Computer Vision

CSE 455
Interest Regions, Recognition, and Matching

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The Kadir Operator Saliency, Scale and Image Description

Timor Kadir and Michael Brady
University of Oxford

The issues…

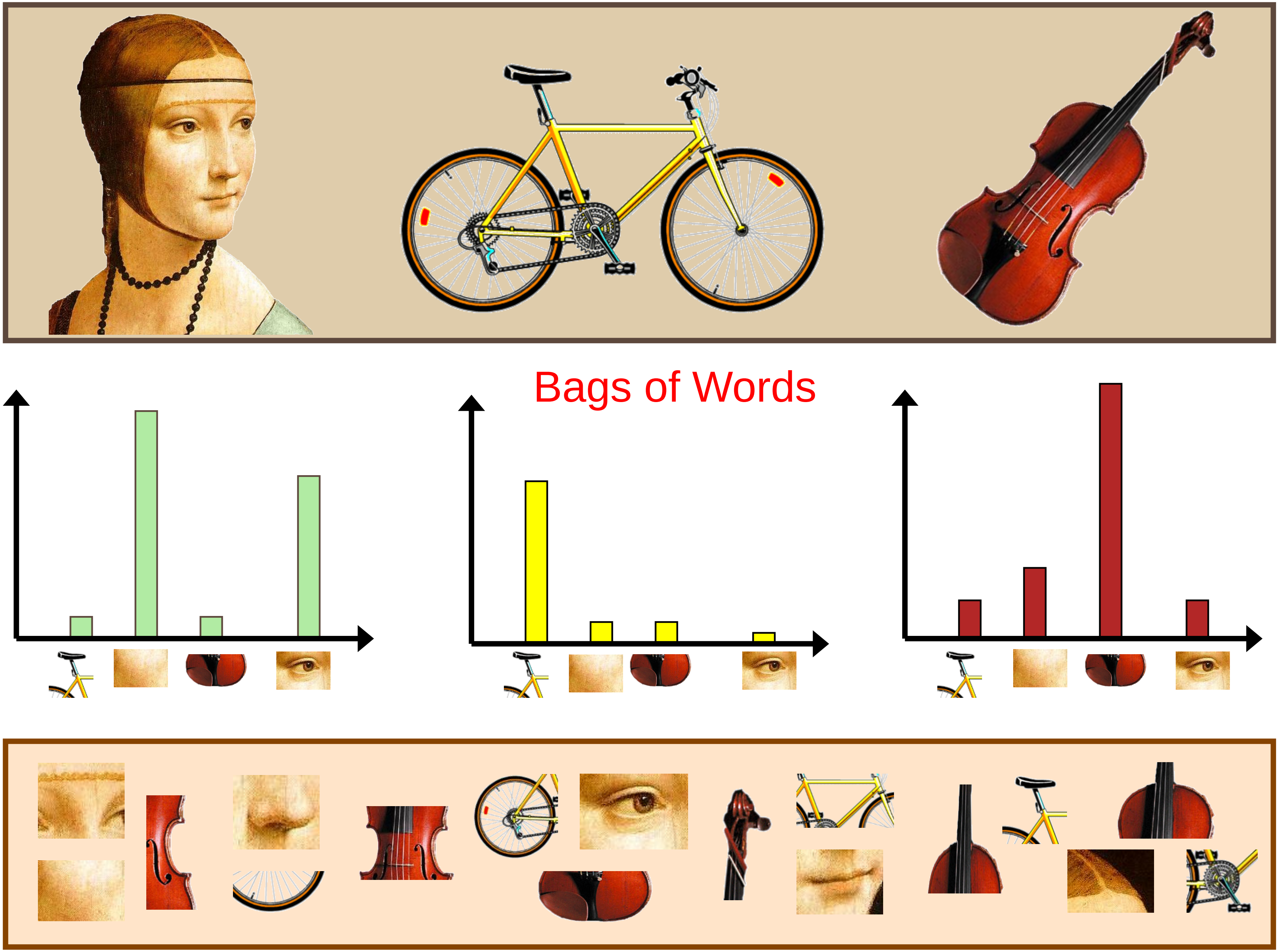
- salient – standing out from the rest, noticeable, conspicous, prominent

- scale – find the best scale for a feature

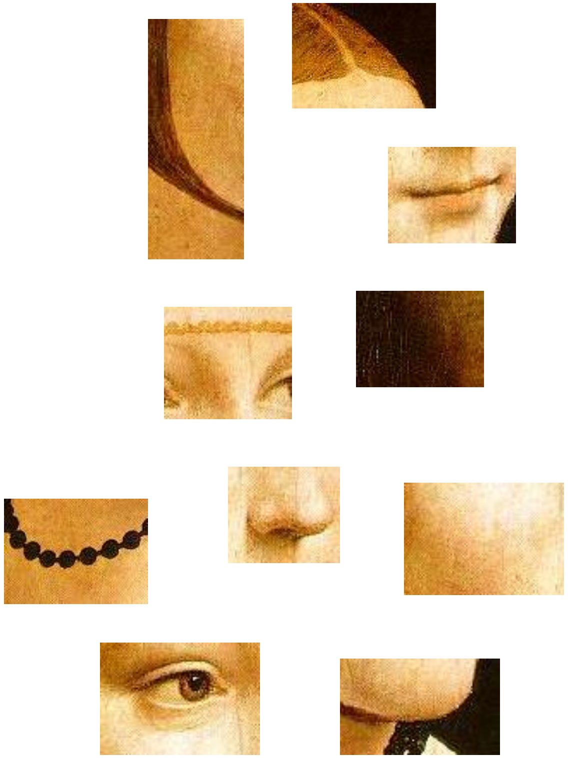
- image description – create a descriptor for use in object recognition

Early Vision Motivation

- pre-attentive stage: features pop out
- attentive stage: relationships between features and grouping


Bags of Words

Detection of Salient Features for an Object Class



How do we do this?

1. fixed size windows
   (simple approach)

2. Harris detector,
   Lowe detector, etc.

3. Kadir’s approach

Kadir's Approach

- Scale is intimately related to the problem of determining saliency and extracting relevant descriptions.

- Saliency is related to the local image complexity, ie. Shannon entropy.

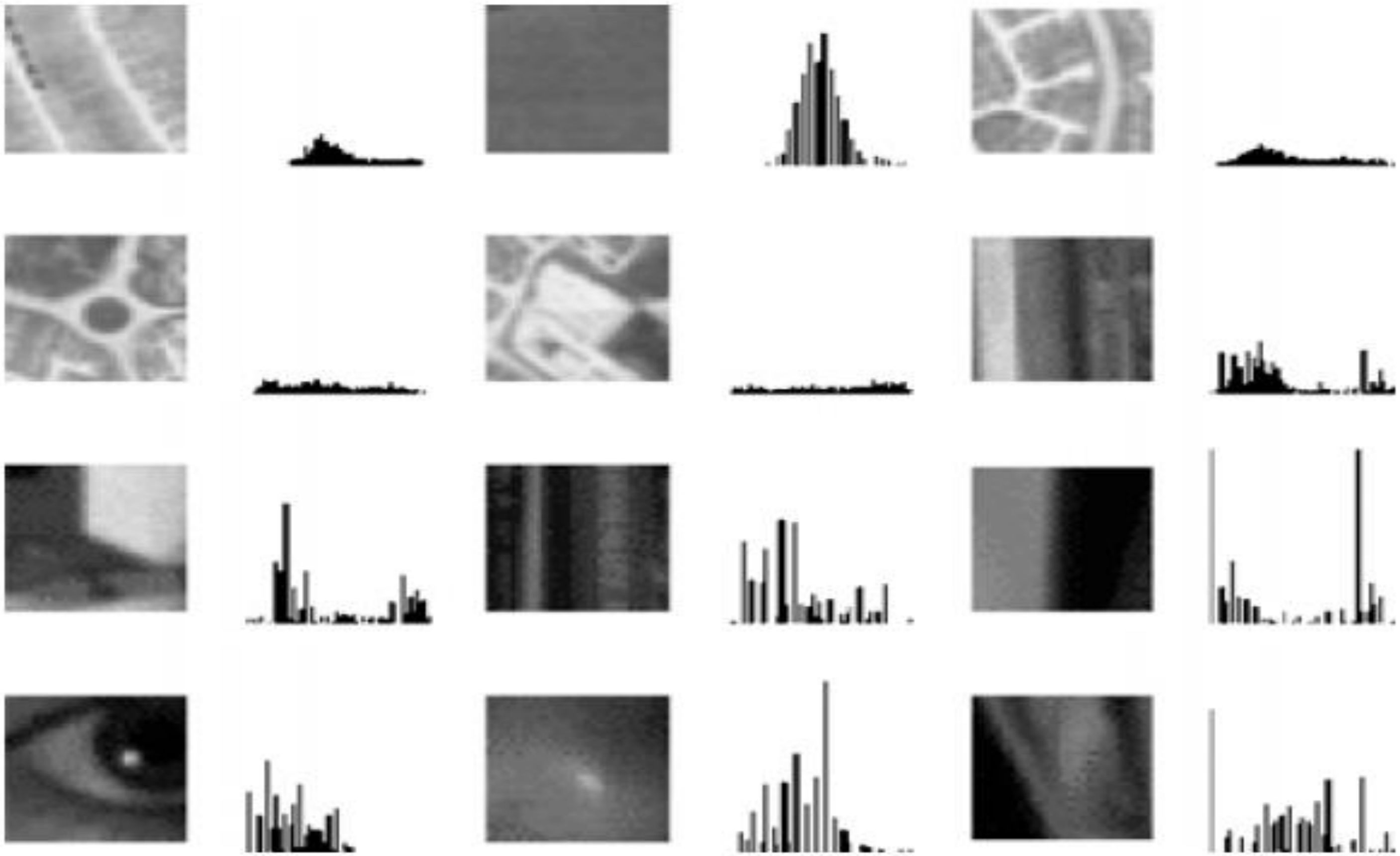
- entropy definition $H = -\sum_{i \text{ in set of interest}} P_i \log_2 P_i$

Specifically

- x is a point on the image
- R_x is its local neighborhood
- D is a descriptor and has values $\{d_1, \ldots d_r\}$.
- $P_{D,Rx}(d_i)$ is the probability of descriptor D taking the value d_i in the local region R_x. (The normalized histogram of the gray tones in a region estimates this probability distribution.)

$$H_{D,R_X} = -\sum_i P_{D,R_X}(d_i) \log_2 P_{D,R_X}(d_i)$$

Local Histograms of Intensity



Neighborhoods with structure have flatter distributions which converts to higher entropy.

Problems Kadir wanted to solve

1. Scale should not be a global, preselected parameter

2. Highly textured regions can score high on entropy, but not be useful

3. The algorithm should not be sensitive to small changes in the image or noise.

Kadir's Methodology

- use a scale-space approach

- features will exist over multiple scales
  - Berghoml (1986) regarded features (edges) that existed over multiple scales as best.

- Kadir took the opposite approach.
  - He considers these too self-similar.
  - Instead he looks for peaks in (weighted) entropy over the scales.

The Algorithm

1. For each pixel location x
    a. For each scale s between smin and smax

        i. Measure the local descriptor values within a window of scale s
        ii. Estimate the local PDF (use a histogram)

    b. Select scales (set S) for which the entropy is peaked (S may be empty)
    c. Weight the entropy values in S by the sum of absolute difference of the PDFs of the local descriptor around S.

Finding salient points

- the math for saliency discretized

$$Y_D(\mathbf{s},\mathbf{x}) = H_D(\mathbf{s},\mathbf{x})W_D(\mathbf{s},\mathbf{x})$$

$$H_D(\mathbf{s},\mathbf{x}) = -\sum_{d\in D} p_{\mathbf{s},\mathbf{x}}(d)\log_2 p_{\mathbf{s},\mathbf{x}}(d)$$

$$W_D(\mathbf{s},\mathbf{x}) = \frac{s^2}{2s-1}\sum_{d\in D}\left|p_{\mathbf{s},\mathbf{x}}(d) - p_{\mathbf{s}-1,\mathbf{x}}(d)\right|$$

$\mathbf{x}$ = point

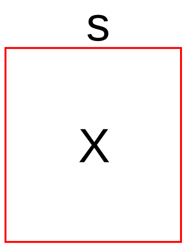
$\mathbf{s} = (\mathrm{s}, \mathrm{r}, \theta) = ($scale, [redacted] $)$

D = low-level feature domain (gray tones)

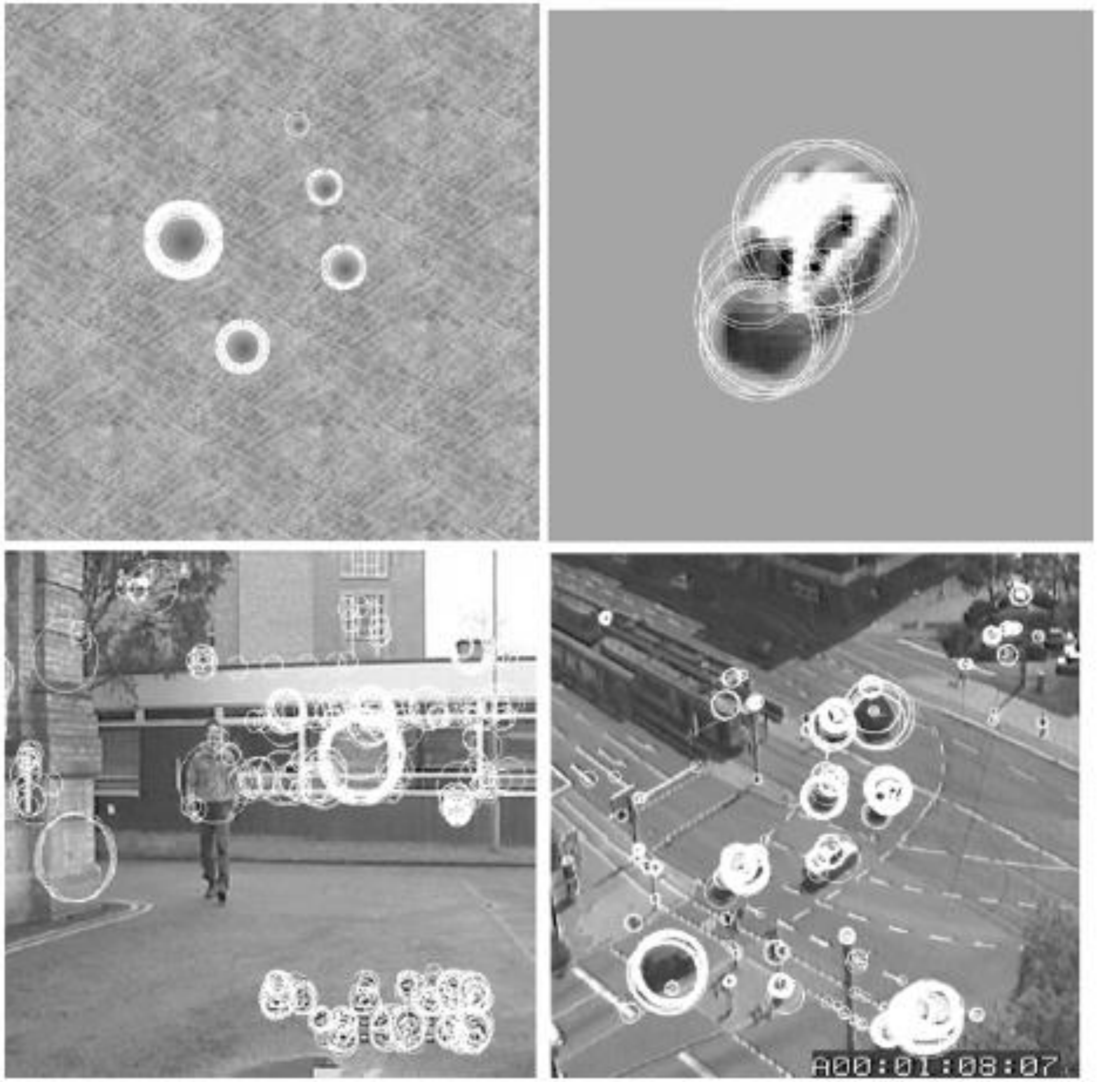
$p_{\mathbf{s},\mathbf{x}}(d)$ = probability of descriptor D taking value d in the region centered at $\mathbf{x}$ with scale $\mathbf{s}$

= normalized histogram count for the bin representing gray tone d.

- saliency
- entropy
- weight based on difference between scales



Picking salient points and their scales



Getting rid of texture

- One goal was to not select highly textured regions such as grass or bushes, which are not the type of objects the Oxford group wanted to recognize

- Such regions are highly salient with just entropy, because they contain a lot of gray tones in roughly equal proportions

- But they are similar at different scales and thus the weights make them go away

Salient Regions

- Instead of just selecting the most salient points (based on weighted entropy), select salient regions (more robust).
- Regions are like volumes in scale space.
- Kadir used clustering to group selected points into regions.
- We found the clustering was a critical step.

