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

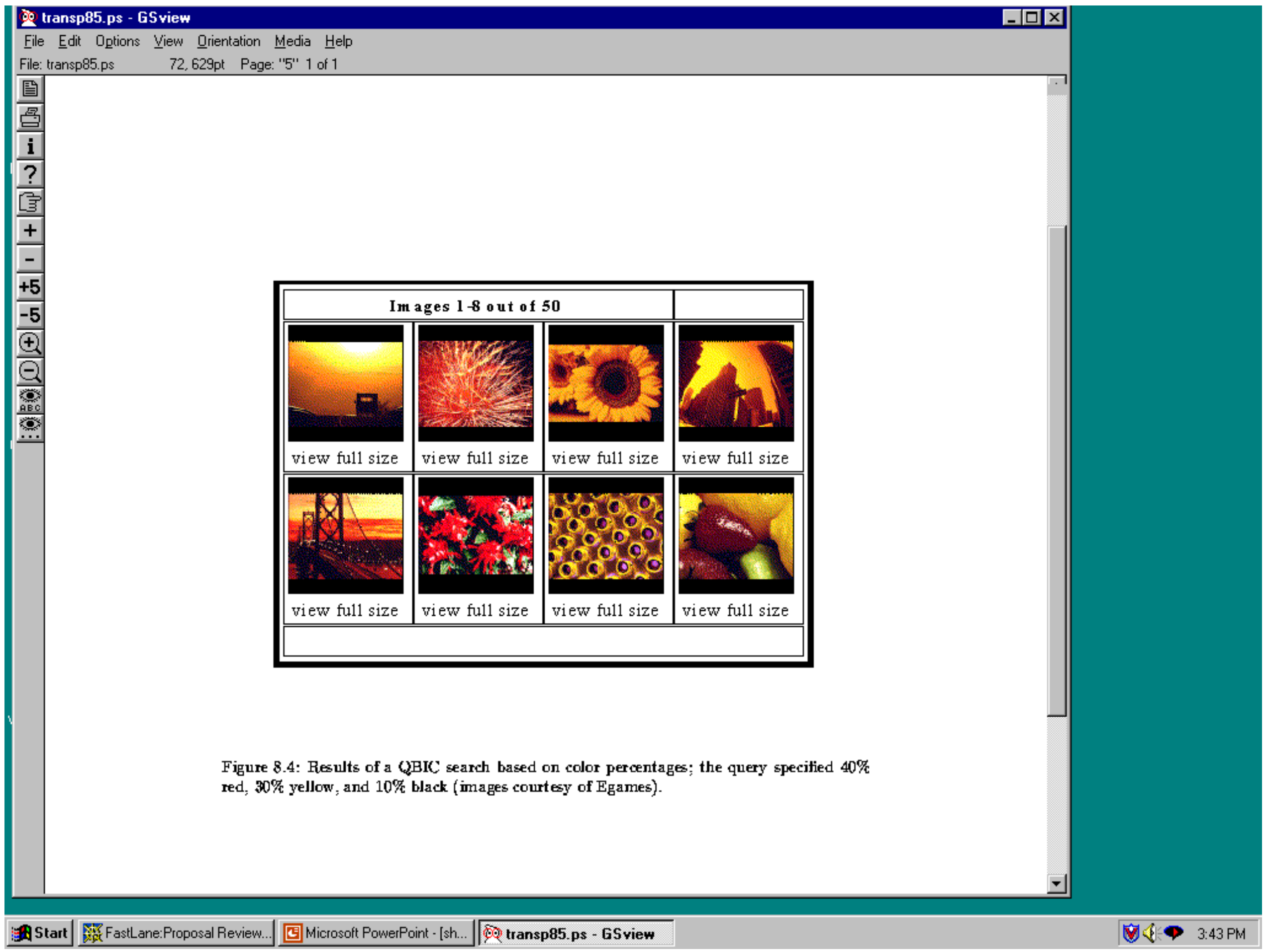
- Retrieval for pigs for the color chapter of my book
- Small company (was called Ditto)
- Allows you to search for pictures from web pages

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

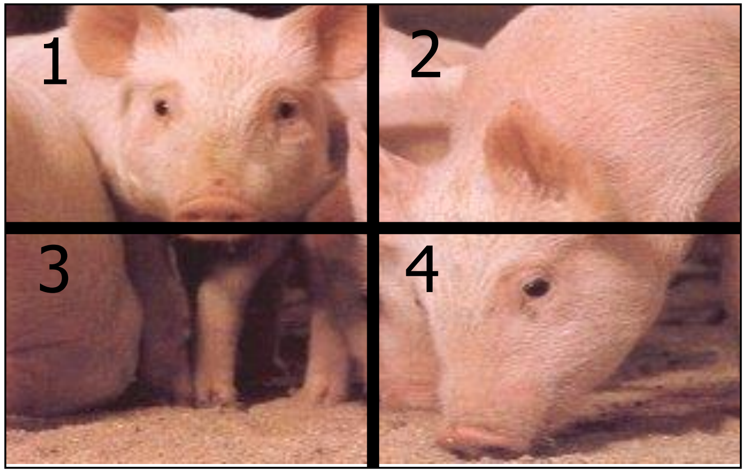
This is the most powerful, but you have to be able to recognize the objects!

