 9 | 9 | 9 | 9 |



Other Example Averaging Filter

Original Image

| Other Example Averaging Filter |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Original Image |  |  |  |  |  |  |  |  |
| 0 | 0 | 8 | 8 | 8 | 5-point weighted averaging mask |  |  |  |
| 0 | 0 | 8 | 8 | 8 | 0 | 1/8 | 0 |  |
| 0 | 0 | 8 | 16 | 8 | 1/8 | 1/2 | 1/8 |  |
| 0 | 0 | 8 |  | 8 | 0 |  |  |  |
| Spatial averaging of original image using this 5-point weighted averaging mask ? (homework due Feb. 4) |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  | 16 |

5-point weighted averaging mask

- unsuccessful at removing outlier pixel (18)
- reduced height of outlier but increased its width
- sharp vertical edge changed to gradually sloped edge 14


| Median Filter: Examples |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Original image |  |  |  |  | $\Rightarrow$ Median filter using $3 \times 3$ window |  | Output image ? |
| 5 | 5 | 9 | 9 | 9 |  |  |  |
| 5 | 5 | 9 | 9 | 9 |  |  |  |
| 5 | 5 | 9 | 18 | 9 |  |  |  |
| 5 | 1 | 9 | 9 | 9 |  |  |  |
| 5 | 5 | 9 | 9 | 9 |  |  |  |
| Original image |  |  |  |  | $\Rightarrow$ Median filter using $3 \times 3$ window |  | Output image ? |
| 0 | 0 | 0 | 0 | 0 |  |  |  |
| 0 | 0 | 0 | 0 | 0 |  |  |  |
| 5 | 5 | 5 | 5 | 5 |  |  |  |
| 0 | 0 | 0 | 0 | 0 |  |  |  |
| 0 | 0 | 0 | 0 | 0 |  |  |  |
| Comments? |  |  |  |  |  |  | 18 |



## Basic Definitions: first/second-order derivatives

Important definitions: book pages 125-127, figure 3.38
Derivatives of a digital function: defined in terms of differences
Derivatives will have different behaviors in constant areas, and in areas with step or ramp discontinuities.

First-order derivative for one-dimensional function $f(x)$ : $\partial \mathrm{f} / \partial \mathrm{x}=\mathrm{f}(\mathrm{x}+1)-\mathrm{f}(\mathrm{x})$
$\Longrightarrow$ Produce thicker edges in the image
Second-order derivative:
$\partial^{2} f / \partial x^{2}=f(x+1)+f(x-1)-2 f(x)$
$\Longrightarrow$ Stronger response to fine details, produce double response at step changes in gray level.


## Image Segmentation - Basics

Goal: Divide the image into REGIONS

Two classes of region definition techniques:
Algorithms for construction of regions
Algorithms for contour extraction

## Thresholding

1.Definitions

Histogram: Calculation of number of pixels at each intensity value in the image

Displays peaks and valleys corresponding to subpopulations of the image


Choosing intensity level (I) allows thresholding effect $=$ defines 2 subpopulations in the resulting image.

26

Histogram of gray level image:
Case 1: Image has a bimodal histogram. Define a threshold located in between maxima (the two subpopulations in the image) and separating intensity levels into two groups: C, D.


Result of thresholding (using threshold value T): Binary image All points in group C (with intensity values $<\mathrm{T}$ ) take intensity value 0 , all points in group D (intensities $>=\mathrm{T})_{28}$ take the value 1 .


## Thresholding Example 1

                                    (vert=80, horiz=180)
                                    (vert=80, horiz=180)
    ?? Which
thresholds were
thresholds were
chosen in images 2
and 3 ?


Global Threshold: choice of threshold depends on the intensity values of the image

Local Threshold: choice of threshold is made depending on intensity values in local neighborhood calculated at each pixe

## Homework for Feb 4 (descriptive only):

Find 2 images (online, book, magazine etc. - please cite sources): - one which could be well segmented using a global threshold (explain what would be segmented and how)

- second one presents an histogram which is NOT bimodal, and therefore would require some rule(s) to extract object/segment, please explain. Descriptive only, be creative !

Histogram of gray level image:
Case 2: Histogram NOT bimodal.


Necessary to define a rule in order to select an acceptable threshold for context of study

32


## Thresholding: properties

- No spatial coherence/rule for detected objects: if image is noisy, thresholding can lead to over-segmented binary image
- Histogram provides information on intensity subpopulations, but does not provide spatial information about objects


Both images have the same histogram


- Any inhomogeneity due to image modality will bias results
- The number of classes (subpopulations in the image) is generally less than 5 .




## Answer:

- Number of boundary points between black and white regions is much larger in Image $\mathbf{B}$ than in Image $A$.
- After smoothing, the boundary points will have a different value from black or white, so the two histograms will be different.