Kadir's clustering (VERY ad hoc)

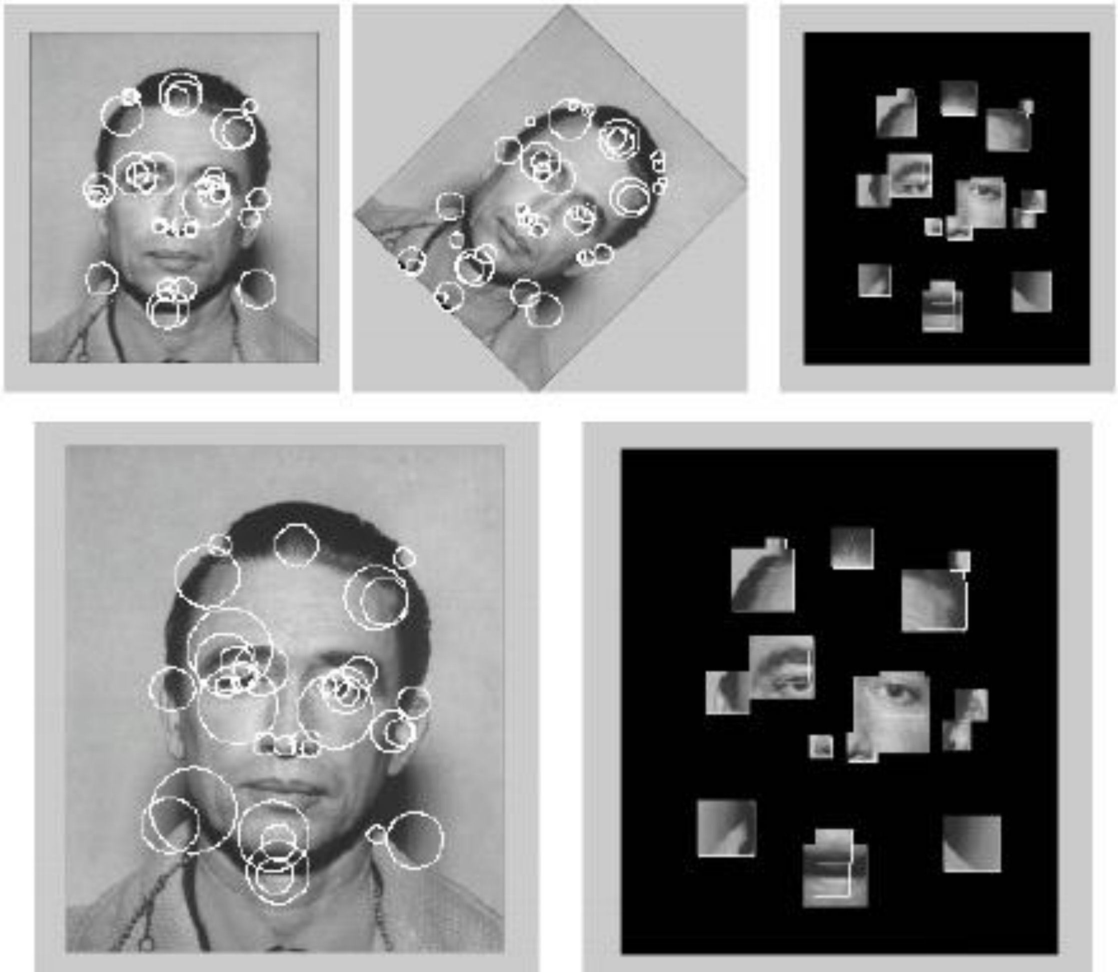
- Apply a global threshold on saliency.
- Choose the highest salient points (50% works well).
- Find the K nearest neighbors (K=8 preset)
- Check variance at center points with these neighbors.
- Accept if far enough away from existant clusters and variance small enough.
- Represent with mean scale and spatial location of the K points
- Repeat with next highest salient point

More examples

Robustness Claims

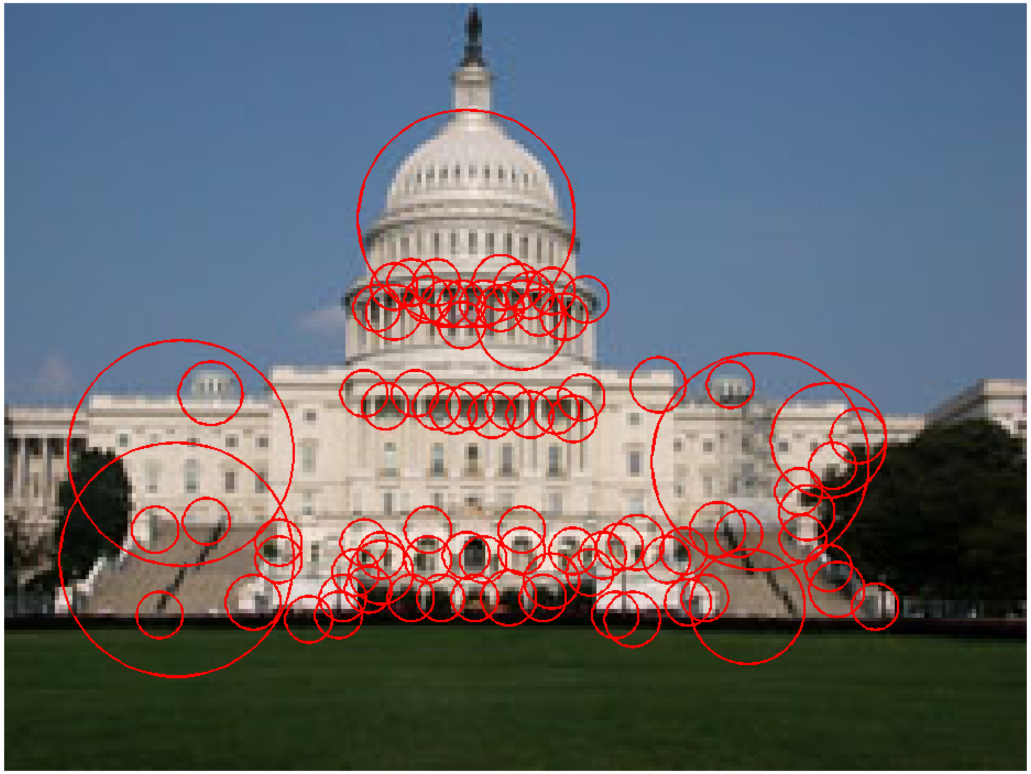
- scale invariant (chooses its scale)
- rotation invariant (uses circular regions and histograms)
- somewhat illumination invariant (why?)
- not affine invariant (able to handle small changes in viewpoint)

More Examples



Temple

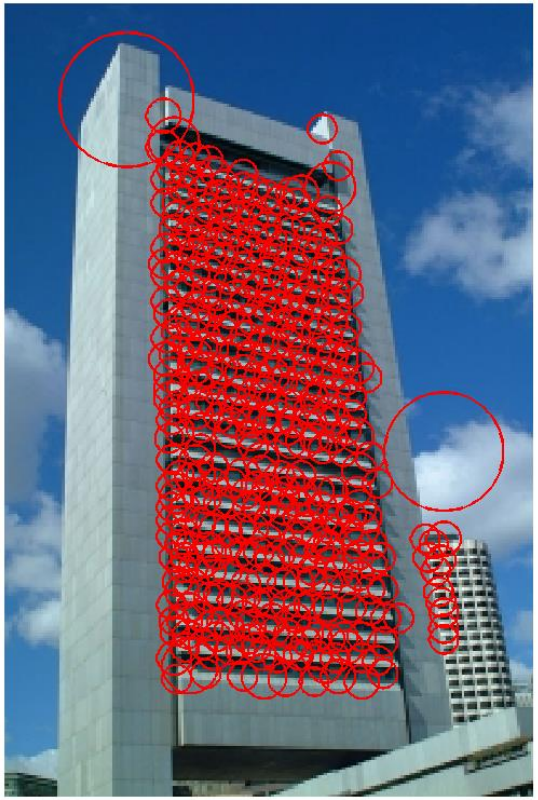
Capitol



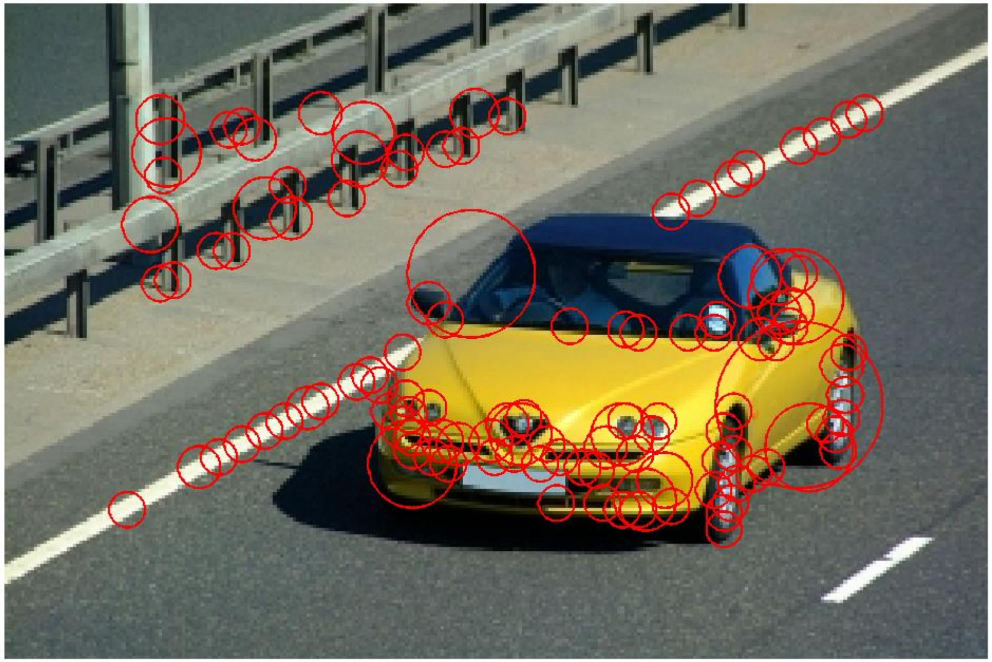
Houses and Boats

Houses and Boats

Sky Scraper

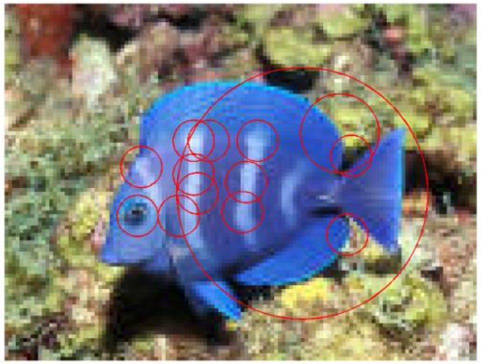


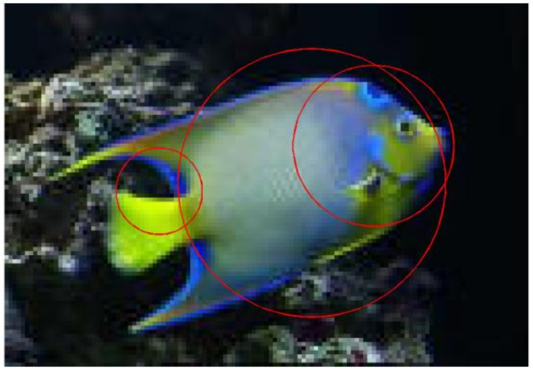
Car



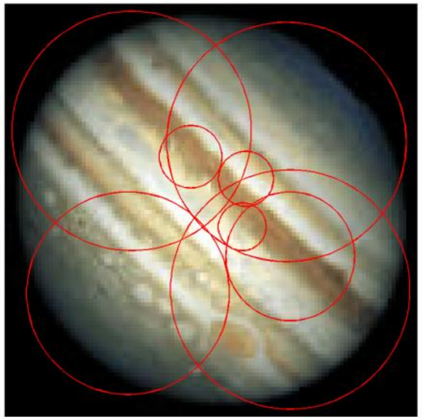
Trucks

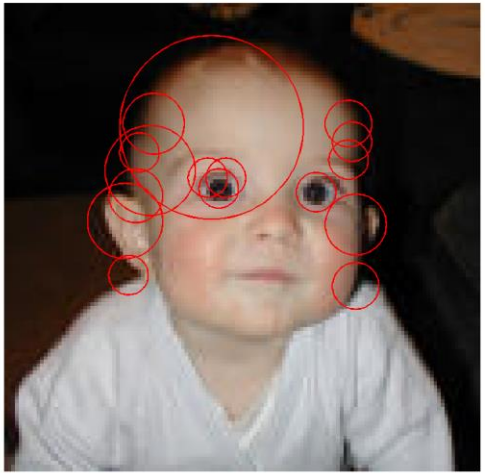
Fish



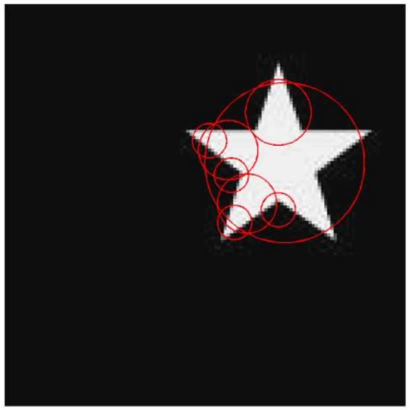


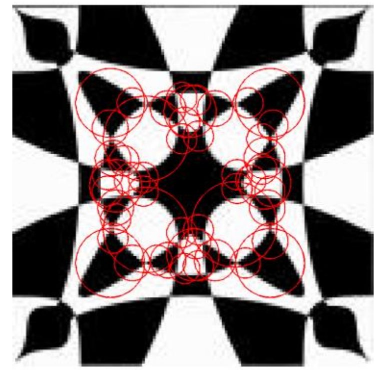
Other





Symmetry and More





Benefits

- General feature: not tied to any specific object
- Can be used to detect rather complex objects that are not all one color
- Location invariant, rotation invariant
- Selects relevant scale, so scale invariant
- What else is good?
- Anything bad?

Object Recognition with Interest Operators

- Object recognition started with line segments.

  - Roberts recognized objects from line segments and junctions.

  - This led to systems that extracted linear features.

  - CAD-model-based vision works well for industrial.

- An “appearance-based approach” was first developed for face recognition and later generalized up to a point.

- The interest operators have led to a new kind of recognition by “parts” that can handle a variety of objects that were previously difficult or impossible.

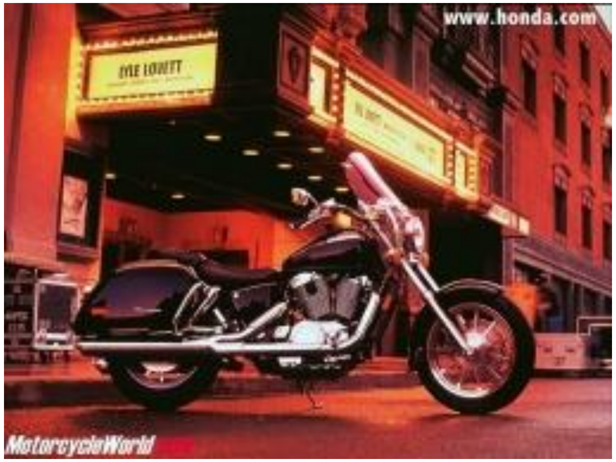
Object Class Recognition by Unsupervised Scale-Invariant Learning

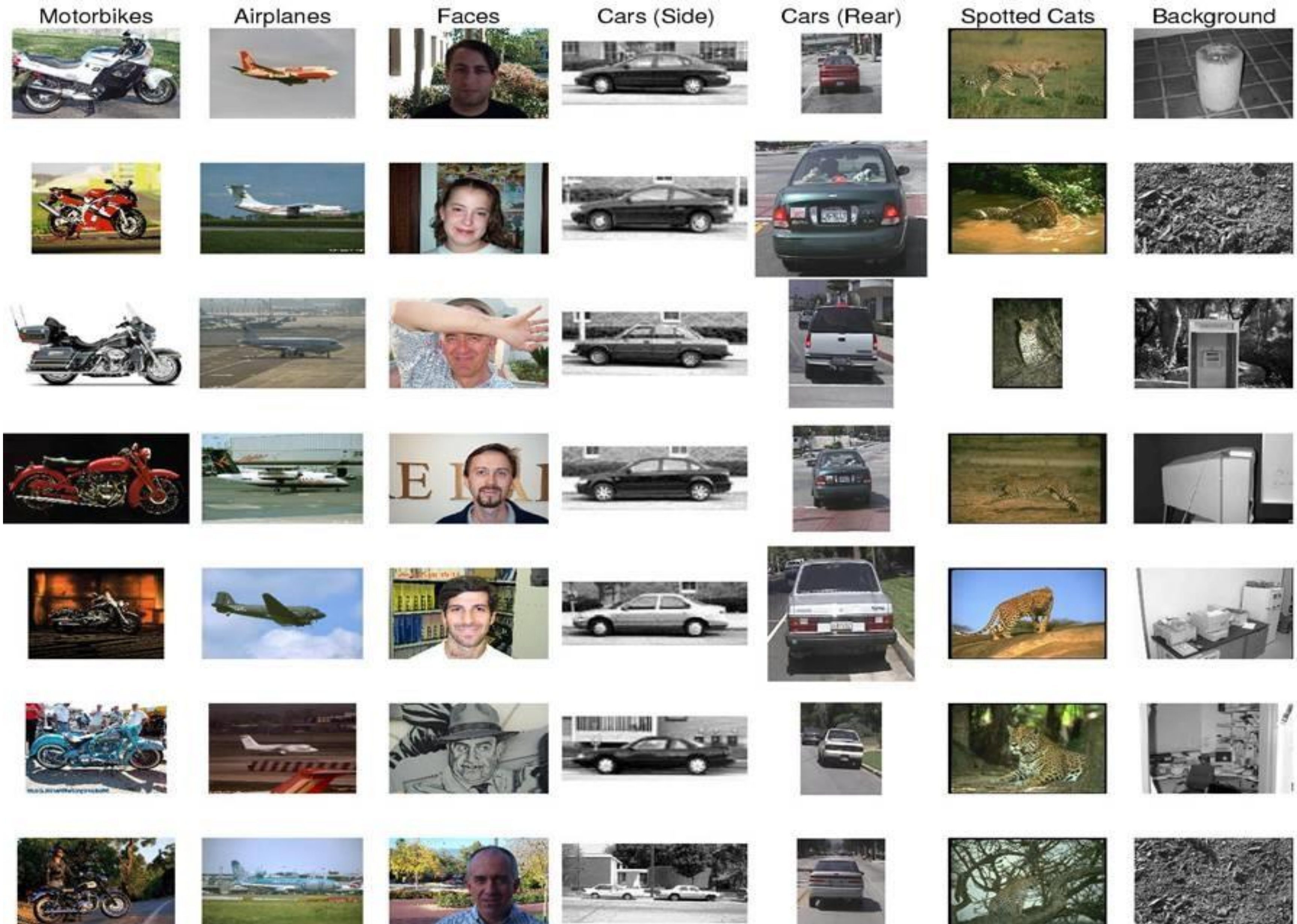
R. Fergus, P. Perona, and A. Zisserman
Oxford University and Caltech

CVPR 2003
won the best student paper award
CVPR 2013
won the best 10-year award

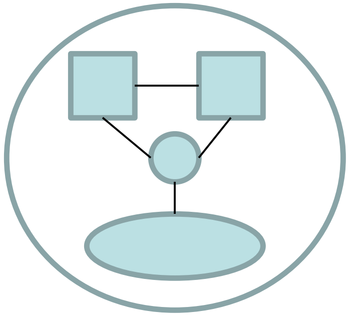
Goal:

- Enable Computers to Recognize Different Categories of Objects in Images.




