#### Focus of Attention

CS 510 Lecture #15 April 8<sup>th</sup>, 2013



#### What is attention?

- "The selective aspect of processing" Kosslyn<sup>1</sup>
- "processes that enable an observer to recruit resources for processing selected aspects of the retinal image more fully than nonselected aspects" – Palmer<sup>2</sup>



## **Overt vs. Covert Attention**

- Overt attention: observable movements of eyes, head & body to orient eyes
  - Foveas: 90% of receptors, ±2°
  - Allocation to 3D point in space
    - Vergence & focus
  - Average dwell time: ~300ms<sup>4</sup>
  - Saccadic movement
    - Very fast: ~30ms, up to 900°/sec
    - Suppression: no input during saccade
  - World appears as sequence of displaced, small, high resolution, stereo images with low resolution peripheries



## Overt vs. Covert Attention (II)

- You don't process all the data in your foveal image
- Covert attention: selection of retinal data to process ("inner eye")
  - Cannot be observed directly
  - Its existence is not in dispute
  - Its form is a matter of intense debate
  - Assumption: insufficient resources necessitate covert attention.
- Covert attention is the subject of this lecture

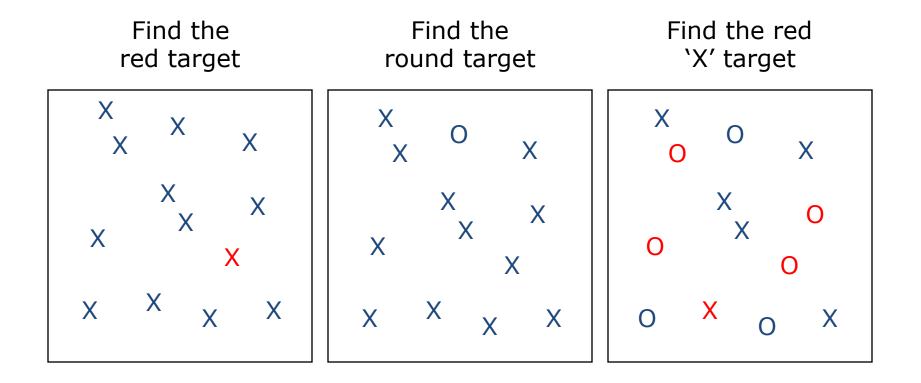


## **3 Models of Covert Attention**

- 1. Feature Integration Theory
  - "Pre-attentive" low-level features computed in parallel across the image
    - E.g. color, edge orientations, motion
  - In visual search, attention can jump to locations based on pre-attentive features ("pop-out")
  - Conjunctions of features or complex features require sequential search
  - O Implicitly assumes attention is like a spotlight



## Feature Integration Theory (II)



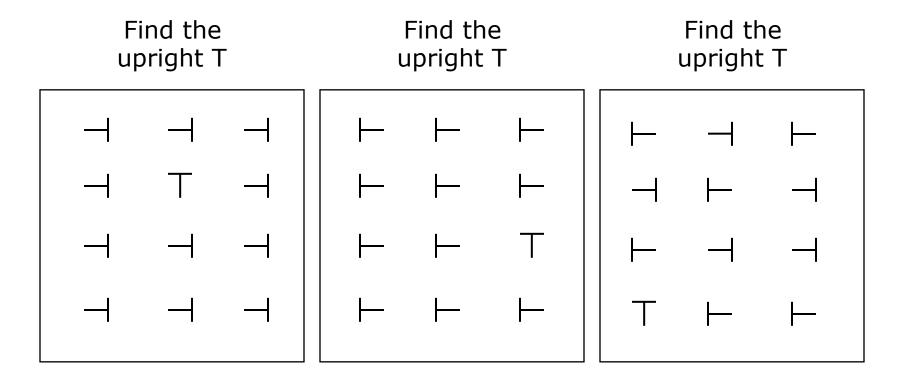


# 3 Models (II)

- 2. Integrated Competition Hypothesis
  - O "Pop-out" effect depends on:
    - Homogeneity of distractors
    - Homogeneity of targets (seq. pres.)
  - O Primary role of attention is segmentation (or grouping)
  - O Low-level features important as the basis of segmentation



#### Integrated Competition Hypothesis (II)





## Task: Which Line is Longer?



# 3 Models (III)

- Inattentional Blindness Theory
  - When concentrating on the task, most subjects will not see additional objects
    - Depends on semantics of additional object
  - Additional objects are interpreted
    - Cause priming effects
  - Hypothesis: all objects in visual field are interpreted
    - Attention is a late effect, caused by attentional bottleneck



#### How does this effect computer vision?

- Scale space theory
  - Image pyramids
- Difference of Gaussians (DoGs)
  - Impulse detection
  - Determines location & scale
- Refinements
  - Corners
  - Entropy



#### Resolution

#### • Definition:

The *resolution* of an image is the inverse of the spatial area covered by each pixel. This depends on:

- 1. The image size of the camera
- 2. The field of view of the lens
- 3. The distance to the target

Note that doubling the distance to the target halves the image resolution.



#### Scale space

- The appearance of an object is a function of the image resolution:
  - A checkerboard becomes a uniform gray surface as the resolution decreases.
  - A thin black bar goes from being a bar (with parallel lines) to a single line to nothing.
- The goal of scale space theory is to simulate what happens to the appearance of an object as resolution decreases.



## Base Case: Raw Image

- We model pixels in raw images a point-wise intensity estimates, covering no area.
  - Not quite right: pixels sample over a small area
  - Areas don't overlap
    - Except for blooming
  - Gaps between areas
- Highly sensitive to microtranlsations
- Same model our ray tracers used...