## Optimum Thresholding: computation

Input: Gray level image, size NxM pixels 256 gray level values

1. Compute Histogram of image, $h(i)$, $i$ : intensity levels
2. Smoothes histogram curve $h$ using $T \times 1$ pixels filter,
3. Locate valley between two peaks, use that level for thresholding
4. Create binary image

Output: Binary image $\longrightarrow$ (homework for Feb 4)

## Histogram Features

Goal: Use some statistical parameters obtained directly from the histogram

Mean
$\bar{Y}=\sum_{i=1}^{N} Y_{i} / N$

Median: Estimated from a histogram by finding the smallest number such that the area under the histogram to the left of that number is $50 \%$

Skewness $=\frac{\sum_{i=1}^{N}\left(Y_{i}-\bar{Y}\right)^{3}}{(N-1) s^{3}}$
Measure of symmetry
("skewed right" distribution = tail \&q right
side) side)
Histogram Features
Goal: Use some statistical parameters obtained directly
from the histogram

Mean $\bar{Y}=\sum_{i=1}^{N} Y_{i} / N$ \begin{tabular}{l}

Median: | Estimated from a histogram by finding the smallest number |
| :--- |
| such that the area under the histogram to the left of that |
| number is $50 \%$ | <br>

Skewness $=\frac{\sum_{i=1}^{N}\left(Y_{i}-\bar{Y}\right)^{3}}{(N-1) s^{s}} \quad$| Measure of symmetry |
| :--- |
| ("skewed right" distribution = tail an right |
| side) | <br>

\hline
\end{tabular}

## Histogram Features

Goal: Use some statistical parameters obtained directly from the histogram
Mean $\bar{Y}=\sum_{i=1}^{N} Y_{i} / N$
Kurtosis $=\frac{\sum_{i=1}^{N}\left(Y_{i}-\bar{Y}\right)^{4}}{(N-1) s^{4}} \quad \begin{aligned} & \text { Measure of data: peaked (high } \\ & \text { kurtosis)/flat (low kurtosis) }\end{aligned}$
Variance $s^{2}=\sum_{i=1}^{N}\left(Y_{i}-\bar{Y}\right)^{2} /(N-1)$

| Example: <br> 3 MODES: <br> 3,4,and 6 (values that appear most often)  <br> MEAN: <br> The arithmetic mean of a set of values is a sum of all values, divided by their number $\begin{aligned} & (1+2+2+2+3+3+3+3+ \\ & 3 \ldots \ldots+6+6+6+6+6) / 20 \\ & =3.85 \end{aligned}$ <br> MEDIAN: the middle piece of data, after data sorted from smallest to largest: $1,2,2,2,3,3,3,3,3,4,4,4,4,4,5,6,6,6,6$, 6. <br> There is an even number of values, so middle (or median) is between the first and second 4 . Since they are identical, the median is four, but if they were different, (i.e. if the median was between a 3 and a 4 ), we would do $(3+4) / 2=3.5$. |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |


| Image analysis techniques |  |  |
| :--- | :--- | :--- |
|  |  |  |
| Feature Extraction | Segmentation | Classification |
| Spatial features <br> Transform features <br> Edges and boundaries <br> Share features <br> Moments <br> Texture Thresholding <br> Detection of <br> discontinuities <br> Boundary Detection <br> Edge linking <br> Region oriented <br> segmentation Clustering <br> Statistical <br> Decision trees <br> Similarity measures <br>  Clustering  |  |  |

## Alternative Measures of Location

A few of the more common alternative location measures are:

1. Mid-Mean - computes a mean using the data between the 25 th and 75 th percentiles.
2. Trimmed Mean - similar to the mid-mean except different percentile values are used. A common choice is to trim $5 \%$ of the points in both the lower and upper tails, i.e., calculate the mean for data between the 5 th and 95 th percentiles.
3. Winsorized Mean - similar to the trimmed mean. However, instead of trimming the points, they are set to the lowest (or highest) value. For example, all data below the 5th points, they are set to the lowest (or highest) value. For example, all data below the 5 th
percentile are set equal to the value of the 5 th percentile and all data greater than the 95 th percentile are set equal to the 95 th percentile.

The first 3 alternative location estimators above have the advantage of the median: they are not affected by extremes in tails. However, they generate estimates that are closer to the mean for data that are normal (or nearly so).
4. $\quad$ Mid-range $=($ smallest + largest $) / 2$. Not robust $($ based on two most extreme points $)$ (use typically restricted to situations in which behavior at extreme points is relevant.)

Next Session: Monday February 2

Image Segmentation:
Review Thresholding: Read Book pp 595-600
Edge \& Contour Detection: Read book pp567-585