Motorbikes
Airplanes
Faces
Cars (Side)
Cars (Rear)
Spotted Cats
Background

Approach

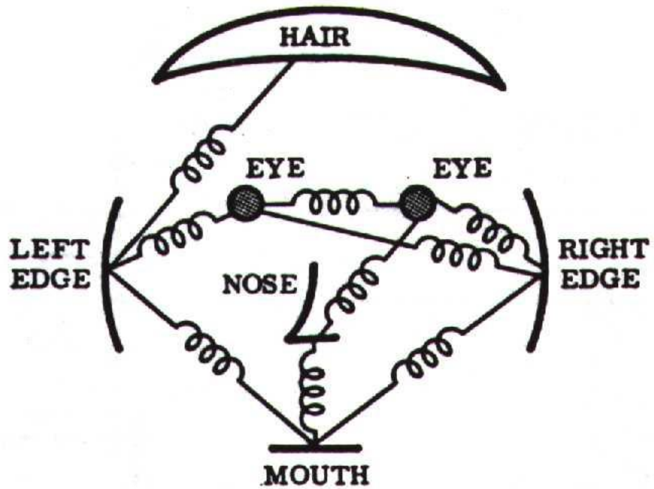


- An object is a constellation of parts (from Burl, Weber and Perona, 1998).
- The parts are detected by an interest operator (Kadir's).
- The parts can be recognized by appearance.
- Objects may vary greatly in scale.
- The constellation of parts for a given object is learned from training images

Components

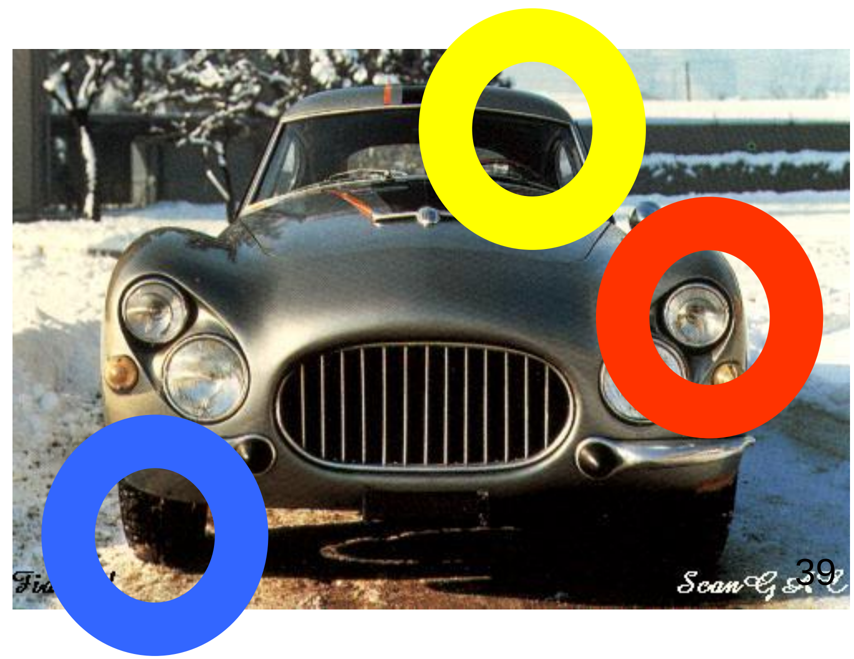
- Model
  - Generative Probabilistic Model including Location, Scale, and Appearance of Parts
- Learning
  - Estimate Parameters Via EM Algorithm
- Recognition
  - Evaluate Image Using Model and Threshold

Model: Constellation Of Parts



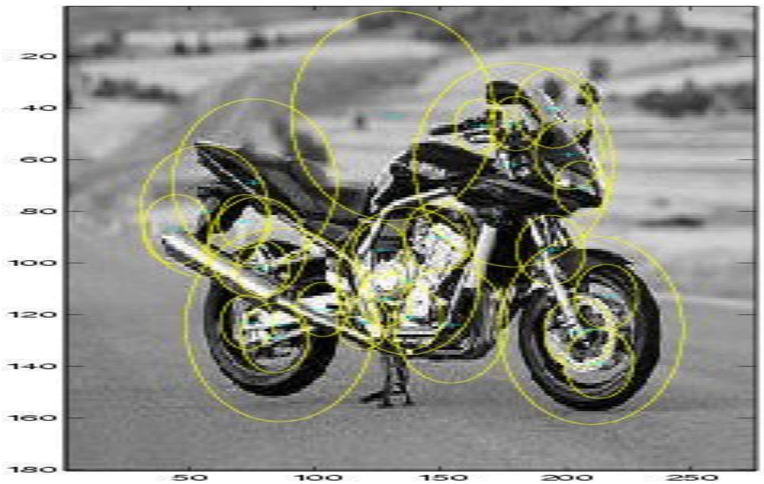
Fischler & Elschlager, 1973

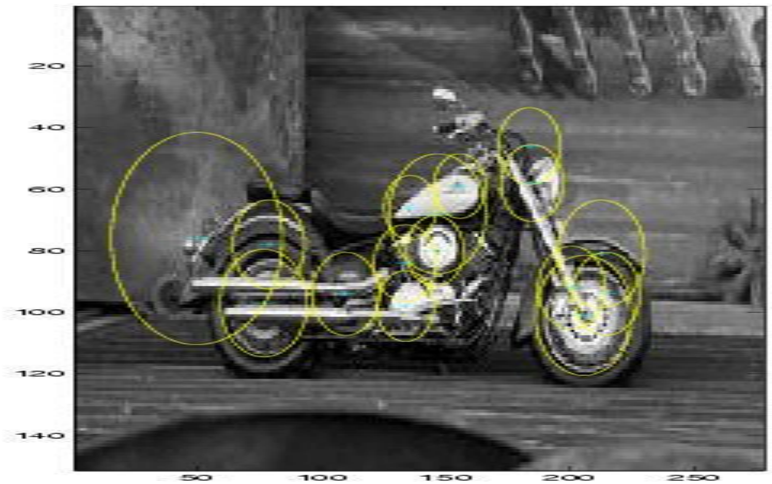
Yuille, 91
Brunelli & Poggio, 93
Lades, v.d. Malsburg et al. 93
Cootes, Lanitis, Taylor et al. 95
Amit & Geman, 95, 99
Perona et al. 95, 96, 98, 00

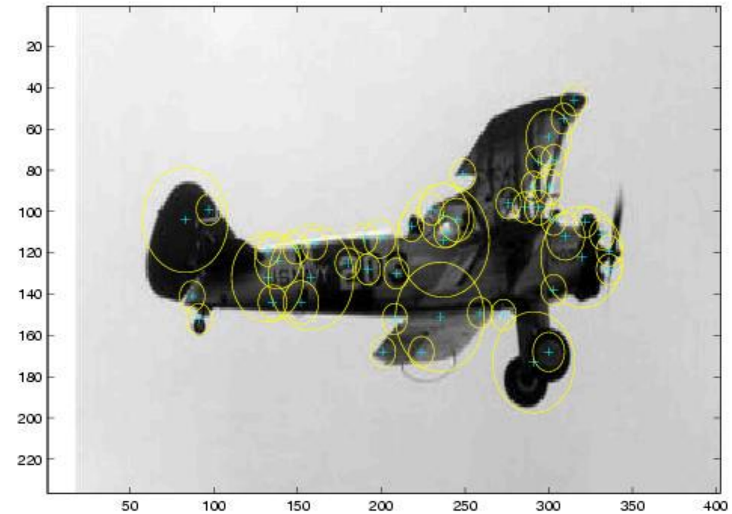


Parts Selected by Interest Operator

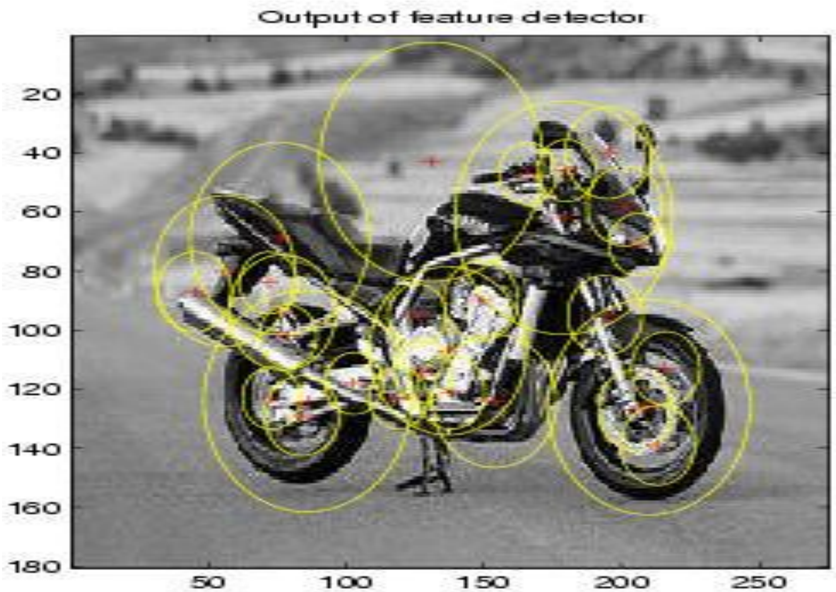
Kadir and Brady's Interest Operator.
Finds Maxima in Entropy Over Scale and Location

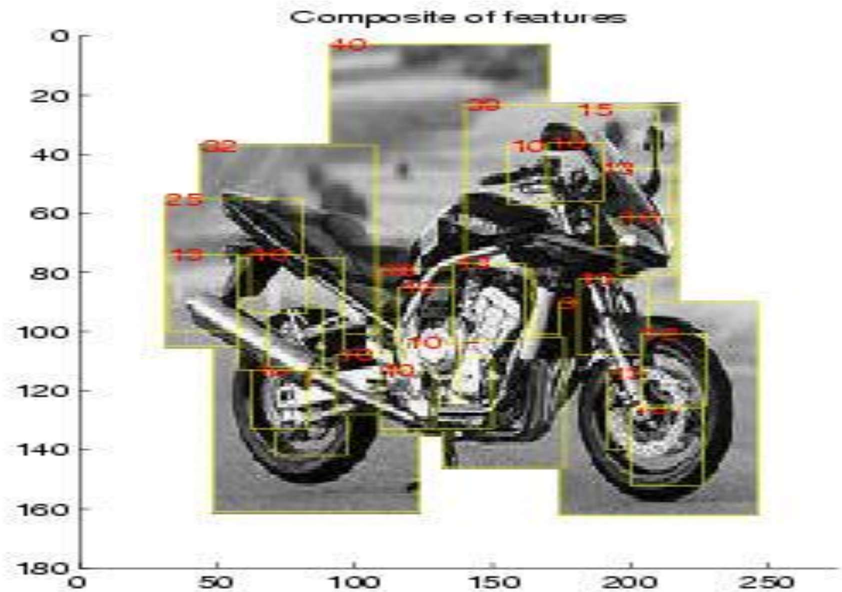


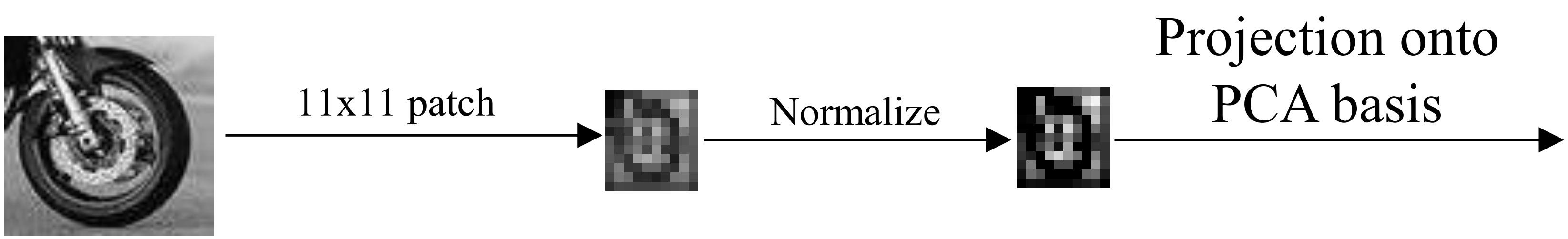




Representation of Appearance







$$\begin{pmatrix} \mathbf{c}_1 \\ \mathbf{c}_2 \\ \vdots \\ \mathbf{c}_{15} \end{pmatrix}$$

121 dimensions was too big, so they used PCA to reduce to 10-15.

Learning a Model

- An object class is represented by a generative model with P parts and a set of parameters θ.

- Once the model has been learned, a decision procedure must determine if a new image contains an instance of the object class or not.

- Suppose the new image has N interesting features with locations X, scales S and appearances A.

Probabilistic Model

$$p(\mathbf{X}, \mathbf{S}, \mathbf{A} | \theta) = \sum_{\mathbf{h} \in H} p(\mathbf{X}, \mathbf{S}, \mathbf{A}, \mathbf{h} | \theta) =$$

$$\sum_{\mathbf{h} \in H} \underbrace{p(\mathbf{A} | \mathbf{X}, \mathbf{S}, \mathbf{h}, \theta)}_{Appearance} \underbrace{p(\mathbf{X} | \mathbf{S}, \mathbf{h}, \theta)}_{Shape} \underbrace{p(\mathbf{S} | \mathbf{h}, \theta)}_{Rel.\ Scale} \underbrace{p(\mathbf{h} | \theta)}_{Other}$$

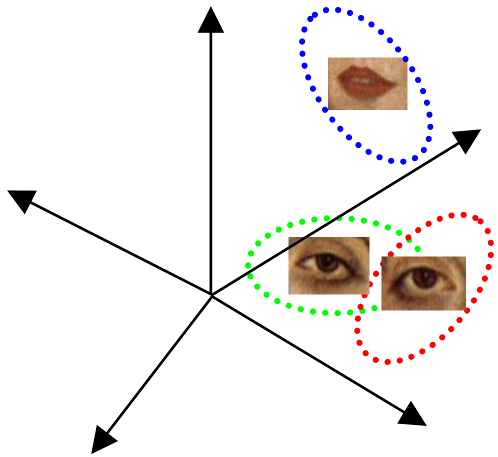
- X is a description of the shape of the object (in terms of locations of parts)
- S is a description of the scale of the object
- A is a description of the appearance of the object
- θ is the (maximum likelihood value of) the parameters of the object
- h is a hypothesis: a set of parts in the image that might be the parts of the object
- H is the set of all possible hypotheses for that object in that image.
- For N features in the image and P parts in the object, its size is $O(N^P)$

Appearance

The appearance (A) of each part p has a Gaussian density with mean c_p and covariance V_P.

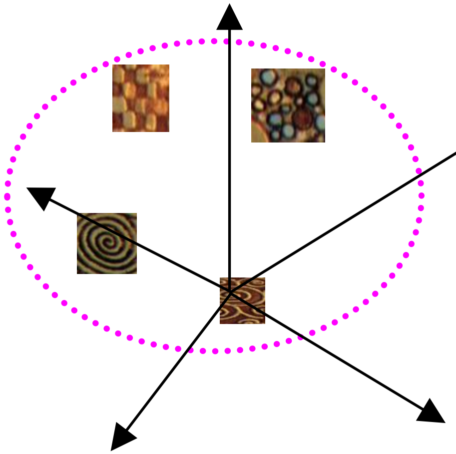
Background model has mean c_{bg} and covariance V_{bg}.

Gaussian Part Appearance PDF



Object

Gausian Appearance PDF

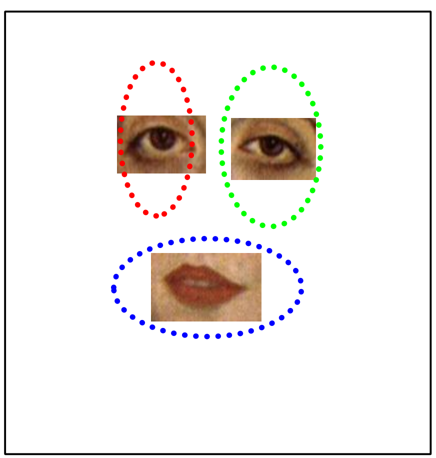


Background

Shape as Location

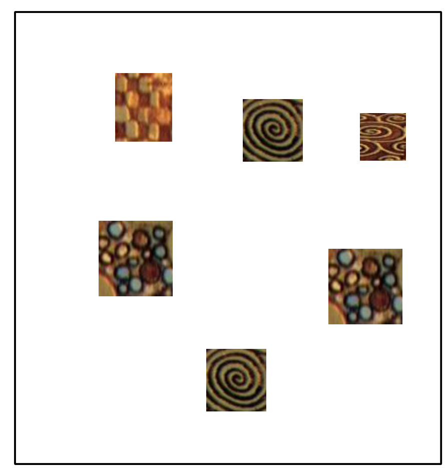
Object shape is represented by a joint Gaussian density of the locations (X) of features within a hypothesis transformed into a scale-invariant space.

Gaussian Shape PDF



Object

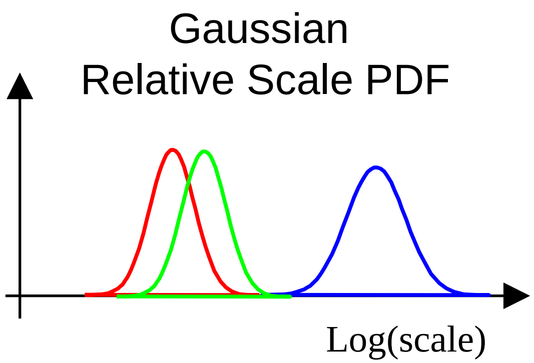
Uniform Shape PDF

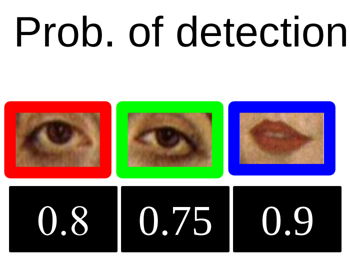


Background

Scale

The relative scale of each part is modeled by a Gaussian density with mean t_p and covariance U_p.