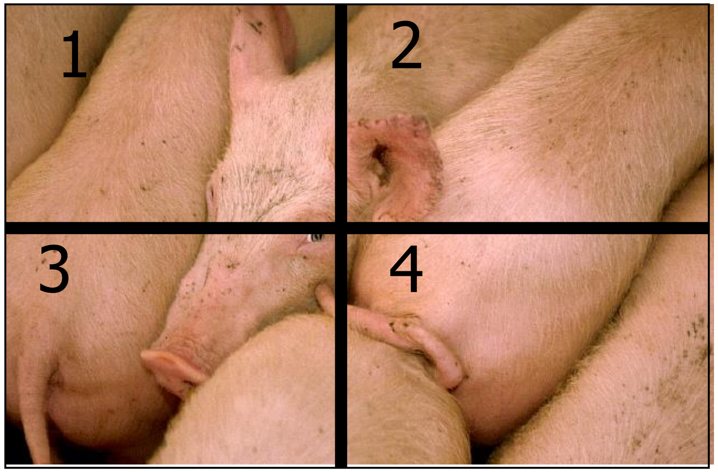
Color Histograms



Gridded Color

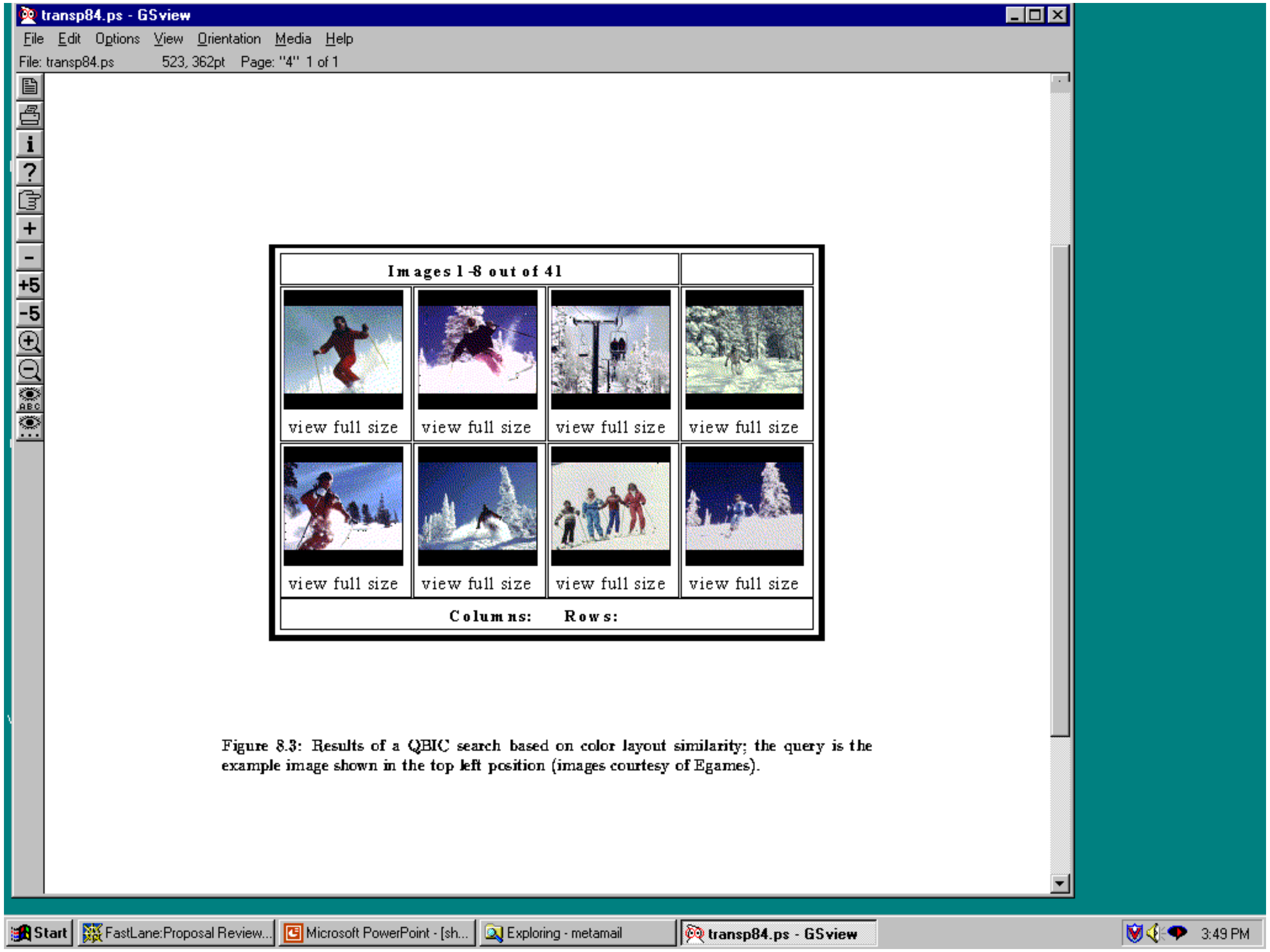
Gridded color distance is the sum of the color distances in each of the corresponding grid squares.





