Image Matching, Edges & Cross Correlation

Lecture #08 February 13th, 2013



Similarity Transforms

- So we can compensate for image translation using the shift theorem
 – O(n log(n)) correlation in Frequency Space
- Can we compensate for
 - image rotation? Yes
 - image scaling? Yes
 - perspective distortion? No
- How? By using the shift theorem again...



Rotation →Translation

- Our goal is to apply a coordinate transformation to the original spatial domain image such that a change in rotation becomes a change in translation.
- How? By converting from Cartesian Coordinates to Polar Coordinates.
 - Remember that the Polar Coordinates of a point in 2D are its distance from the origin d and the angle of the vector from the origin to the point \u03c6



Polar Coordinates

Image (3x3)Cartesian Polar [0,0]=255[0,0]=0 [1,0]=255[0,45]=0 [1,45]=224[0,1]=250[0,90]=0 [1,90]=250[0,2]=224[0,135]=0 [1,135]=255 [1,0]=225 [1,1]=0[0,180]=0 [1,180]=225[0,225]=0 [1,225]=249 [1,2]=255 [0,270]=0 [1,270]=255[2,0]=249[2,1]=255 [0,315]=0 [1,315]=235[2,2]=235Polar coordinates imply an

image resampling - use bilinear interpolation



Polar Coordinates (cont.)

- Why convert into polar coordinates?
 - Because a cartesian rotation becomes a polar translation
 - 2nd coordinate -- angle -- advances...
 - Apply Fourier transform to polar image, find maximum shift
 - Shift in distance coordinate must be zero!
 - Shift implies rotation in cartesian space.



Scale →Shift

- What if one image is scaled relative to another?
- Convert image to LogPolar Coordinates
 - Just like Polar Coordinates, except that the distance coordinate is expressed by its logarithm
- Now a shift in the distance coordinate is equivalent to a scale change
- Note that the shift theorem finds shifts in both dimensions, so you can match images that are both rotated and scaled.



Limitations

- We can only match rotated and/or scaled image if we know the point they are rotated and/or scaled about!
- We can match translated images or rotated & scaled images, but not both.
- There is an informal, iterative way to handle small changes in translation, rotation & scale
 - Fix translation, adjust rotation & scale shift,
 - Fix rotation/scale, adjust translation
 - Repeat until peak in shift theorem reaches a threshold, or fails to improve



Gross Translation & Rotation

- The brute force approach to making correlation insensitive to gross translations and rotations is to generate R templates at R different angles.
 - Increase complexity by the factor R
 - Only accurate if R is fairly large
- Can one guess orientation and only consider one template per pixel location?
 - measure the orientation of a pixel?
 - What does it even mean?
- One of many ways to motivate <u>Edges</u>



Image as Surface

- View the image as a 3D surface
 - For every (x,y) pixel location, the intensity can be thought of as the z (height) value.
 - Color images are 5D surfaces hard to think about.
 - Color can also be thought of as 3 3D surfaces
 - Pretend the surface is continuous
- Every point on the image surface has a direction of maximum change (remember your multivariate calculus?), and a magnitude of change in that direction



Surface in 1D



1D cross-section of simple image surface



Image from http://ars.els-cdn.com/content/image/1s2.0-S1077314204001675-gr1.jpg



Image Edges

 To find direction and magnitude of change, compute the mag. in any 2 orthogonal directions and interpolate

– Again, this assumes a continuous surface

• WLOG choose the X & Y directions:

$$- dx(x,y) = I(x,y) - I(x-1,y) - dy(x,y) = I(x,y) - I(x,y-1)$$

• The edge magnitude and orientation is:

$$|\Delta| = \sqrt{dx^2 + dy^2}$$
 $\theta = \cos^{-1}\left(\frac{dy}{|\Delta|}\right)$



Estimating Edge Orientation

- Problem: images are not continuous surfaces
 - estimates of dx, dy based on grid sampling
 - note that if accurate,

$$I(x, y) - I(x+1, y) = I(x-1, y) - I(x, y)$$

 – estimating derivatives from two values is highly error prone.



Accurate Edge Estimation

- We want to compute a real-valued function

 The partial derivatives dx & dy
- All we have to work with are samples at equidistant points
- So model the function in terms of its Taylor series expansion:

$$f(x+h) = f(x) + \frac{h^1}{1!}f'(x) + \frac{h^2}{2!}f''(x) + \cdots$$



Accurate (II)

Look at equations for f(x+h) and f(x-h):

$$f(x+h) = f(x) + hf'(x) + \frac{h^2}{2}f''(x) + \cdots$$
(1)
$$f(x-h) = f(x) - hf'(x) + \frac{h^2}{2}f''(x) - \cdots$$
(2)

subtract equation 2 from 1

$$f(x+h) - f(x-h) = 2hf'(x) + \cdots$$

and solve for f'

$$f'(x) = \frac{f(x+h) - f(x-h)}{2h} + \cdots$$



Accurate (III)

So the best ±1 mask is [-1,0,1], from

$$\frac{d}{dx}f(x,y) = \frac{f(x+1,y) - f(x-1,y)}{2}$$

 As an exercise, the best ±2 mask is [1,-8,0,8,-1]

$$\frac{d}{dx}f(x,y) = \frac{-f(x+2,y)+8f(x+1,y)-8f(x-1,y)+f(x-2,y)}{12}$$



Stable Edges (III)

- Of course, pixels are still noisy and pixels are related to adjacent rows.
- The Sobel Edge Masks





Sobel Explanation

- In any row (dx) or column (dy), this is a [-1,0,1] mask to estimate the derivative
- [1,2,1] weights approximate a σ=1 Gaussian.
 Over-constrained fit of a plane to 9 points
 Minimizes the sum of equared error.
 - Minimizes the sum-of-squared error
- Multiply result by $\frac{1}{4}$ to keep results < 255
- Multiply results by 1/8 to generate 8-bit response





Rotation-Free Cross Correlation

- Make sure template is centered on an edge

 Measure it's orientation
- For every pixel location:
 - compute edge orientation at pixel
 - rotate template until pixel edge matches the orientation of the template edge
 - rotate using bilinear interpolation
 - correlate template with image
- Makes correlation insensitive to rotation
 - If edge direction estimates are accurate
 - We will find ways to make them more accurate...