Occlusion and Part Statistics

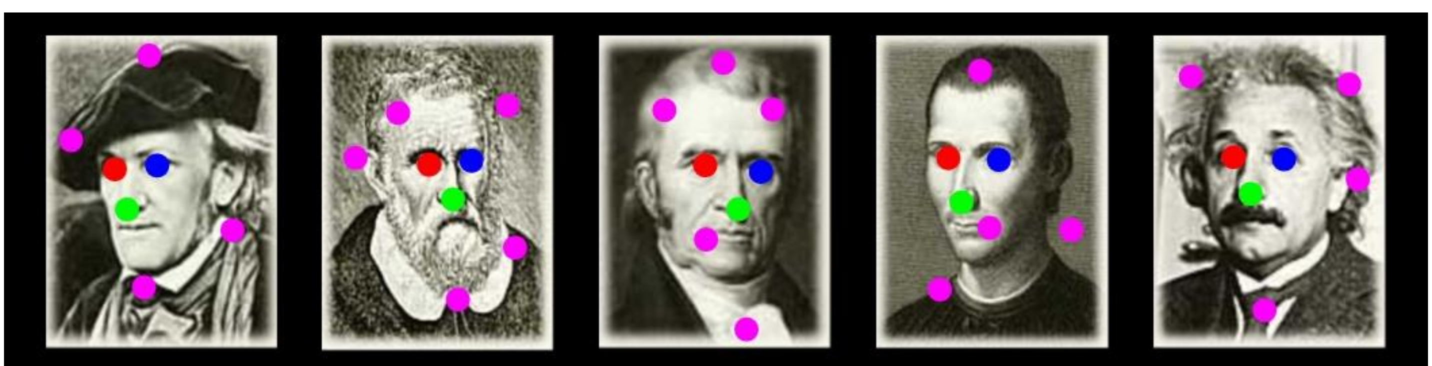
This was very complicated and turned out to not work well and not be necessary, in both Fergus’s work and other subsequent works.

Learning

- Train Model Parameters Using EM:
  - Optimize Parameters
  - Optimize Assignments
  - Repeat Until Convergence

$$\theta = \{\underbrace{\mu, \Sigma}_{\text{location}}, \underbrace{\mathbf{c}, V}_{\text{appearance}}, \underbrace{M, p(\mathbf{d}|\theta)}_{\text{occlusion}}, \underbrace{t, U}_{\text{scale}}\}$$

$$\hat{\theta}_{ML} = \underset{\theta}{arg\,max}\; p(\mathbf{X}, \mathbf{S}, \mathbf{A}|\,\theta)$$



Recognition

Make this likelihood ratio:

$$
\begin{aligned}
R &= \frac{p(\text{Object}|\mathbf{X},\mathbf{S},\mathbf{A})}{p(\text{No object}|\mathbf{X},\mathbf{S},\mathbf{A})} \\
&= \frac{p(\mathbf{X},\mathbf{S},\mathbf{A}|\text{Object})\; p(\text{Object})}{p(\mathbf{X},\mathbf{S},\mathbf{A}|\text{No object})\; p(\text{No object})} \\
&\approx \frac{p(\mathbf{X},\mathbf{S},\mathbf{A}|\,\theta)\; p(\text{Object})}{p(\mathbf{X},\mathbf{S},\mathbf{A}|\theta_{bg})\; p(\text{No object})}
\end{aligned}
$$

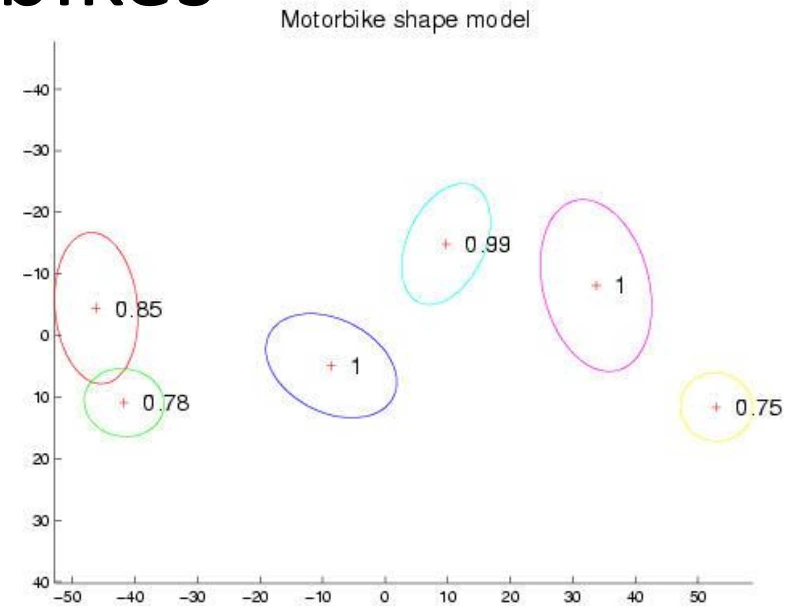
greater than a threshold.

RESULTS

- Initially tested on the Caltech-4 data set
  - motorbikes
  - faces
  - airplanes
  - cars
- Now there is a much bigger data set: the Caltech-101 http://www.vision.caltech.edu/archive.html

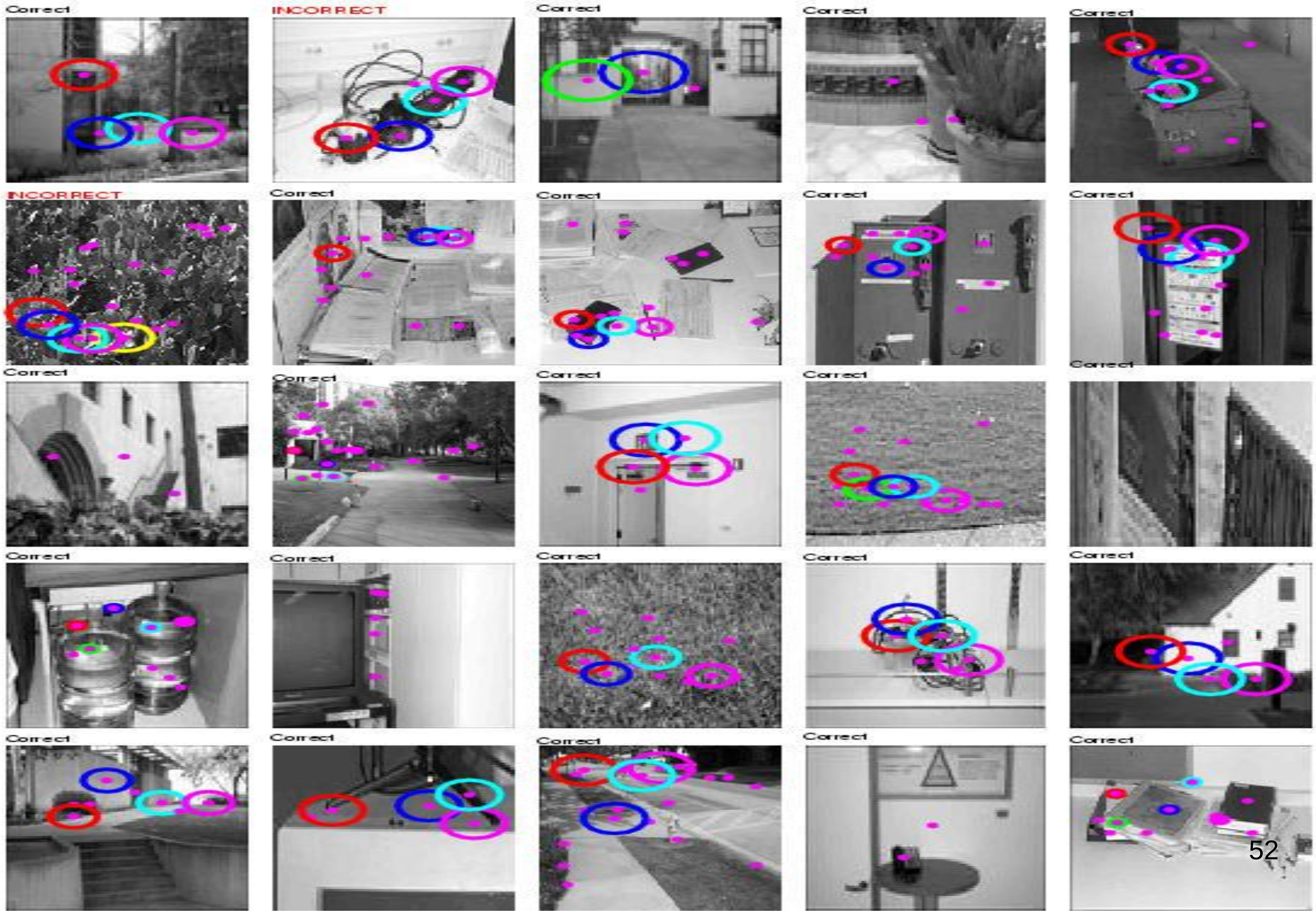
Motorbikes

Equal error rate: 7.5%



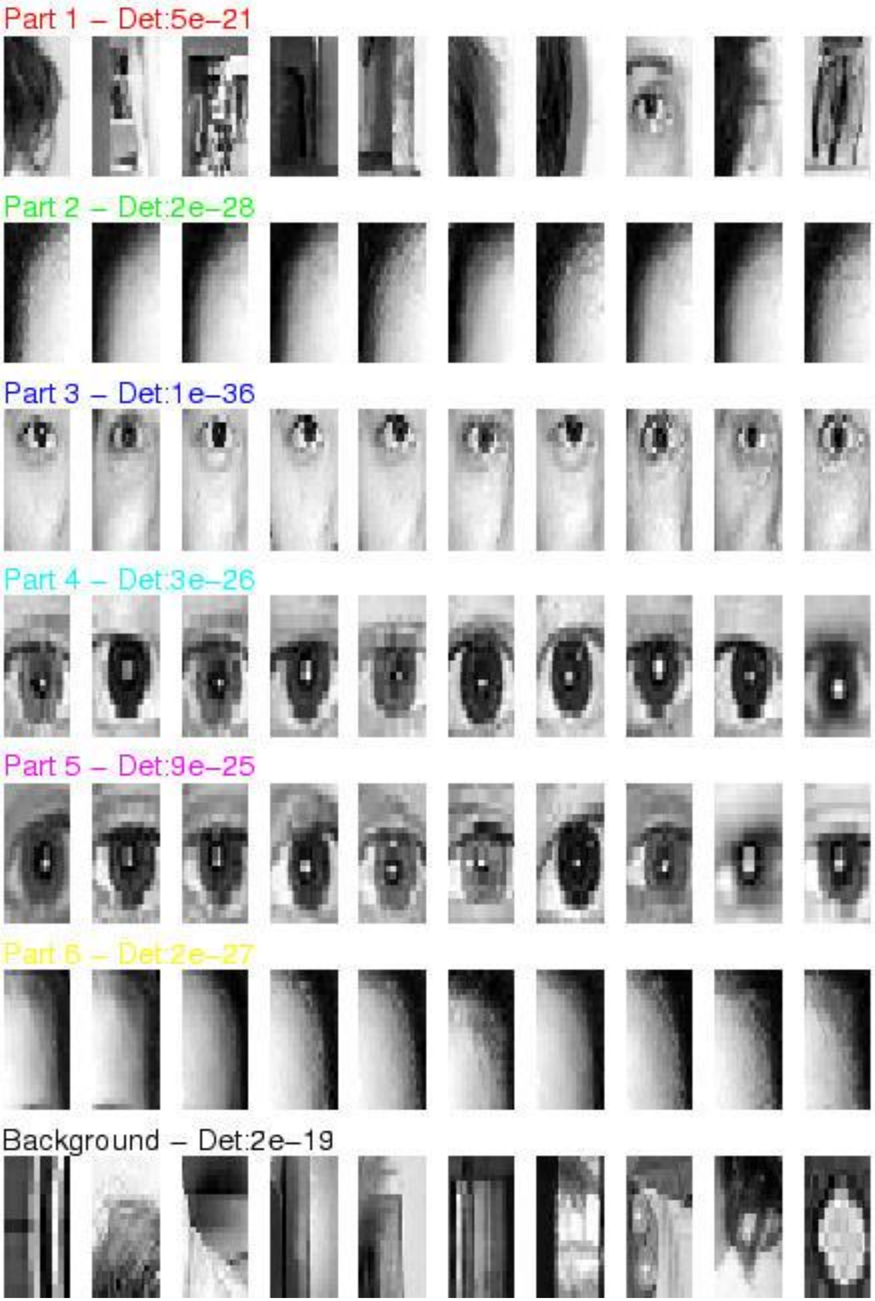
Background Images

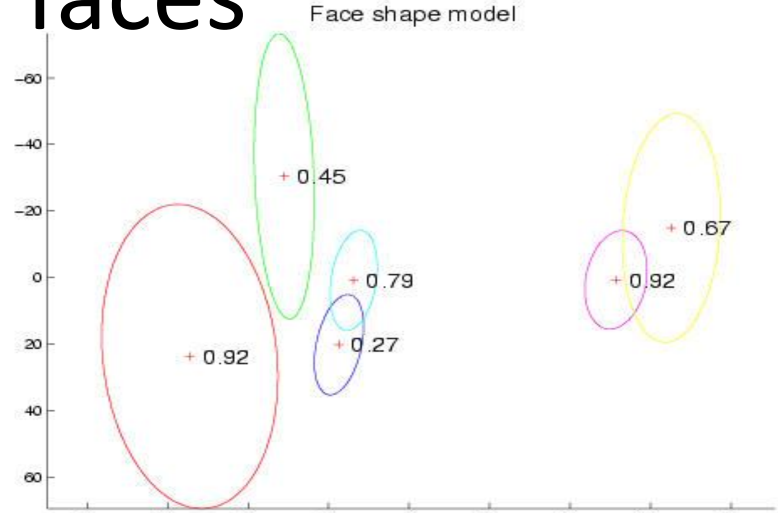
It learns that these are NOT motorbikes.