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

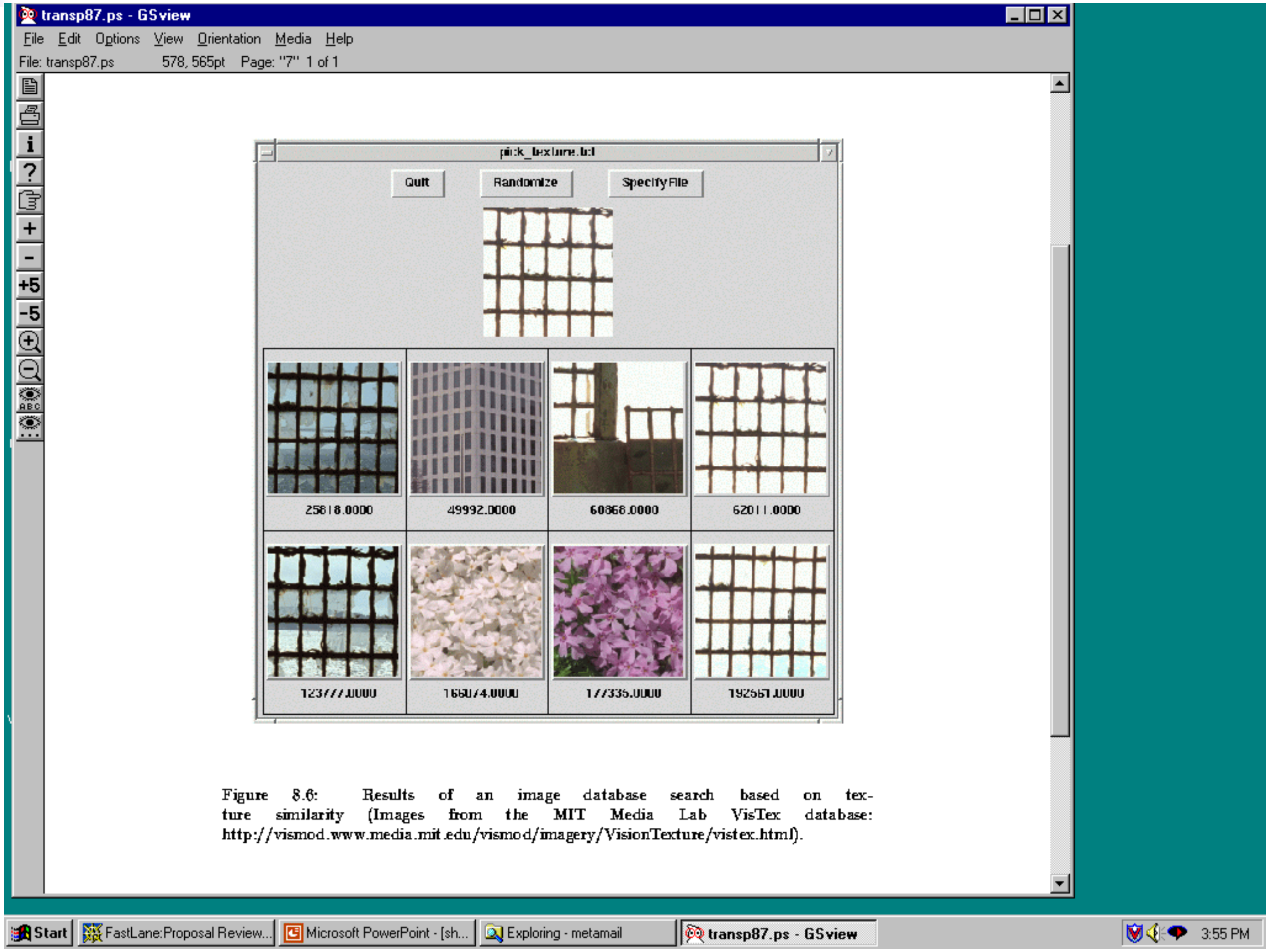
Color Layout (IBM's Gridded Color)



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).

