# Image Matching 

Lecture \#8
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## How do we (directly) compare two images?



## Are these images the same? Are they similar?

## Pixel-wise Comparison



Or, normalized by image area, about 5 grey values per pixel.

$$
8,140=\sum_{x}^{x<148} \sum_{y}^{y<161}|A(x, y)-B(x, y)|
$$

2/18/19

## Backup - what is "Similarity"?

Consider two vectors/points.

$$
X=\left|\begin{array}{c}
x_{1} \\
x_{2} \\
\ldots \\
x_{n}
\end{array}\right| Y=\left|\begin{array}{c}
y_{1} \\
y_{2} \\
\ldots \\
y_{n}
\end{array}\right|
$$

Distance vs. similarity:

$$
\begin{aligned}
& S: R^{n} \times R^{n} \rightarrow R \\
& D: R^{n} \times R^{n} \rightarrow R
\end{aligned}
$$

$S \propto 1 / D$

Common Approaches
Euclidean (L2) Distance
City Block (L1) Distance
Pearson's Correlation
Slightly Less Common
Mahalanobis Distance
Mutual Information

## Simple Distances (norms)

$L_{1}$ - City Block Distance

$$
\sum_{x, y}(|A(x, y)-B(x, y)|)
$$

$\mathrm{L}_{2}$ - Euclidean Distance
$\mathrm{L}_{\infty}$ - Max Distance

$$
\sqrt{\sum_{x, y}(A[x, y]-B[x, y])^{2}}
$$

Generalized L-norm
$\sqrt[y]{\sum_{x, y}(|A(x, y)-B(x, y)|)^{l}}$
$\mathrm{L}_{1}$ Distance $\mathrm{L}_{2}$ Distance


Curves shown are the set of points that are 'one unit' from the origin using different definitions of distance.

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## Properties of L1 Distance

Consider the following problem:
Find the unique point "closest" to $k$ other points.
For simplicity, do this in R (a line) with $\mathrm{k}=2$.


See the problem yet?

$$
|2-3|+|8-3|=6 \quad|2-4|+|8-4|=6
$$

## In Comparison, Consider L2

Find the unique point "closest" to $k$ other points.


Using L2,


$$
\sqrt{(2-5)^{2}+(8-5)^{2}}=\sqrt{18} \quad \sqrt{(2-4)^{2}+(8-4)^{2}}=\sqrt{20}
$$

Best
Not as Good

## Pearson's Correlation

$$
\frac{\sum_{x, y}(A(x, y)-\bar{A})(B(x, y)-\bar{B})}{\sqrt{\sum_{x, y}(A(x, y)-\bar{A})^{2}} \sqrt{\sum_{x, y}(B(x, y)-\bar{B})^{2}}}
$$

## What is the underlying model?

## Assumptions of Correlation

$$
\frac{\sum_{x, y}(A(x, y)-\bar{A})(B(x, y)-\bar{B})}{\sqrt{\sum_{x, y}(A(x, y)-\bar{A})^{2}} \sqrt{\sum_{x, y}(B(x, y)-\bar{B})^{2}}}
$$

- Two signals vary linearly
- Constant shift to either signal has no effect.
- Increased amplitude has no effect.
- This minimizes sensitivity to:
- changes in (overall) illumination.
- offset or gain.


## Special Cases

- Any two linear functions with positive slope have correlation 1.

- Only the sign of the slope matters.
- Any two linear functions with differently signed slopes have correlation -1.
- This is called anti-correlation
- Anti-correlation = correlation for prediction.
- For matching, it may or may not be as good...
- Correlation undefined for slope $=0(\sigma=0)$


## Correlation (cont.)

- For Images, correlation is sensitive to:
- Translation
- Rotation: in-plane and out-of-plane
- Scale
- Because it ...
- Assumes pixels align one atop the other.
- Compares two images pixel by pixel.
- Translation handled by convolution
- Example, alignment by template matching