Frontal faces

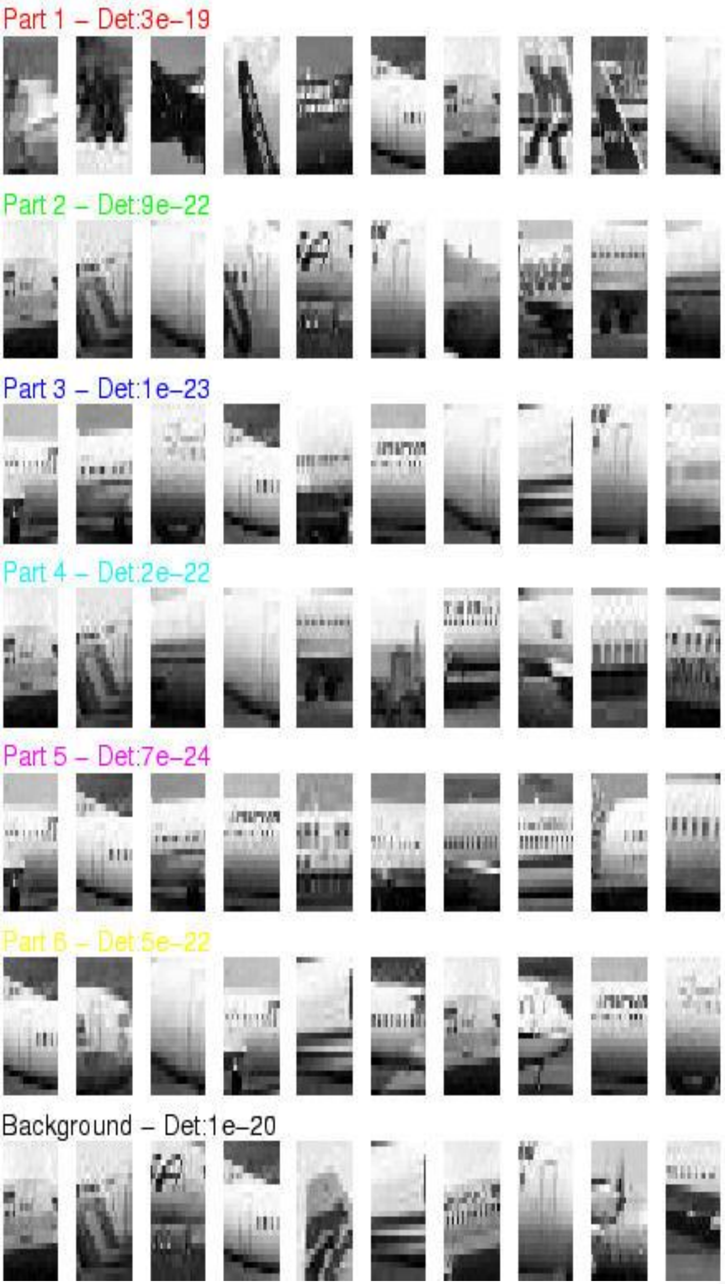
Equal error rate: 4.6%

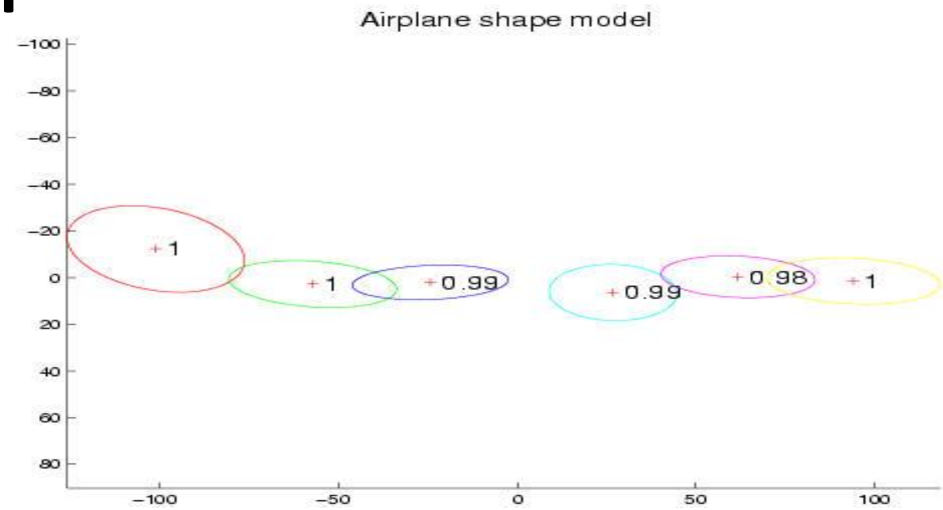


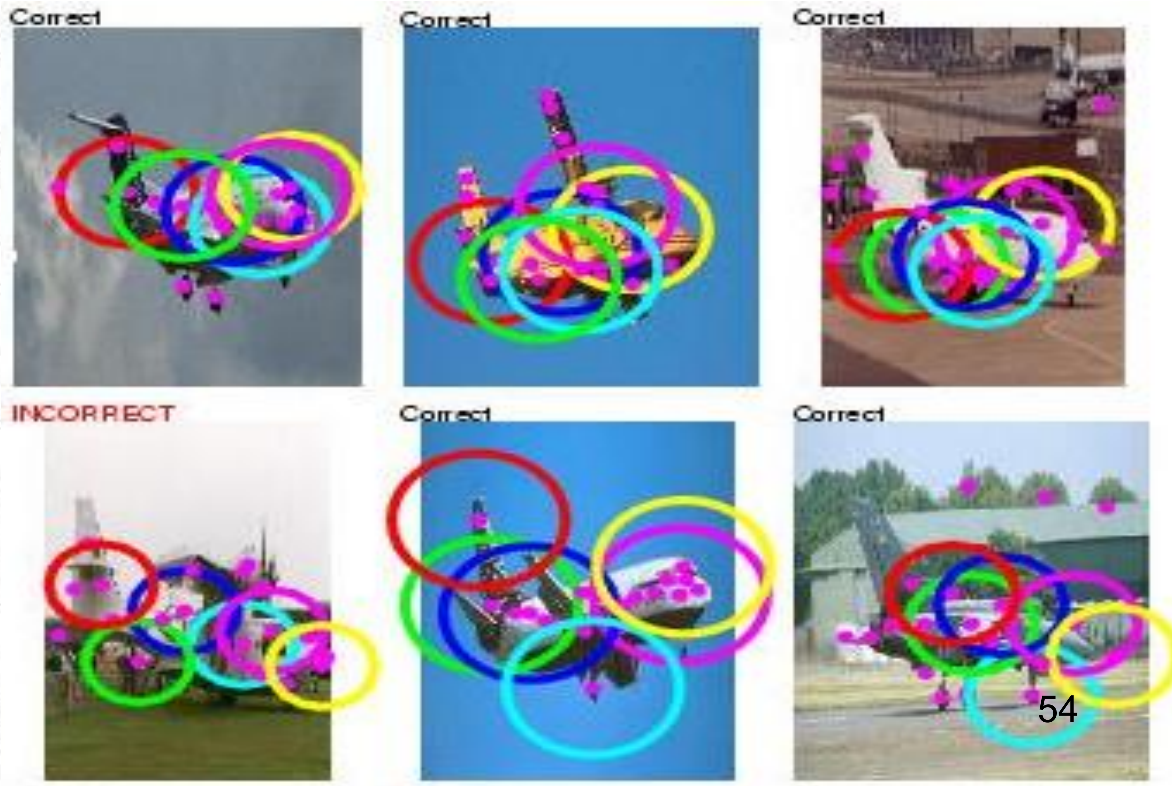


Equal error rate: 9.8%

Airplanes

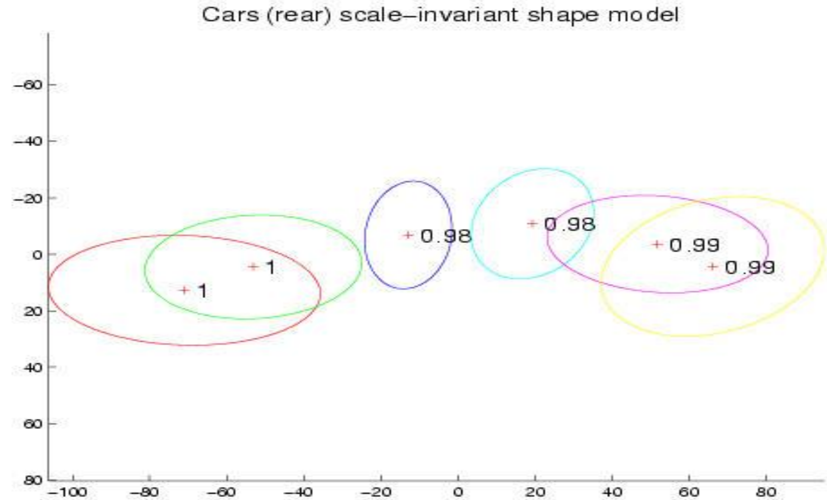






Scale-Invariant Cars

Equal error rate: 9.7%



Accuracy

Initial Pre-Scaled Experiments

Dataset	Ours	Others	Ref.
Motorbikes	92.5	84	[17]
Faces	96.4	94	[19]
Airplanes	90.2	68	[17]
Cars(Side)	88.5	79	[1]

Early Data Set: The CalTech 4

Available Today

- CalTech 101 and Caltech 256
- ImageNet
- Pascal VOC dataset
- CIFAR-10
- MS Coco
- Cityscapes

https://analyticsindiamag.com/10-open-datasets-you-can-use-for-computer-vision-projects/

Content-Based Image Retrieval

- Queries
- Commercial Systems
- Retrieval Features
- Indexing in the FIDS System
- Lead-in to Object Recognition

Content-based Image Retrieval (CBIR)

Searching a large database for images that *match* a query:

- What kinds of databases?
- What kinds of queries?
- What constitutes a match?
- How do we make such searches efficient?

Applications

- Art Collections
  e.g. Fine Arts Museum of San Francisco
- Medical Image Databases
  CT, MRI, Ultrasound, The Visible Human
- Scientific Databases
  e.g. Earth Sciences
- General Image Collections for Licensing
  Corbis, Getty Images
- The World Wide Web
  Google, Microsoft, etc

What is a query?

- an image you already have
- a rough sketch you draw
- a symbolic description of what you want
  e.g. an image of a man and a woman on a beach

Some Systems You Can Try

- Corbis ~~sells~~ sold high-quality images for use in advertising, marketing, illustrating, etc. Corbis was sold to a Chinese company, but

- Getty images now provides the image sales.

- http://www.gettyimages.com/search/2/image?excludenudity=true&sort=best

Google Image

- Google Images
http://www.google.com/imghp

Try the camera icon.

Microsoft Bing

- http://www.bing.com/

Problem with Text-Based Search

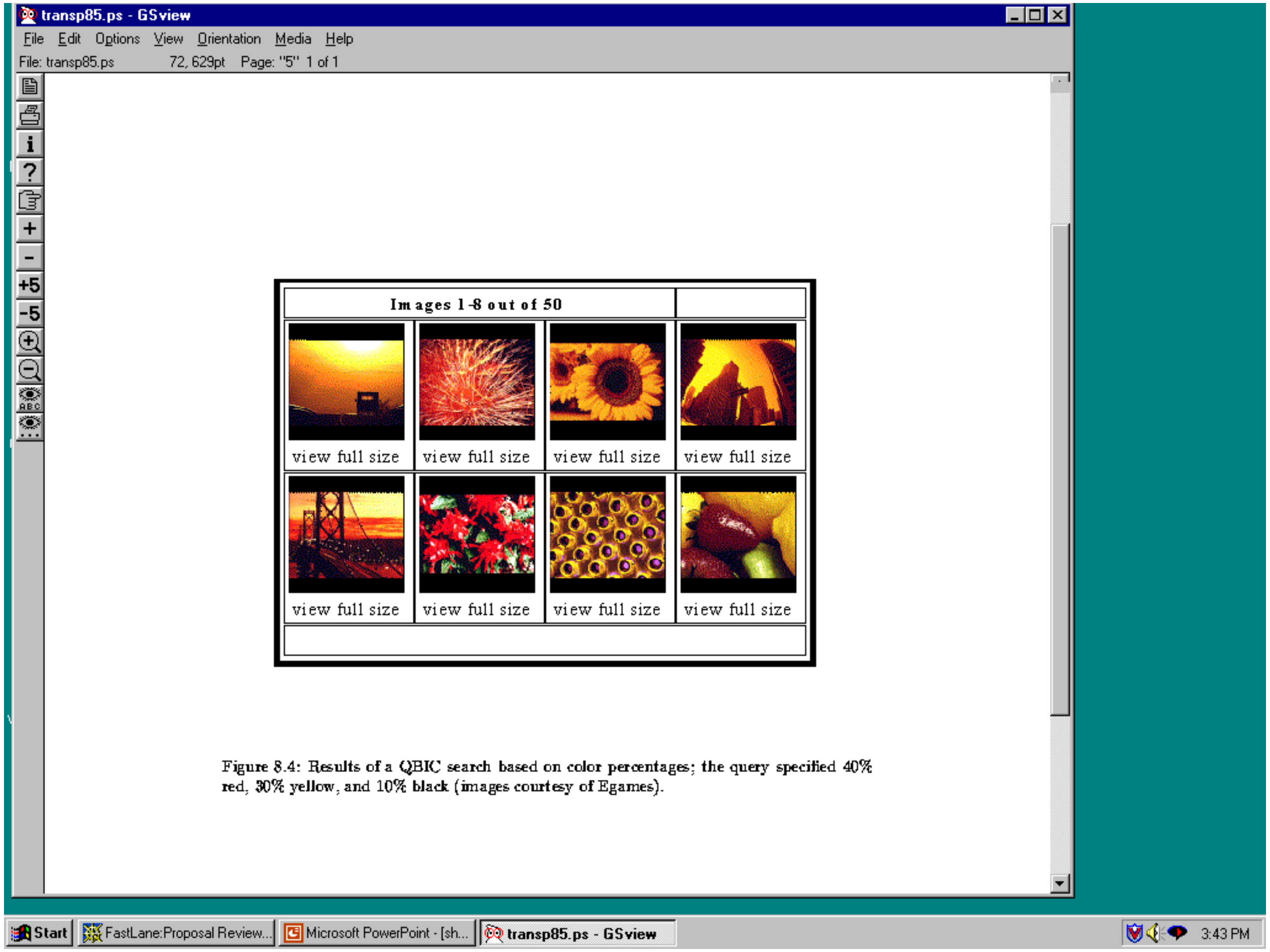
- Retrieval for pigs for the color chapter of my book
- Small company (was called Ditto)
- Allows you to search for pictures from web pages

Features

- Color (histograms, gridded layout, wavelets)
- Texture (Laws, Gabor filters, local binary pattern)
- Shape (first segment the image, then use statistical or structural shape similarity measures)
- Objects and their Relationships

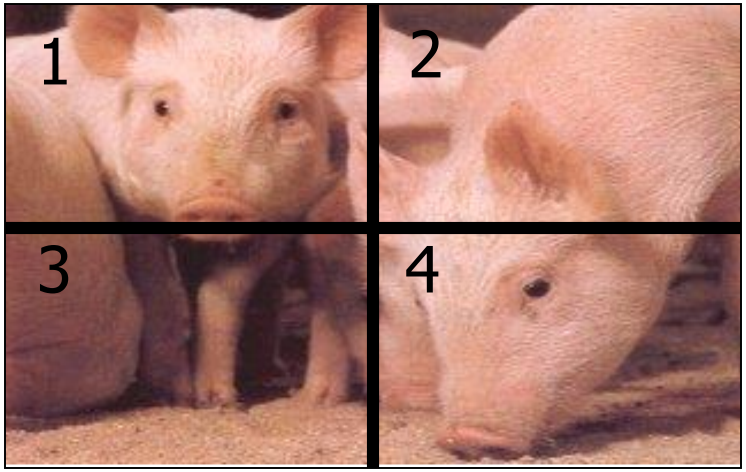
This is the most powerful, but you have to be able to recognize the objects!

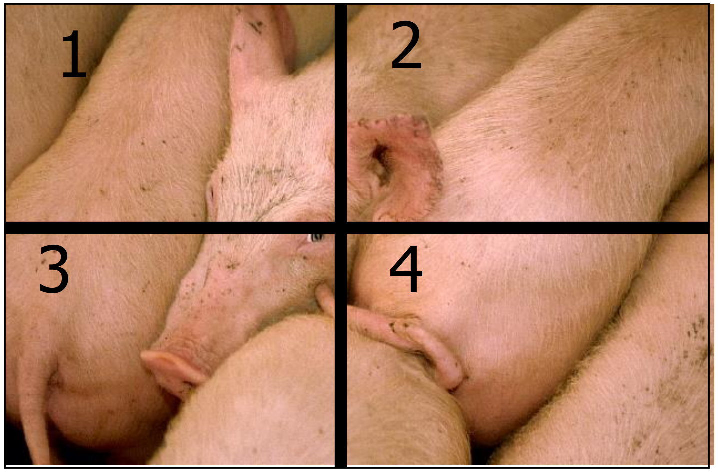
Color Histograms



Gridded Color

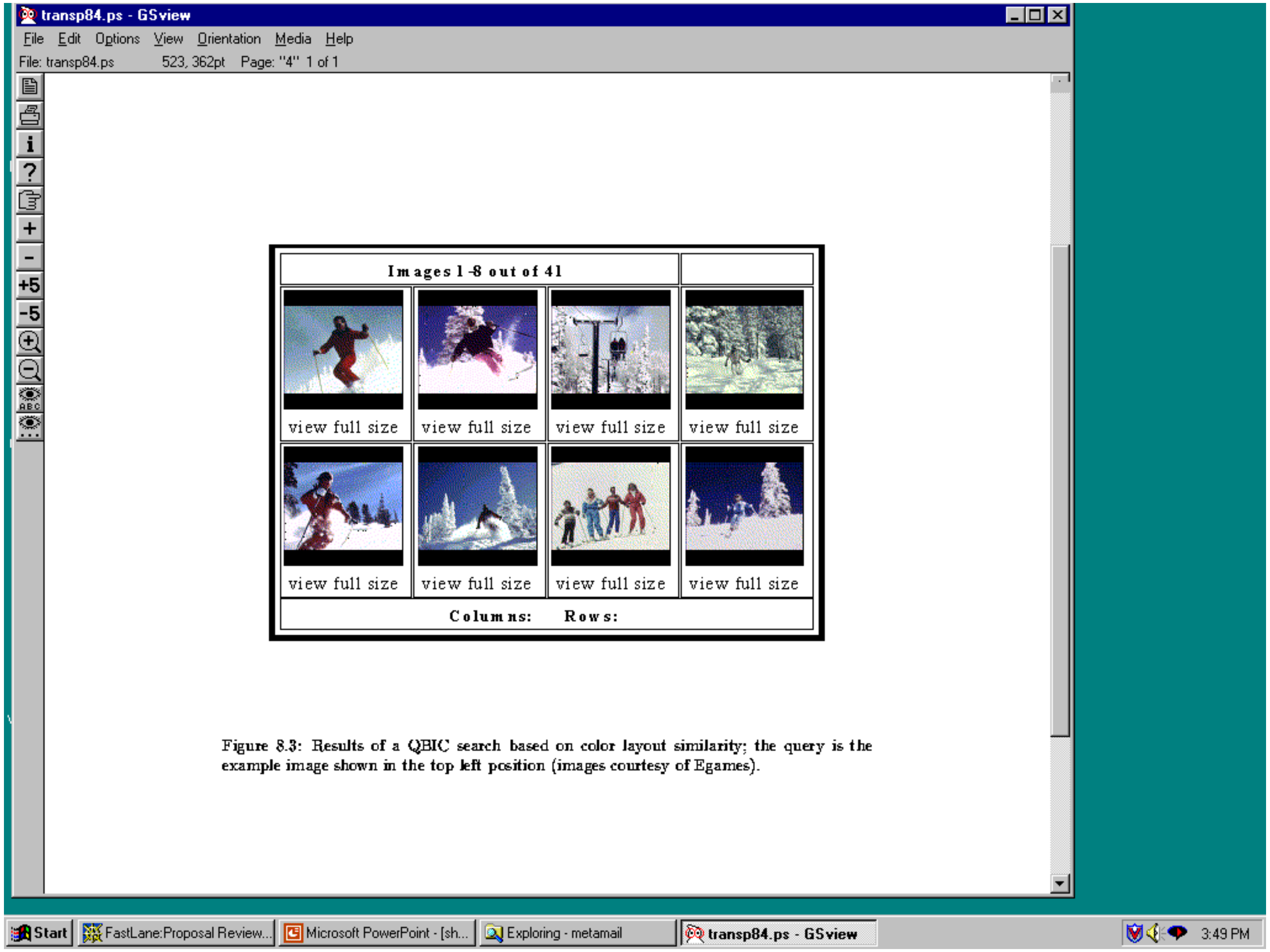
Gridded color distance is the sum of the color distances in each of the corresponding grid squares.





What color distance would you use for a pair of grid squares?