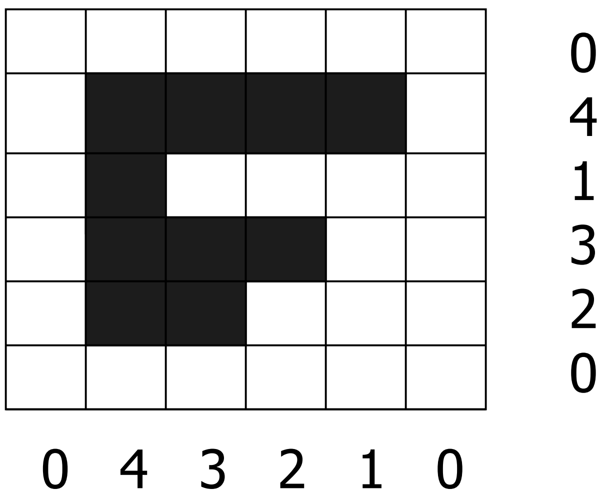
Laws Texture



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

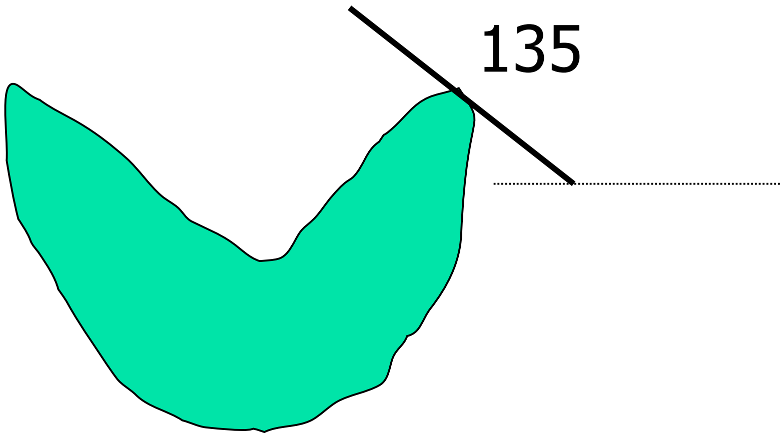


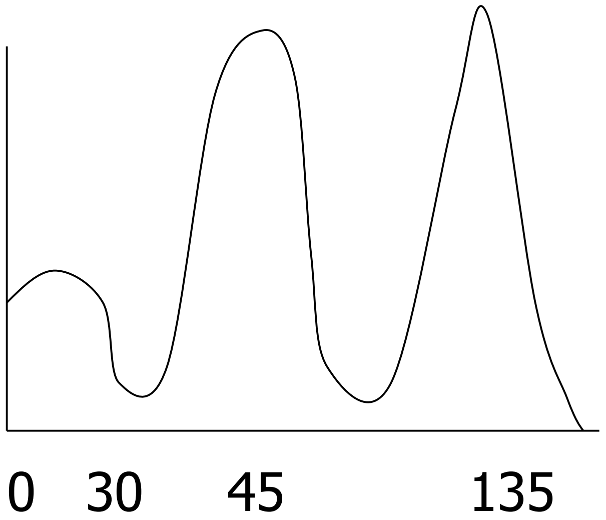
Feature Vector
(0,4,1,3,2,0,0,4,3,2,1,0)

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

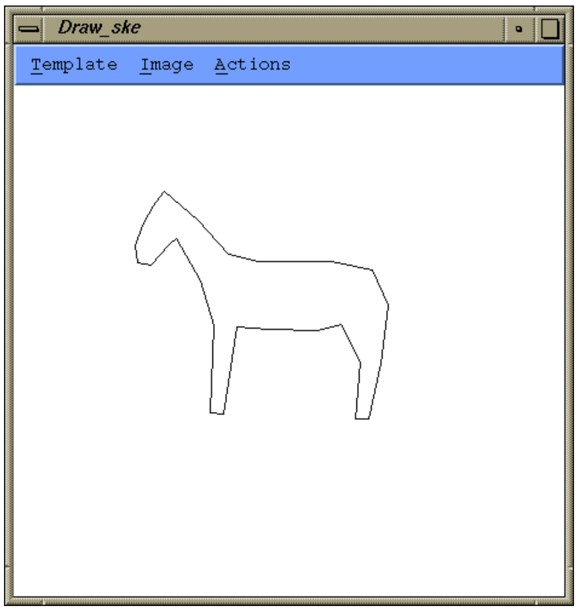
- Fourier Descriptors
- Sides and Angles
- Elastic Matching

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

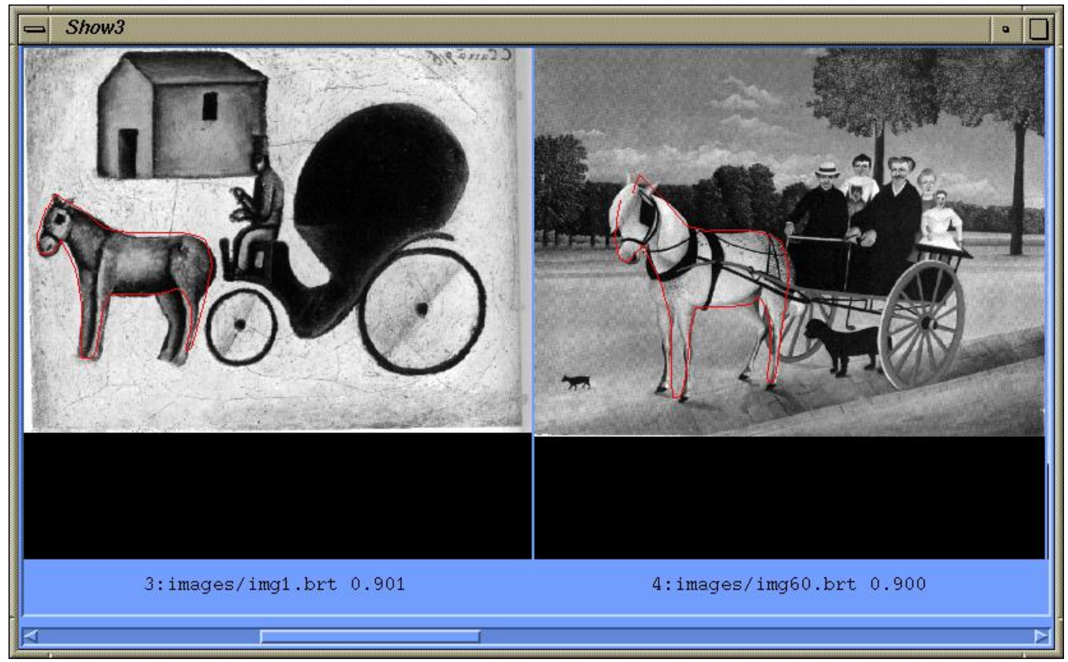
1. energy required to deform the query shape into one that best matches the image shape