•	•	•	•	•
•	•	•	•	•
•	•	•	•	•
•	•	•	•	•
•	•	•	•	•



#### **Scale Space**

- We want pixels to average information over an area, to improve stability and reduce aliasing
- We being by convolving the image with a Gaussian with  $\sigma$  = 1
  - Now most of the information comes from an area one pixel in size
- $\sigma$  = 1 is the "base" resolution



## Varying Resolution

- To cut the resolution in half, we convolve the original image with  $G(\sigma=2)$ .
- To cut the resolution by a quarter, use  $\sigma$  = 4, etc.
- Problem: this is very expensive
  - To cover a lot of scales, the image gets convolved a lot of times
  - The convolution masks keep getting bigger!



#### Image pyramids

- Fortunately, the lower the resolution, the fewer pixels you need.
- $I \otimes G(\sigma=a) = (I \otimes G(\sigma=b)) \otimes G(\sigma=c)$ , iff  $a^2=b^2+c^2$
- Therefore, start with an image with  $\sigma$ =1.
  - Convolve it with G( $\sigma = \sqrt{3}$ )
  - This produces an image with  $\sigma$ =2
  - Now subsample every other pixel
    - Since you have halved the resolution
  - Repeat



# Image Pyramids (II)

- The result is an image pyramid
  - Every image ½ the width and height of its parent
  - Every image has  $\sigma$  =1
    - after subsampling
- Total cost of pyramid construction:
  - 1 convolution & downsample
  - + 1/4(convolution & downsample)
  - + 1/16(convolution &...)
- Total cost < 1.5\*(convolution & downsample)</li>
- Note: it is possible to have intermediate images within scales
  - But only downsample when  $\sigma\text{=}2$





Colorado



#### Focus of Attention

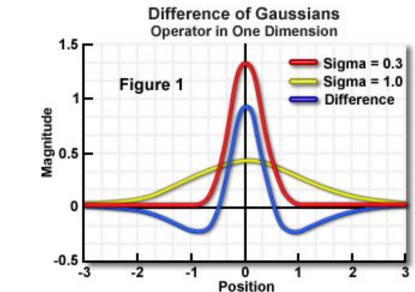
- The goal of focus of attention is to:
  - 1. Pick locations & scales in an image
  - 2. That convey information about the scene
  - 3. Would be identified again if the object occurs in another image
    - i.e. repeatable

Method: find impulses in f(x, y,  $\sigma$ )



#### Image source: <a href="http://micro.magnet.fsu.edu/">http://micro.magnet.fsu.edu/</a> primer/java/digitalimaging/processing/diffgaussians/diffgaussiansfigure1.jpg Difference of Gaussians (DoG)

 A Difference-Of-Gaussians (DoG) function is an impulse filter, constructed by subtracting two Gaussians with different



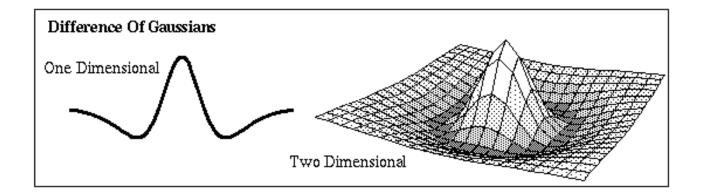
 $\sigma$ 'S.



Image source: <a href="http://www.liden.cc/">http://www.liden.cc/</a>Visionary/Images/DIFFERENCE\_OF\_GAUSSIANS.GIF

## DoG (II)

- DoGs are also called the "Mexican Hat" filter when 2D
- Strong positive response: on-center, off-surround
- Strong negative response: off-center, on-surround



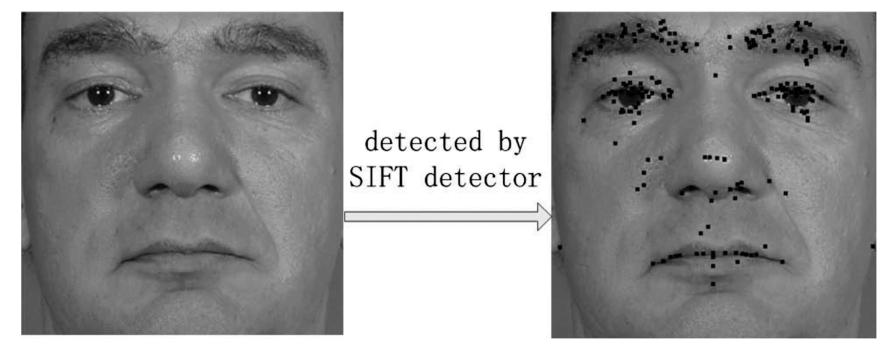


## Focus of Attention

- Basic focus-of-attention strategy
  - Build an image pyramid
  - Subtract one layer from another
    - This creates images of DoG responses
    - $I \otimes (M-N) = (I \otimes M) (I \otimes N)$
  - Find extrema in x, y, and  $\sigma$  of the DoG responses
    - Both positive and negative
- The image windows around the DoG extrema are fixedsize "focus of attention" windows.



#### SIFT (DoG) Interest Points Example



http://opticalengineering.spiedigitallibrary.org/article.aspx?articleid=1089401





This image shows:

- Scale (circle size)
- Dominant Orientation

   1<sup>st</sup> eigenvector of Harris operator

http://

4/10/13

computervisionblog.wordpress.com/tag/ sift-feature-point/

CS 510, Image

Beveridge & Bruce Draper