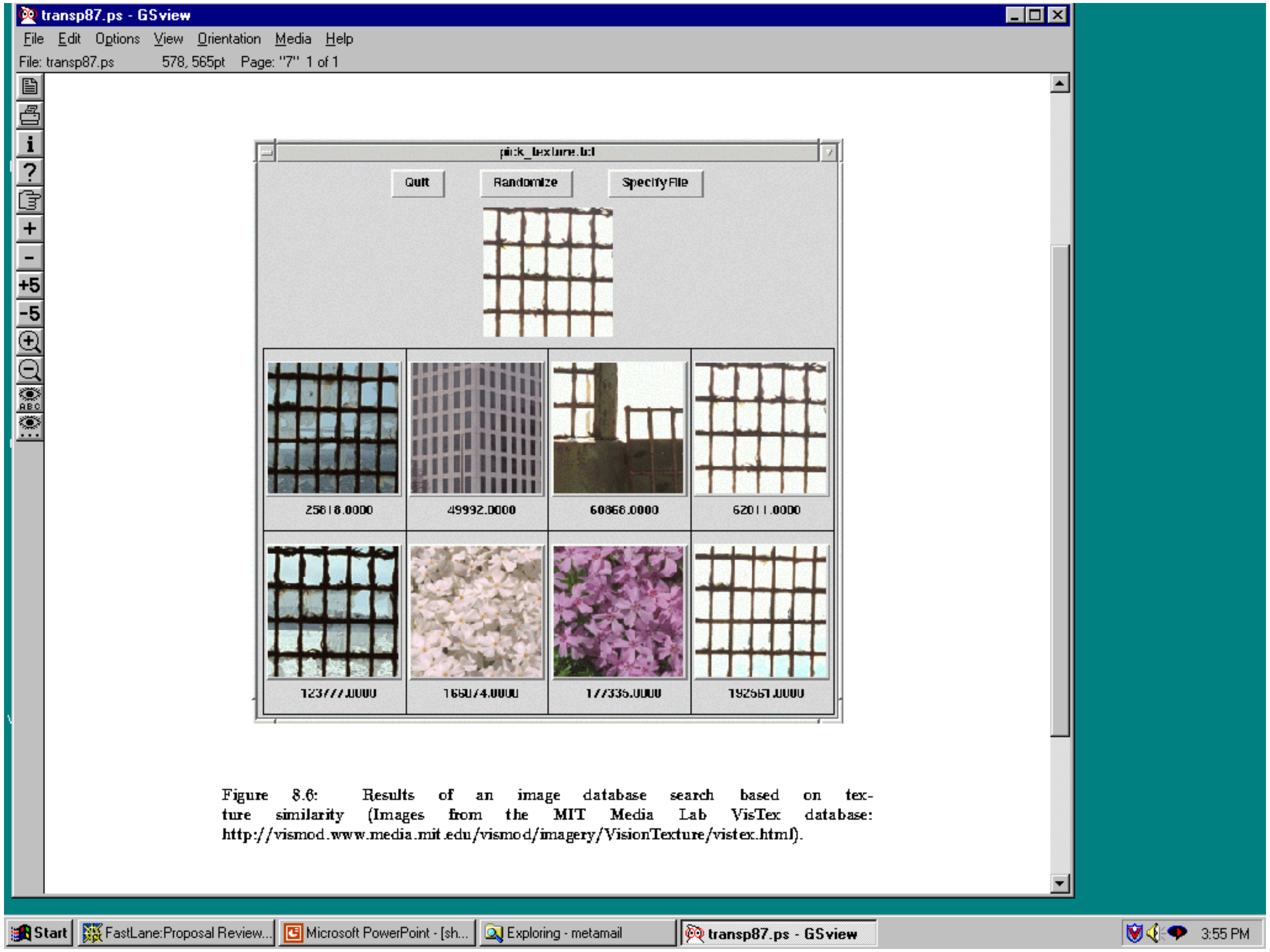
Color Layout
(IBM's Gridded Color)



Texture Distances

- Pick and Click (user clicks on a pixel and system retrieves images that have in them a region with similar texture to the region surrounding it.
- Gridded (just like gridded color, but use texture).
- Histogram-based (e.g. compare the LBP histograms).

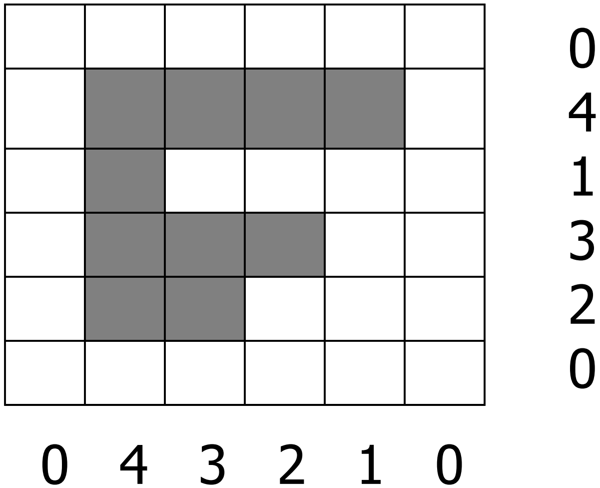
Laws Texture



Shape Distances

- Shape goes one step further than color and texture.
- It requires identification of regions to compare.
- There have been many shape similarity measures suggested for pattern recognition that can be used to construct shape distance measures.

Global Shape Properties: Projection Matching

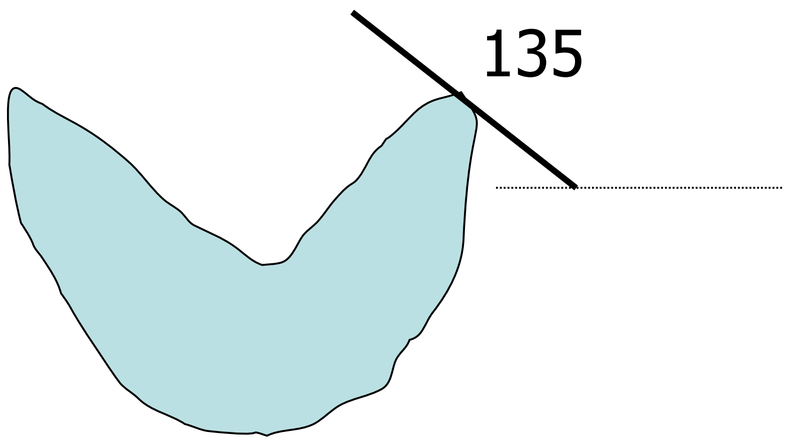


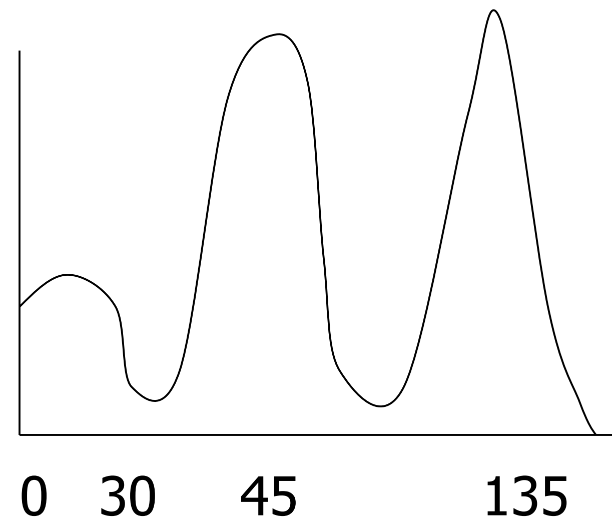
→ Feature Vector
(0,4,1,3,2,0,0,4,3,2,1,0)

In projection matching, the horizontal and vertical projections form a histogram.

What are the weaknesses of this method? strengths?

Global Shape Properties: Tangent-Angle Histograms





Is this feature invariant to starting point?
Is it invariant to size, translation, rotation?

Boundary Matching

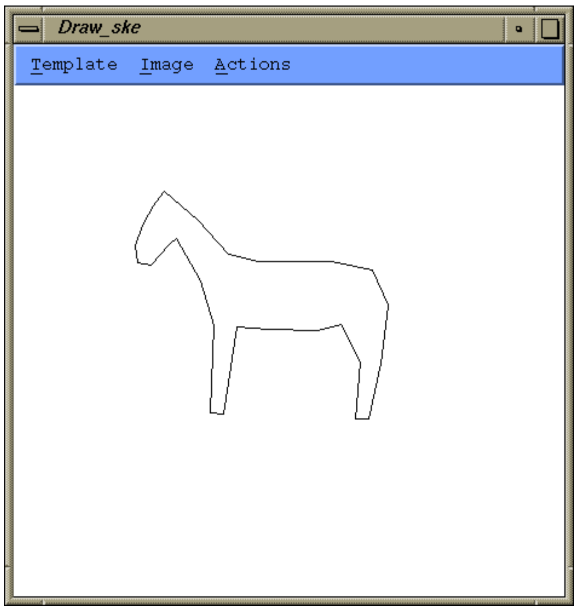
- Fourier Descriptors
- Sides and Angles
- Elastic Matching

  The distance between query shape and image shape has two components:

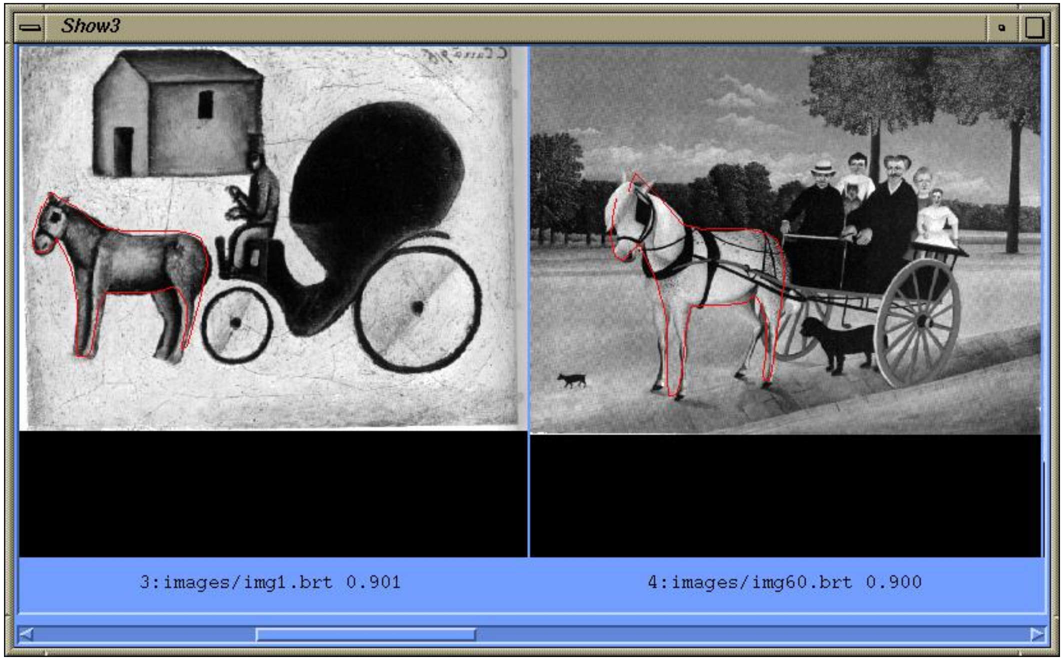
  1. energy required to deform the query shape into one that best matches the image shape

  2. a measure of how well the deformed query matches the image

Del Bimbo Elastic Shape Matching



query



retrieved images

Regions and Relationships

- Segment the image into regions
- Find their properties and interrelationships
- Construct a graph representation with nodes for regions and edges for spatial relationships
- Use graph matching to compare images

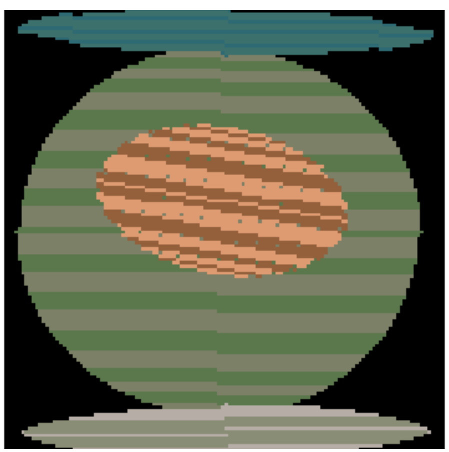
Like what?

Blobworld (Carson et al, 1999)

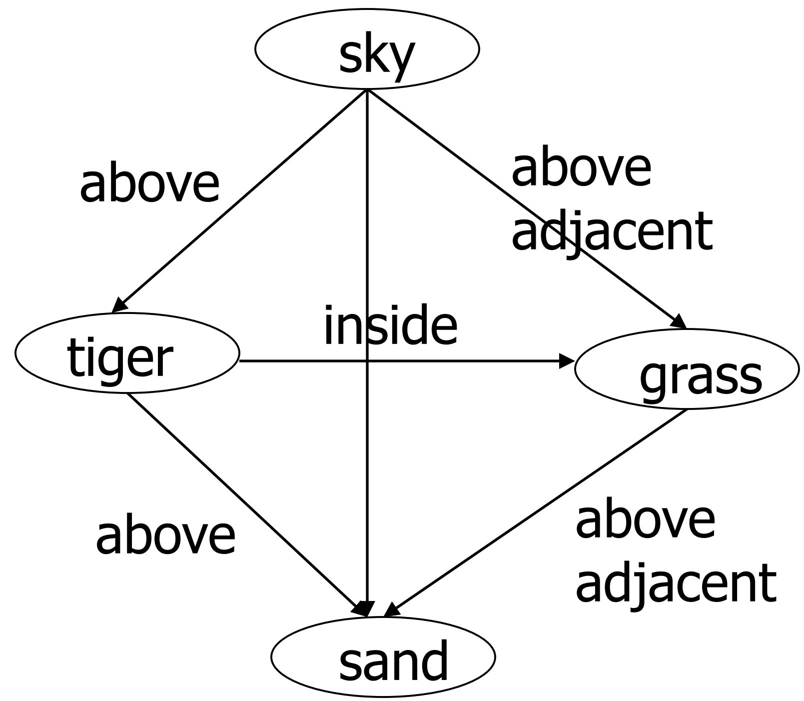
- Segmented the query (and all database images) using EM on color+texture
- Allowed users to select the most important region and what characteristics of it (color, texture, location)
- Asked users if the background was also important

Tiger Image as a Graph (motivated by Blobworld)

image

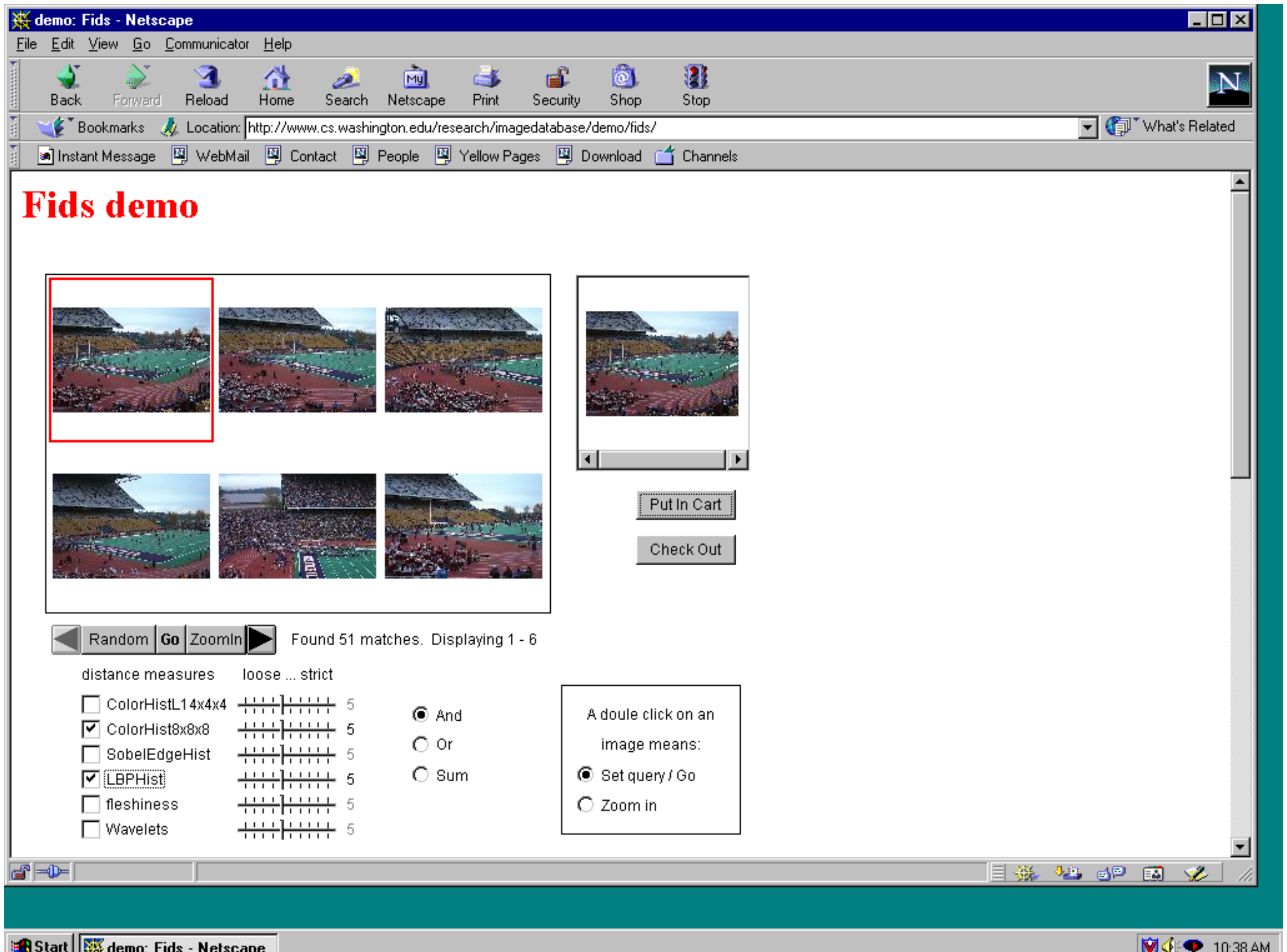


abstract regions



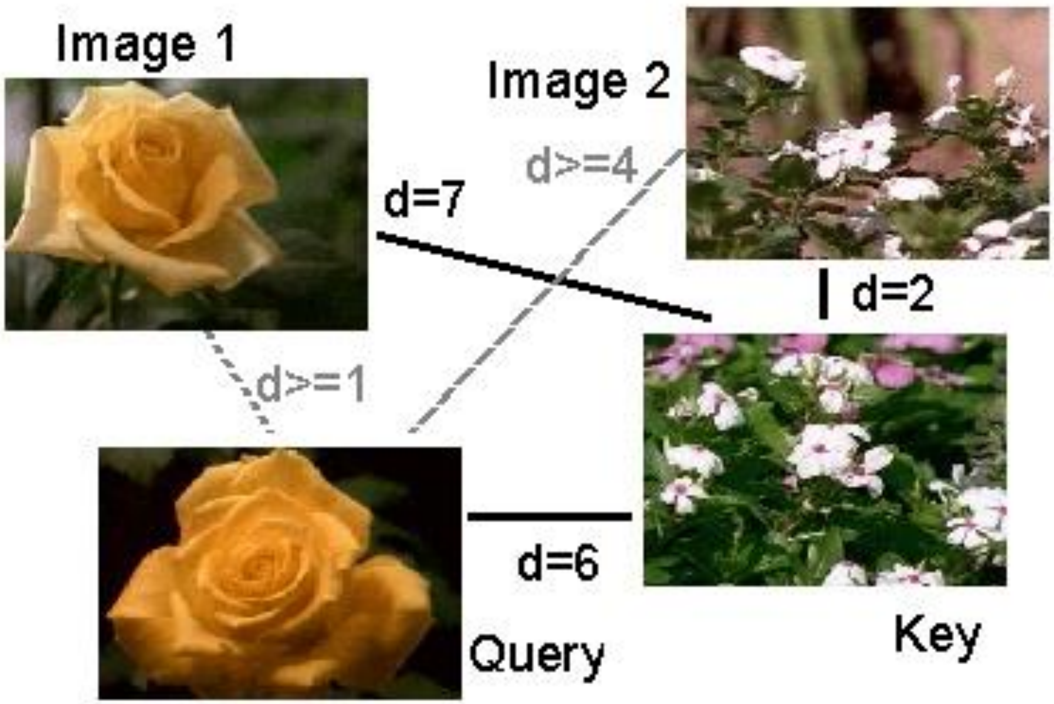
Andy Berman's FIDS System

multiple distance measures
Boolean and linear combinations
efficient indexing using images as keys