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

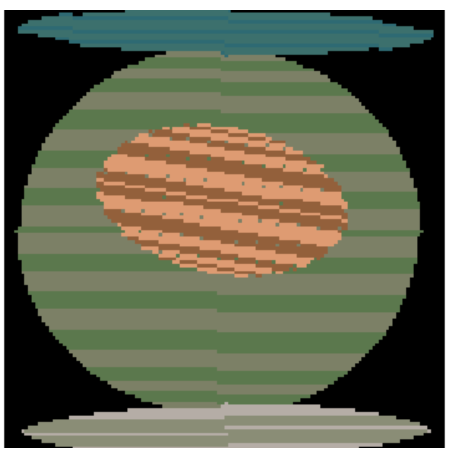
Like what?

Blobworld (Carson et al, 1999)

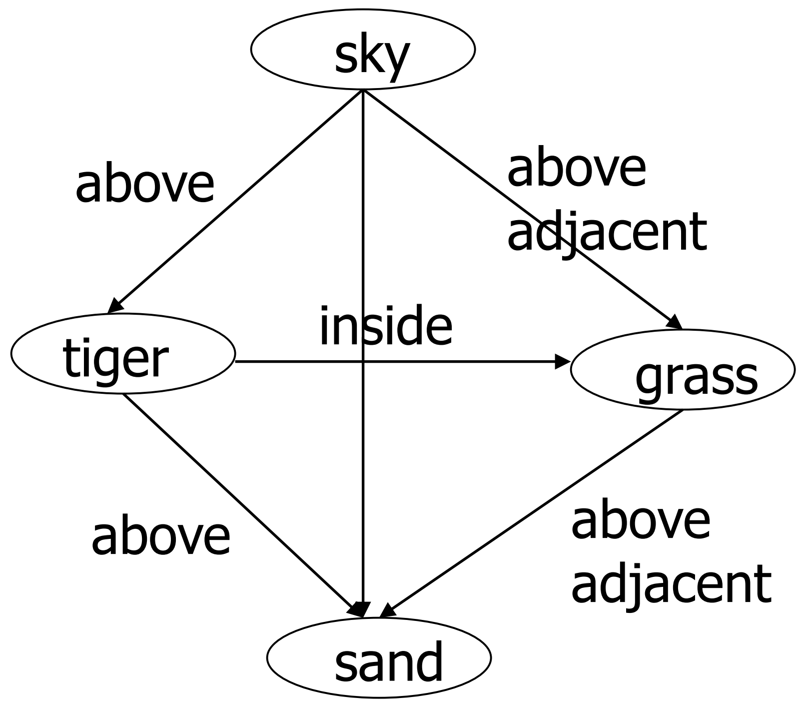
- Segmented the query (and all database images) using EM on color+texture
- Allowed users to select the most important region and what characteristics of it (color, texture, location)
- Asked users if the background was also important

Tiger Image as a Graph (motivated by Blobworld)