## Computing Correlation

- Remember adding a constant does not change correlation to any other signal, so
- Let's subtract average A from A()
- Let's subtract average $B$ from $B()$
- The mean of both signals is now zero
- Then correlation reduces to:

$$
\frac{A \cdot B}{\sqrt{\sum_{x, y}(A(x, y)-\bar{A})^{2}} \sqrt{\sum_{x, y}(B(x, y)-\bar{B})^{2}}}
$$

## Computing Correlation (II)

- For zero-mean signals, we can scale them without changing their correlation scores
- Multiply A by the inverse of its length
- Multiply B by the inverse of its length
- Both signals are now unit length
- Then correlation reduces to:

$$
A \cdot B
$$

- Gives rise to 'Correlation Space'.


## Correlation Space

- Why zero-mean \& unit-length images?
- Consider database retrieval
- Compare new image A ...
- with many images in database.
- When database images are stored in their zero-mean \& unit-length form, then
- Preprocess A (zero-mean, unit-length)
- Compute dot products


## Correlation Space (II)

- New idea: image as a point in an N dimensional space
- $N=$ width $x$ height
- Zero-mean \& unit-length images lie on an N 1 dimensional "correlation space" where the dot product equals correlation.
- This is a highly non-linear projection.
- Points lie on an $\mathrm{N}-1$ surface within the original N dimensional space.
- So consider points in 3-D ....


## Correlation Space (II)

- Subtracting mean - translation.
- Length one - project onto sphere.
- Correlation is then:
- Cosine of angle between vectors (points).



## Useful Connection ...

- Euclidean distance inverse of correlation in correlation space.

$$
\begin{aligned}
\sqrt{\sum_{x, y}(A[x, y]-B[x, y])^{2}} & =\sqrt{\sum_{x, y} A[x, y]^{2}+\sum_{x, y} B[x, y]^{2}-2 A[x, y] B[x, y]} \\
& =\sqrt{1+1-2 \sum_{x, y} A[x, y] B[x, y]} \\
& =\sqrt{2-2 A \cdot B} \\
& =\sqrt{2-2 \operatorname{Corr}(A, B)}
\end{aligned}
$$

Nearest-neighbor classifiers in correlation space maximize correlation

## Limitations

- To match images this way, they must be
- The same width \& height
- In correspondence : coordinates match
- More importantly, objects in the scene must
- Be in the same location
- Be at the same scale
- Be at the same orientation
- Be seen from the same viewpoint


## Find similar patterns in a larger

 image

- The image above is a small piece of the image to the right. But from where?


## Brute-Force Translation Invariance

To find a small image in a large one, "slide" the small one across the large, computing Pearson's correlation at every possible position.


## Statistical Cross-Correlation

- The process of "slide \& correlate" is called crosscorrelation
- Complexity is $\mathrm{O}(\mathrm{nm})$
$-N=\#$ of pixels in image $(w \times h)$
$-M=\#$ of pixels in the template ( $w \times h$ )
- Highly parallel (every position can be computed independently)
- Still sensitive to
- Rotation
- in-plane
- out-of-plane
- Scale
- Perspective


## Computing Cross-Correlation

- In cross-correlation, the mask is correlated repeatedly to image windows
- zero-mean \& unit length the mask
- zero-mean \& unit length the image
- compute the sliding dot product

> This is almost convolving the image with the mask

## Naming conventions

- In Engineering, convolving a normalized mask with the source image is called correlation
- Is this exactly the same as Pearson's correlation?
- Why or why not?
- This is the most common definition of correlation in image processing texts


## Application: Tracking

- Cut out a picture of a target from the first frame of a video
- Use it as a template /mask
- Correlate the target in the following frames
- Find the location with the highest correlation
- Improvement:
- update target with each new frame


## Application: Tracking



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## Application: Mosaicing

- Take several, overlapping images from a translating camera
- Camera cannot move along optical axis
- Correlate the whole images to each other
- Find location where they match the best
- Stitch them into a single, larger image


## Mosaicing (II)



Image 1


Image 2


Image 3


## In OpenCV



## Example



## N $\leftarrow \rightarrow$ 中

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