Andy Berman's FIDS System:

Use of key images and the triangle inequality for efficient retrieval. d(I,Q) >= |d((I,K) – d(Q,K)|



Andy Berman's FIDS System:

Bare-Bones Triangle Inequality Algorithm

Offline

1. Choose a small set of key images
2. Store distances from database images to keys

Online (given query Q)

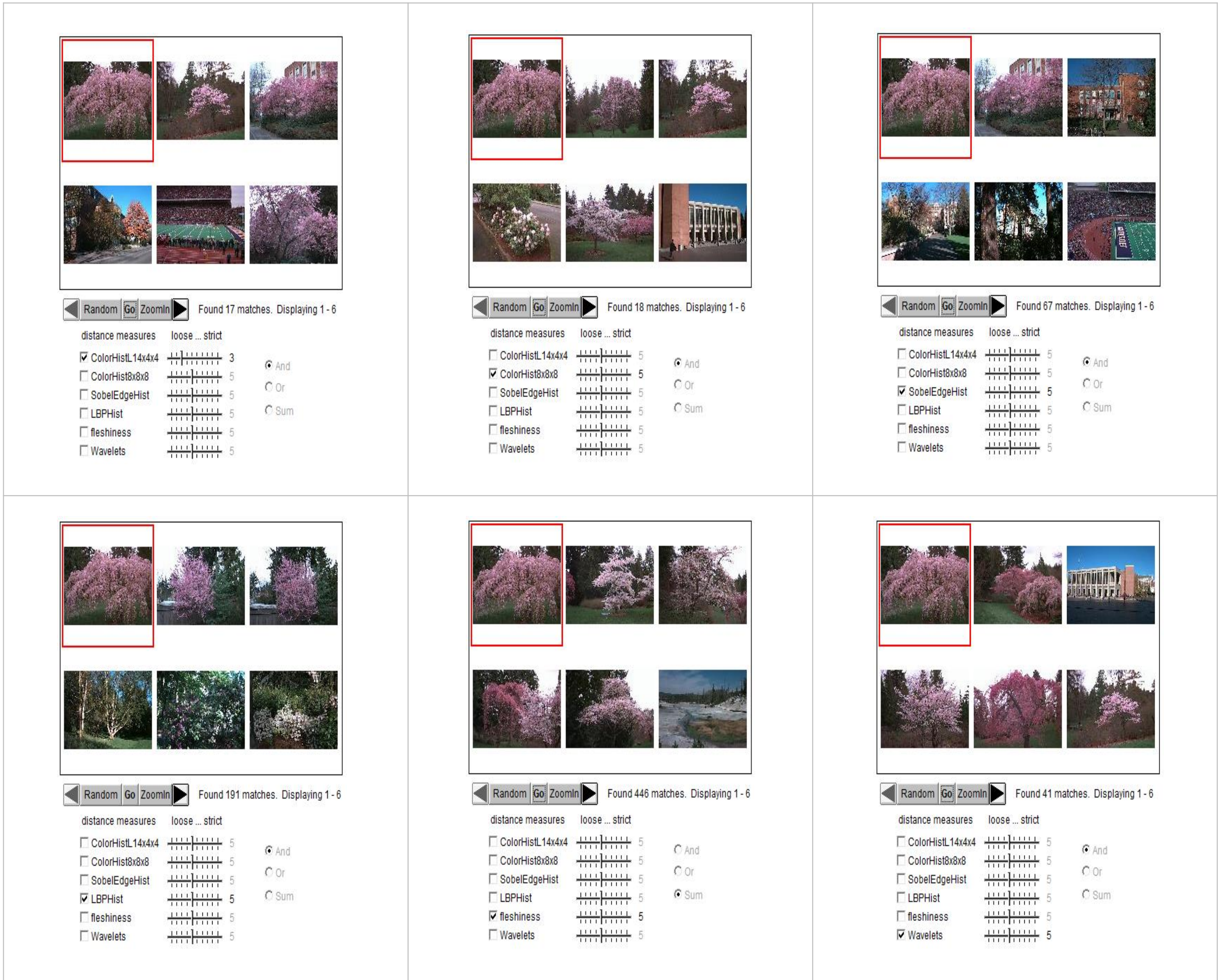
1. Compute the distance from Q to each key
2. Obtain lower bounds on distances to database images
3. Threshold or return all images in order of lower bounds

Andy Berman's FIDS System:

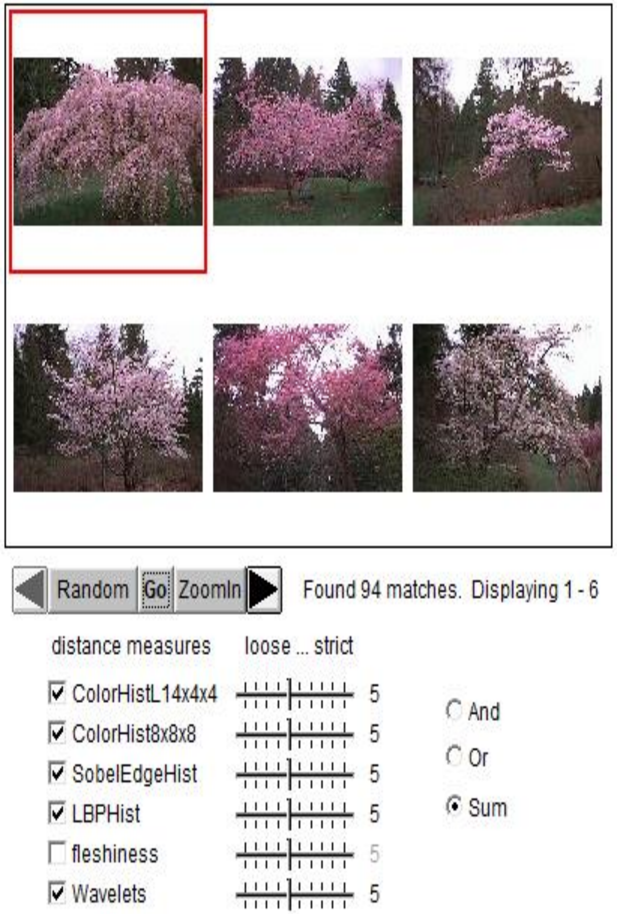
Flexible Image Database System: Example

An example from our system using a simple color measure.
images in system: 37,748
threshold: 100 out of 1000
images eliminated: 37,729