image

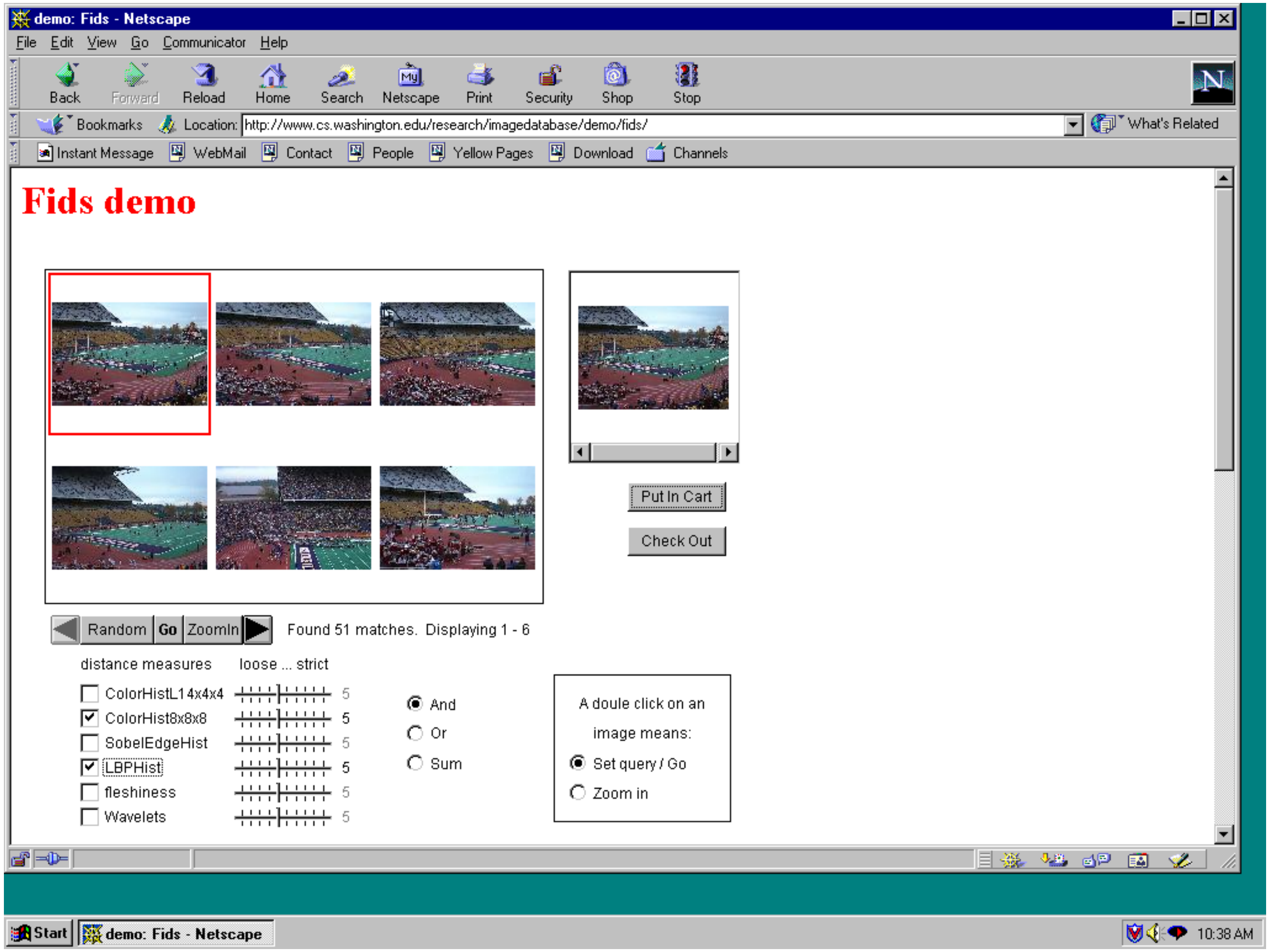


abstract regions



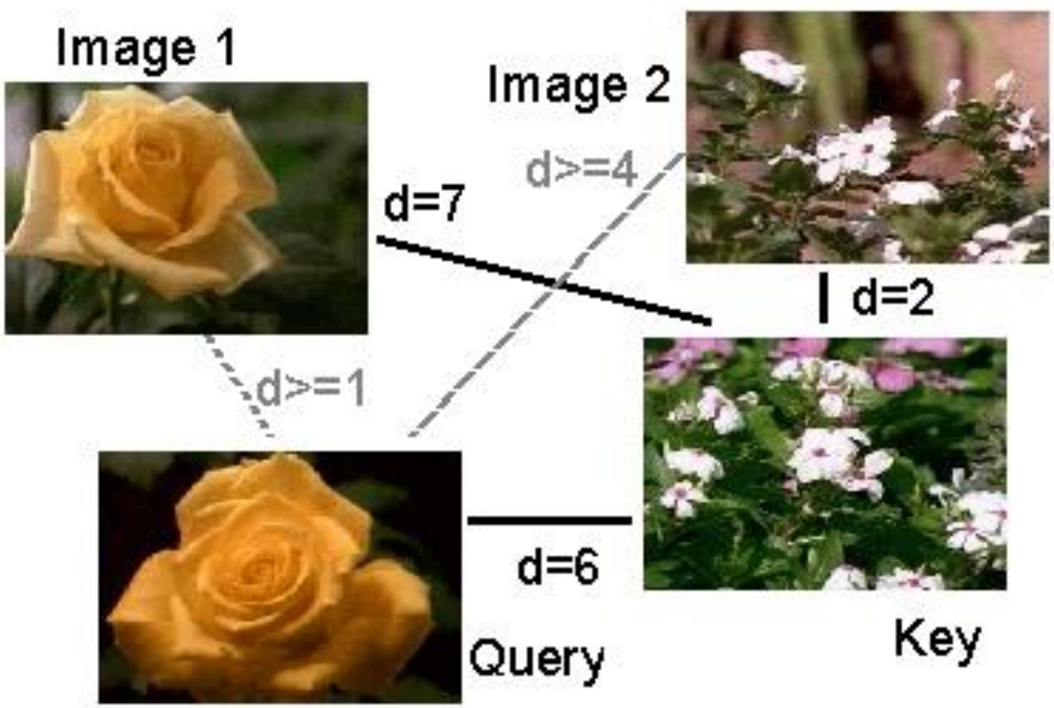
Andy Berman's FIDS System

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

Andy Berman's FIDS System:

Bare-Bones Algorithm with Multiple Distance Measures

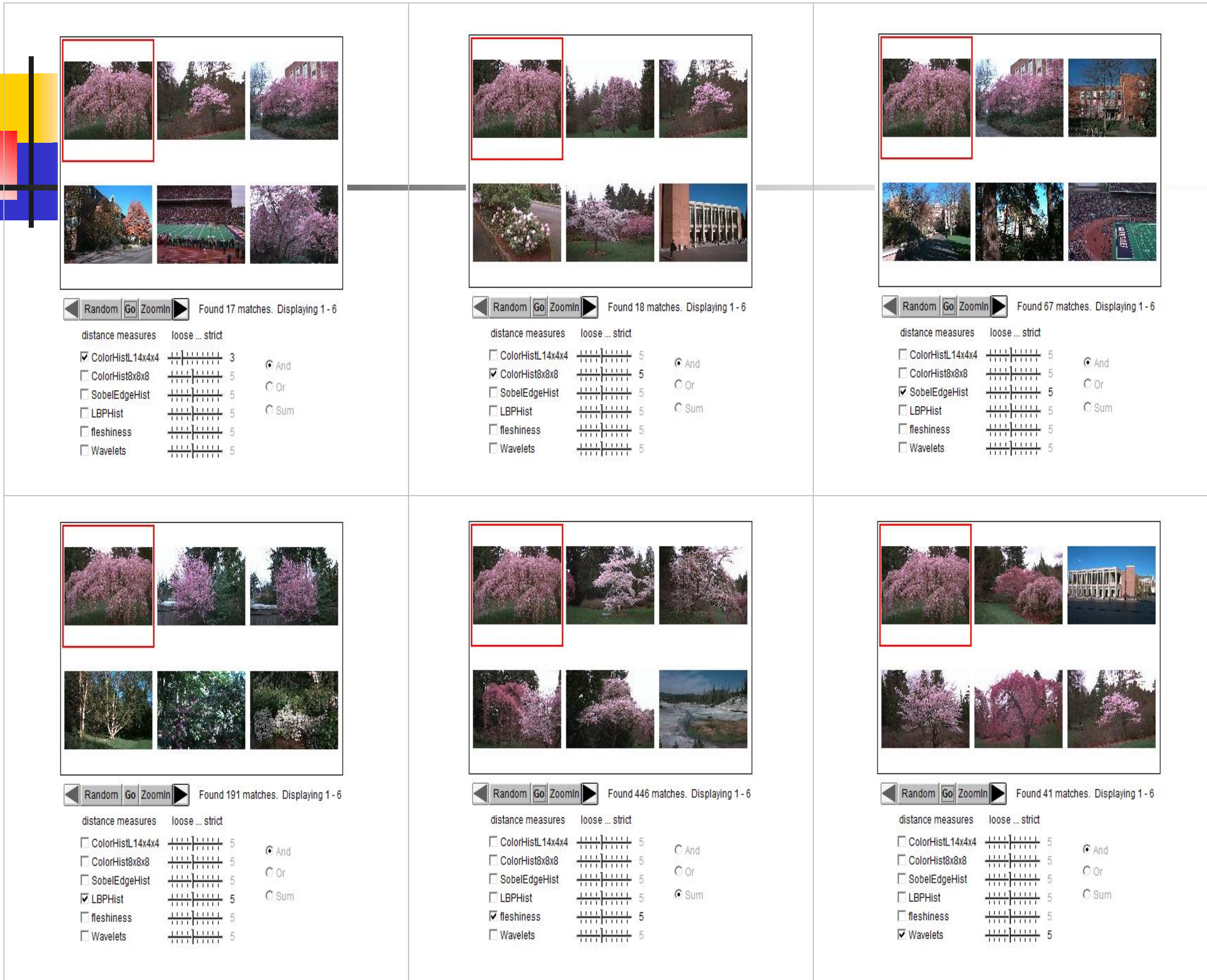
Offline

1. Choose key images for each measure
2. Store distances from database images to keys for all measures

Online (given query Q)

1. Calculate lower bounds for each measure
2. Combine to form lower bounds for composite measures
3. Continue as in single measure algorithm