Different Features

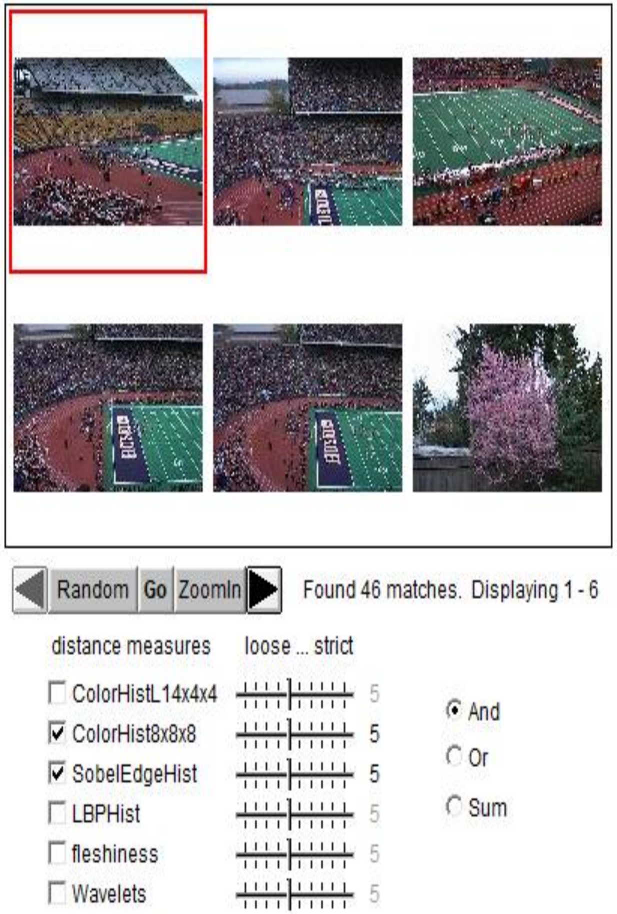


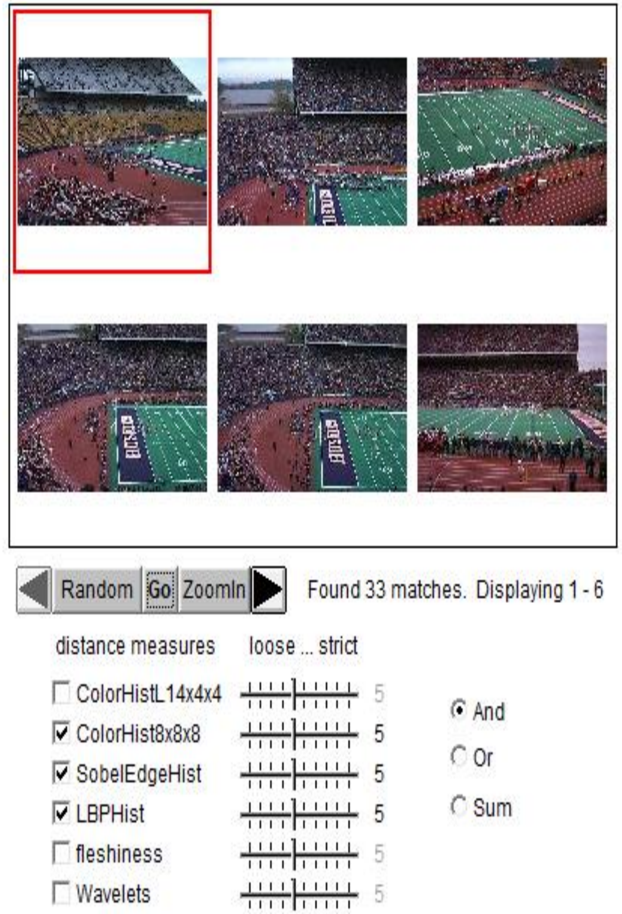
Combined Features



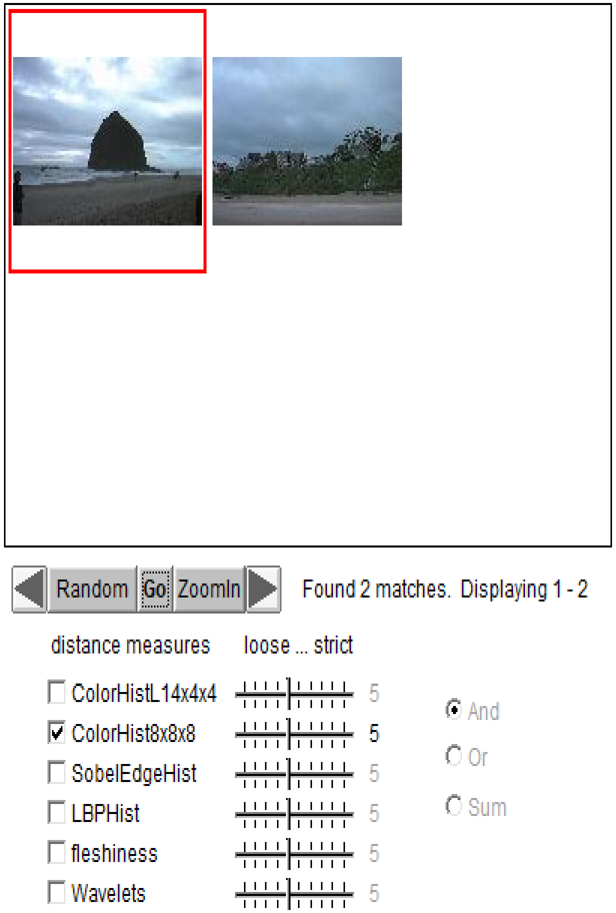
Another example: different features

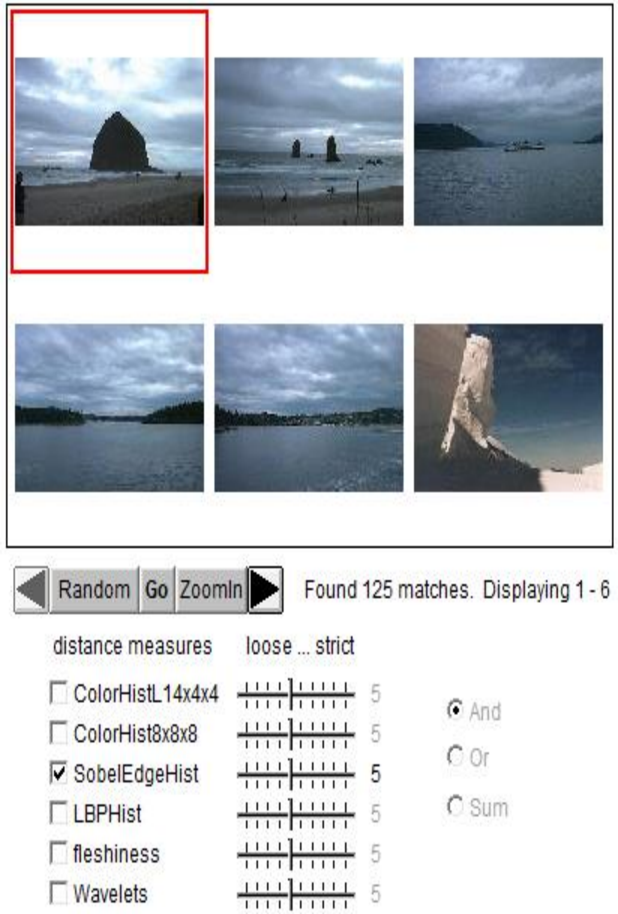
Combined Features

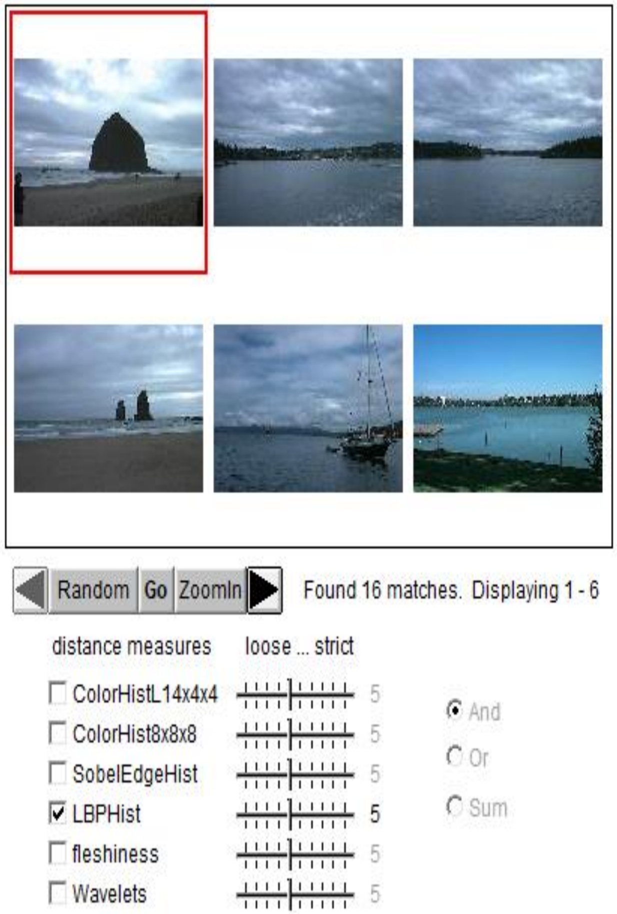




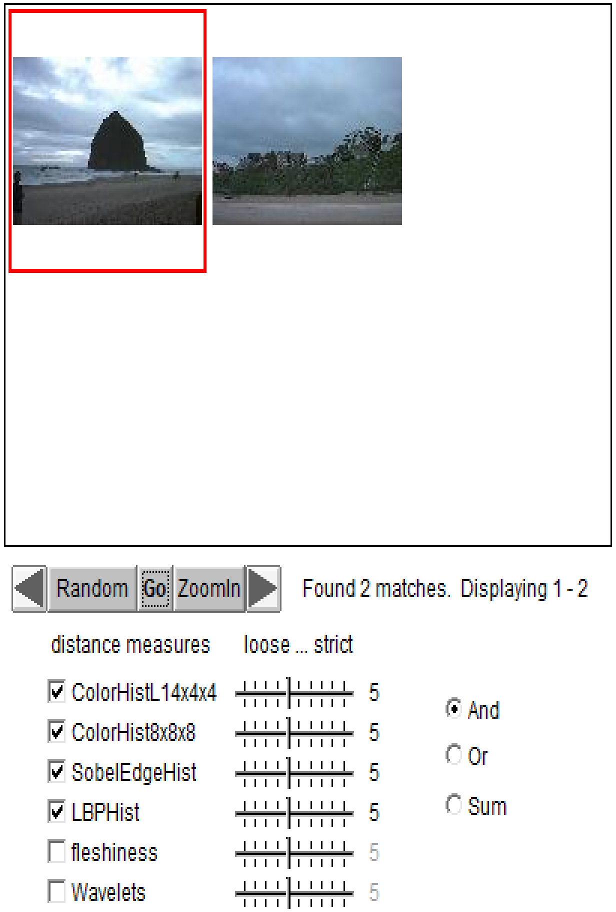
Another example: different features

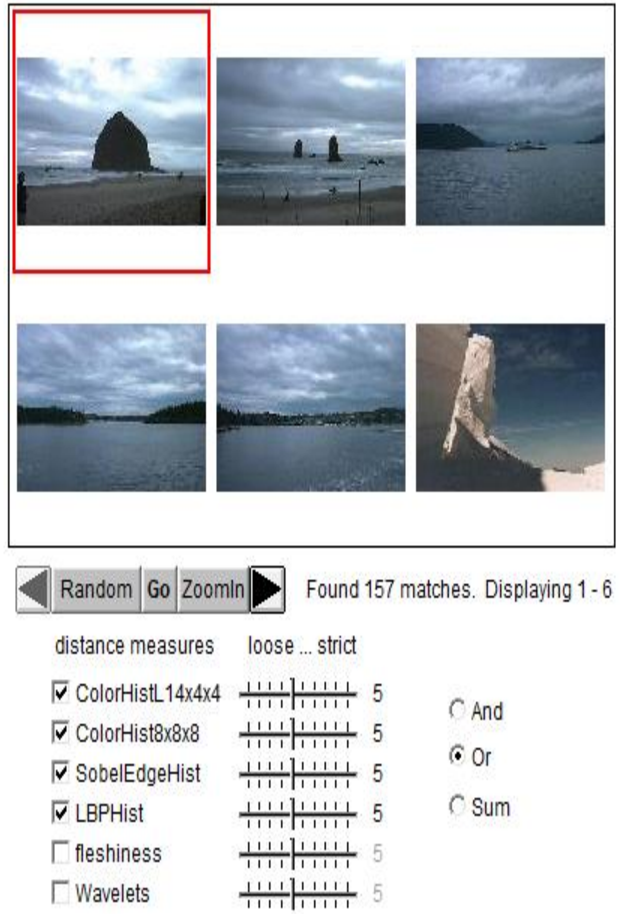




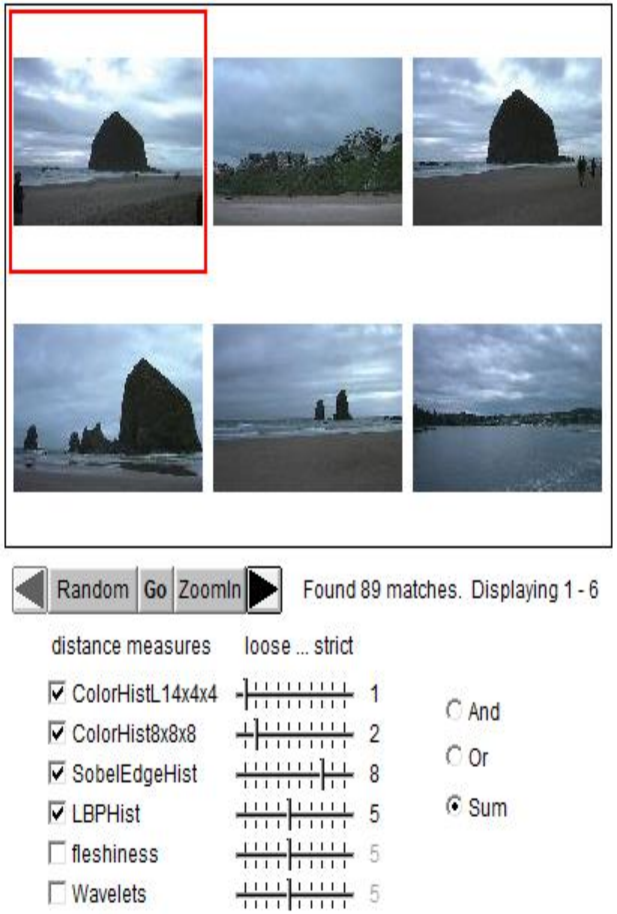


Different ways for combination

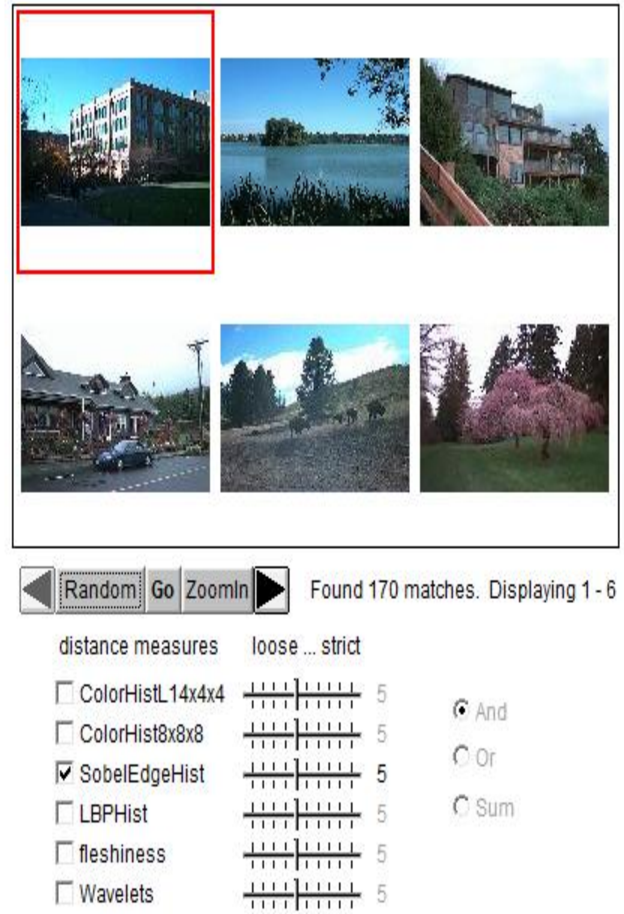


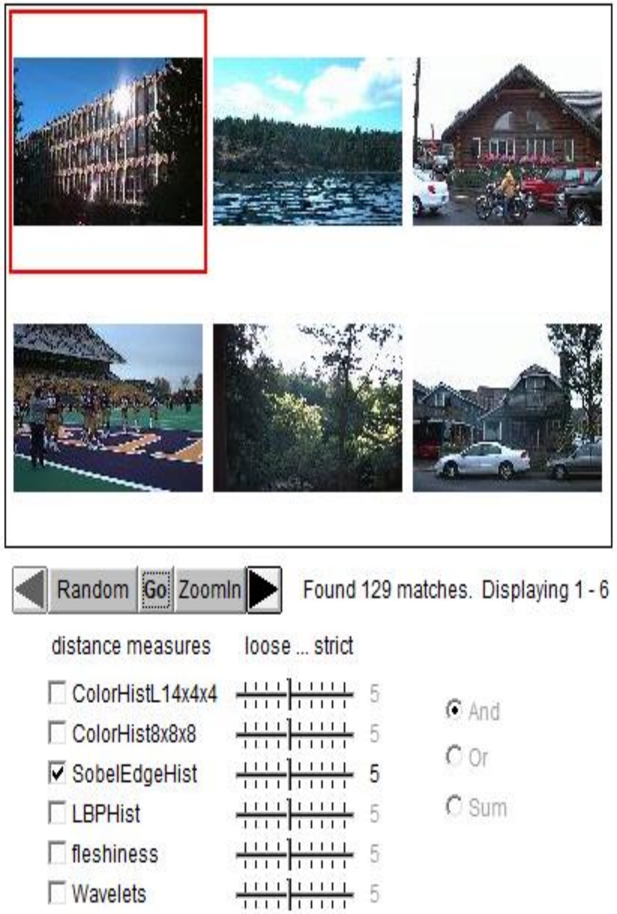


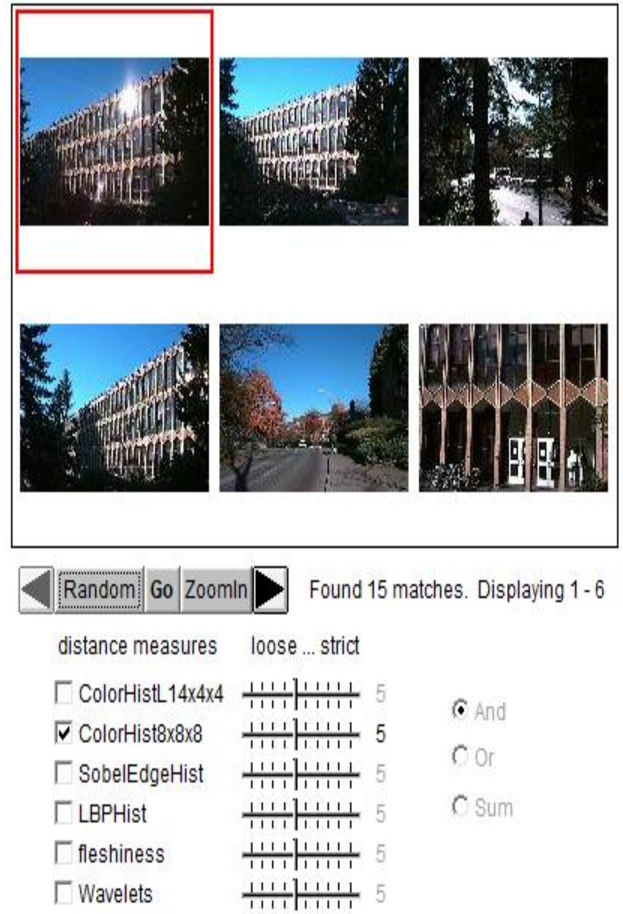
Different weights on features




Random
Go
ZoomIn
Found 170 matches. Displaying 1 - 6
distance measures
loose ... strict
ColorHistL14x4x4
5
ColorHist8x8x8
5
SobelEdgeHist
5
LBPHist
5
fleshiness
5
Wavelets
5
And
Or
Sum


Random
Go
ZoomIn
Found 170 matches. Displaying 1 - 6
distance measures
loose ... strict
ColorHistL14x4x4
5
ColorHist8x8x8
5
SobelEdgeHist
5
LBPHist
5
fleshiness
5
Wavelets
5
And
Or
Sum


Random
Go
ZoomIn
Found 129 matches. Displaying 1 - 6
distance measures
loose ... strict
ColorHistL14x4x4
5
ColorHist8x8x8
5
SobelEdgeHist
5
LBPHist
5
fleshiness
5
Wavelets
5
And
Or
Sum


Random
Go
ZoomIn
Found 15 matches. Displaying 1 - 6
distance measures
loose ... strict
ColorHistL14x4x4
5
ColorHist8x8x8
5
SobelEdgeHist
5
LBPHist
5
fleshiness
5
Wavelets
5
And
Or
Sum

Weakness of Low-level Features

- Can't capture the high-level concepts

Yi Li's Overall Approach

- Develop object recognizers for common objects
- Use these recognizers to design a new set of both low- and mid-level features
- Design a learning system that can use these features to recognize classes of objects

Building Features: Consistent Line Clusters (CLC)

A **Consistent Line Cluster** is a set of lines that are homogeneous in terms of some line features.

- **Color-CLC**: The lines have the same color feature.
- **Orientation-CLC**: The lines are parallel to each other or converge to a common vanishing point.
- **Spatially-CLC**: The lines are in close proximity to each other.

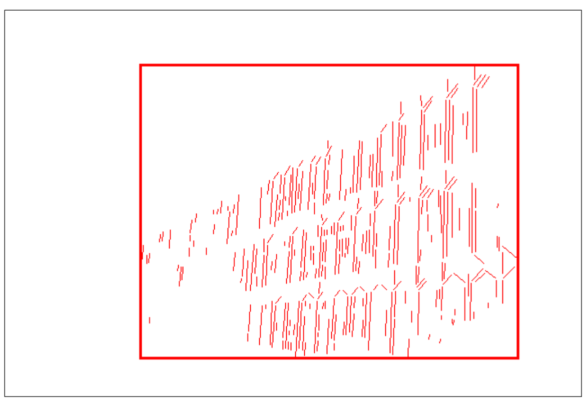
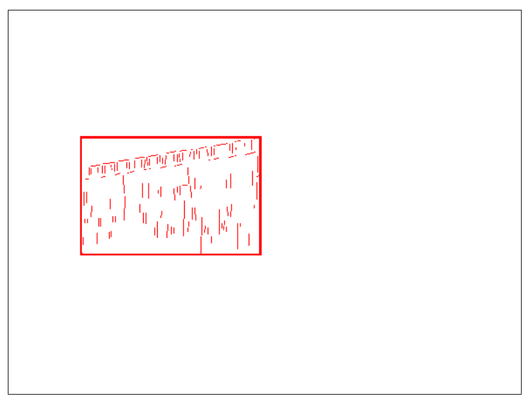
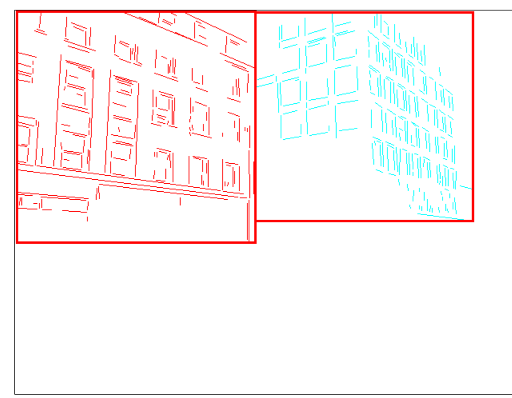
Experimental Evaluation

- Object Recognition
  - 97 well-patterned buildings (bp): 97/97
  - 44 not well-patterned buildings (bnp): 42/44
  - 16 not patterned non-buildings (nbnp): 15/16 (one false positive)
  - 25 patterned non-buildings (nbp): 0/25
- CBIR

Experimental Evaluation

Well-Patterned Buildings

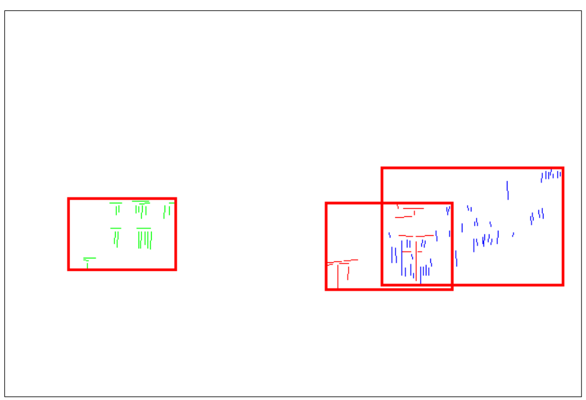
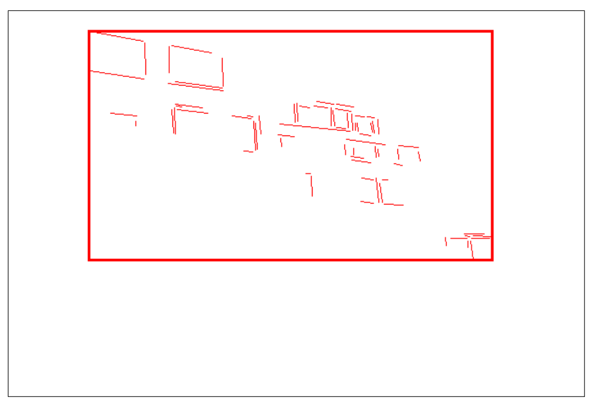


Experimental Evaluation

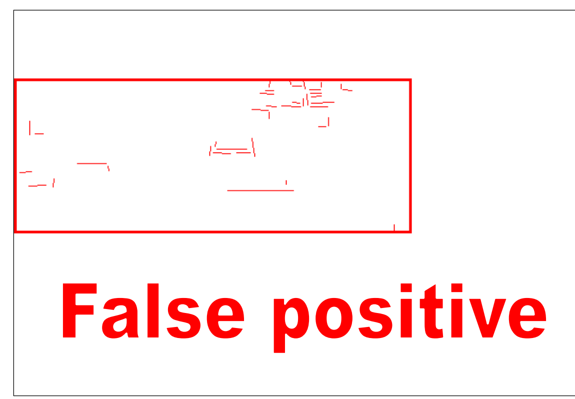
Non-Well-Patterned Buildings




Experimental Evaluation

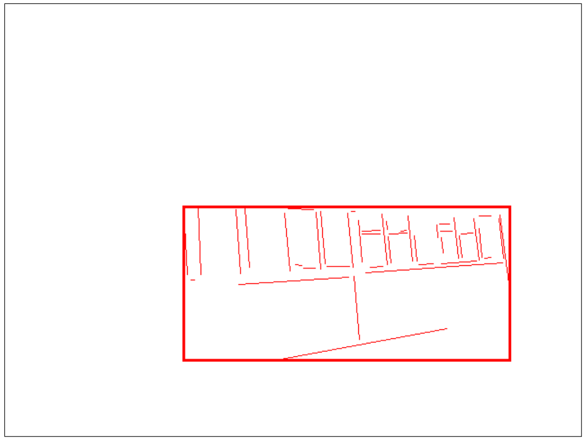
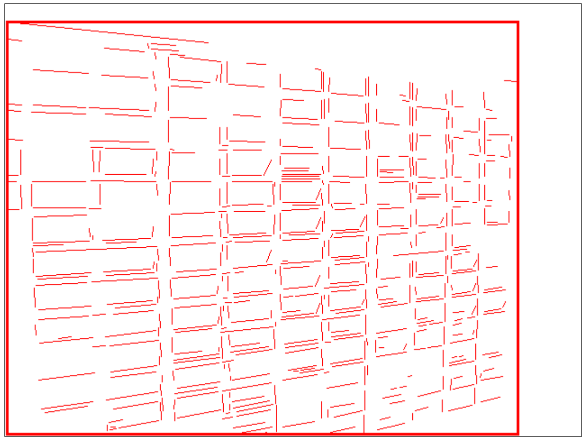
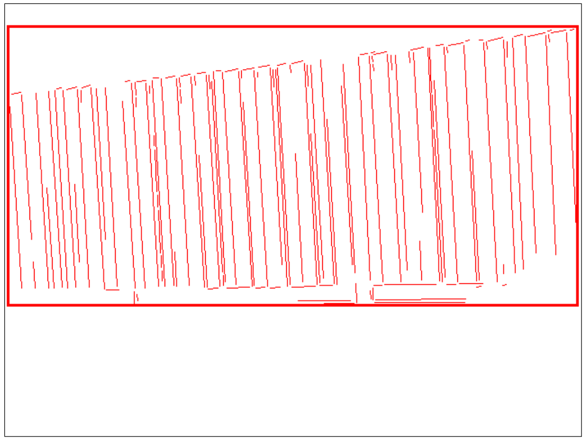
Non-Well-Patterned Non-Buildings



Experimental Evaluation

Well-Patterned Non-Buildings (false positives)

Experimental Evaluation (CBIR)

	Total Positive Classification (#)	Total Negative Classification (#)	False positive (#)	False negative (#)	Accuracy (%)
Arborgreens	0	47	0	0	100
Campusinfall	27	21	0	5	89.6
Cannonbeach	30	18	0	6	87.5
Yellowstone	4	44	4	0	91.7

Experimental Evaluation (CBIR)

False positives from Yellowstone