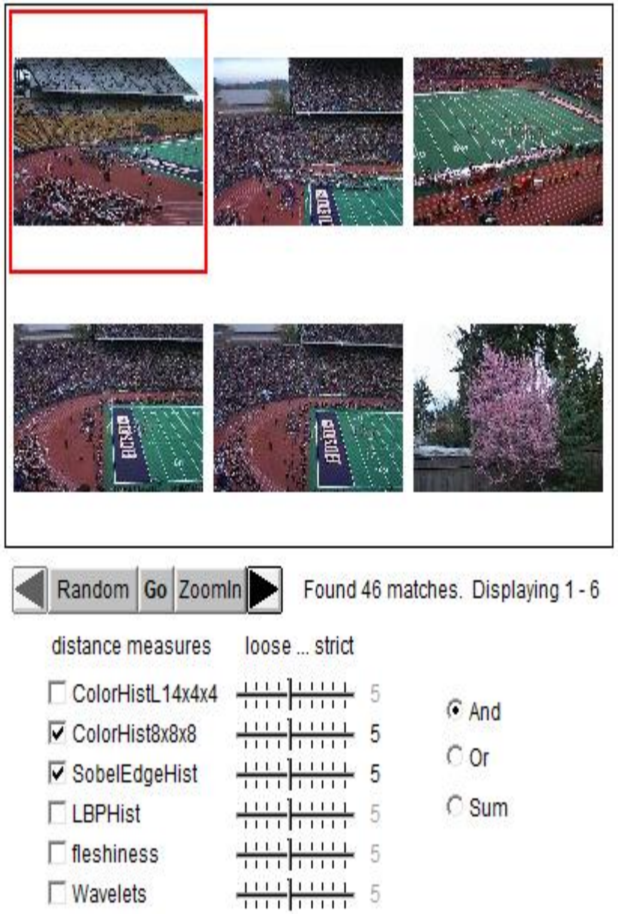
Different Features



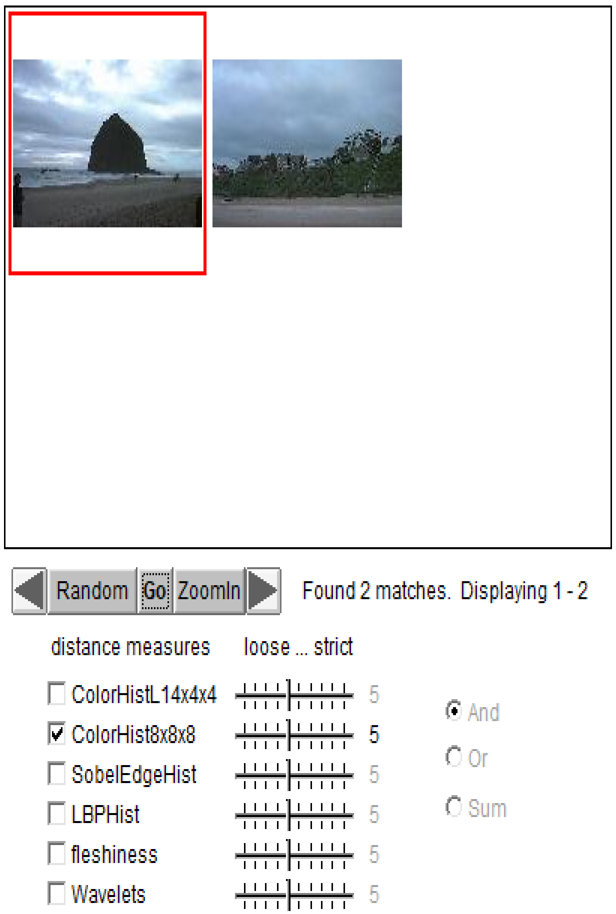
Combined Features

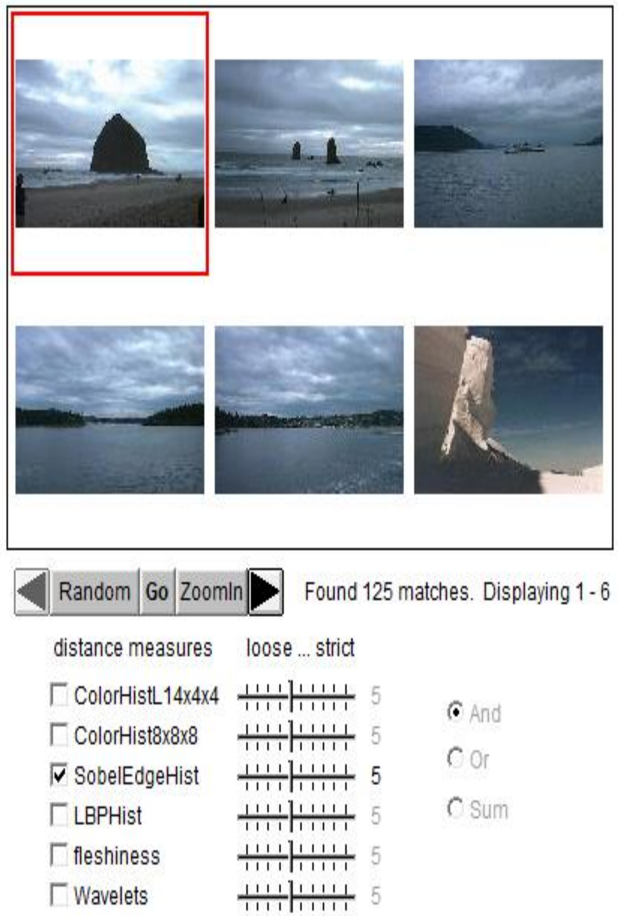
Another example: different features

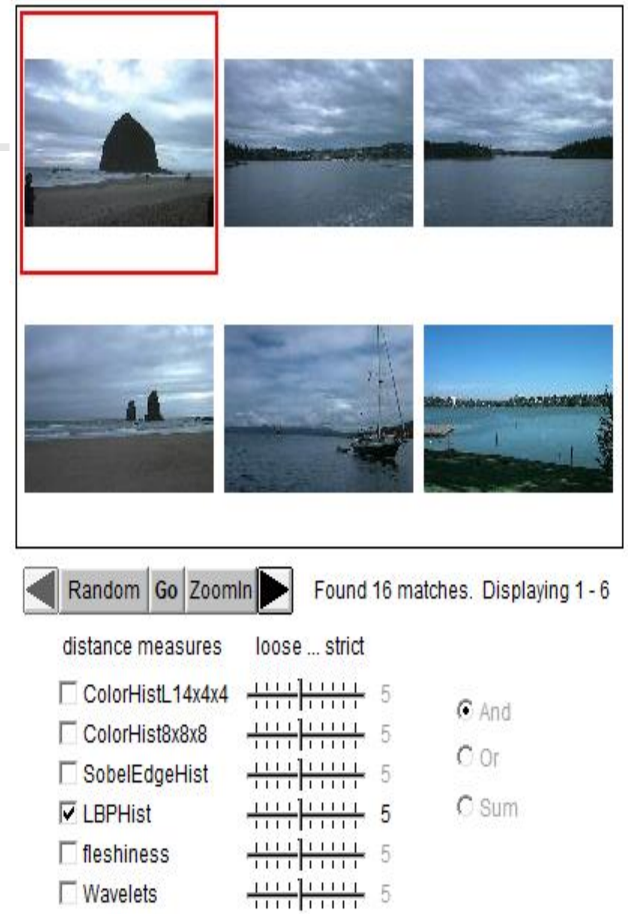
Combined Features



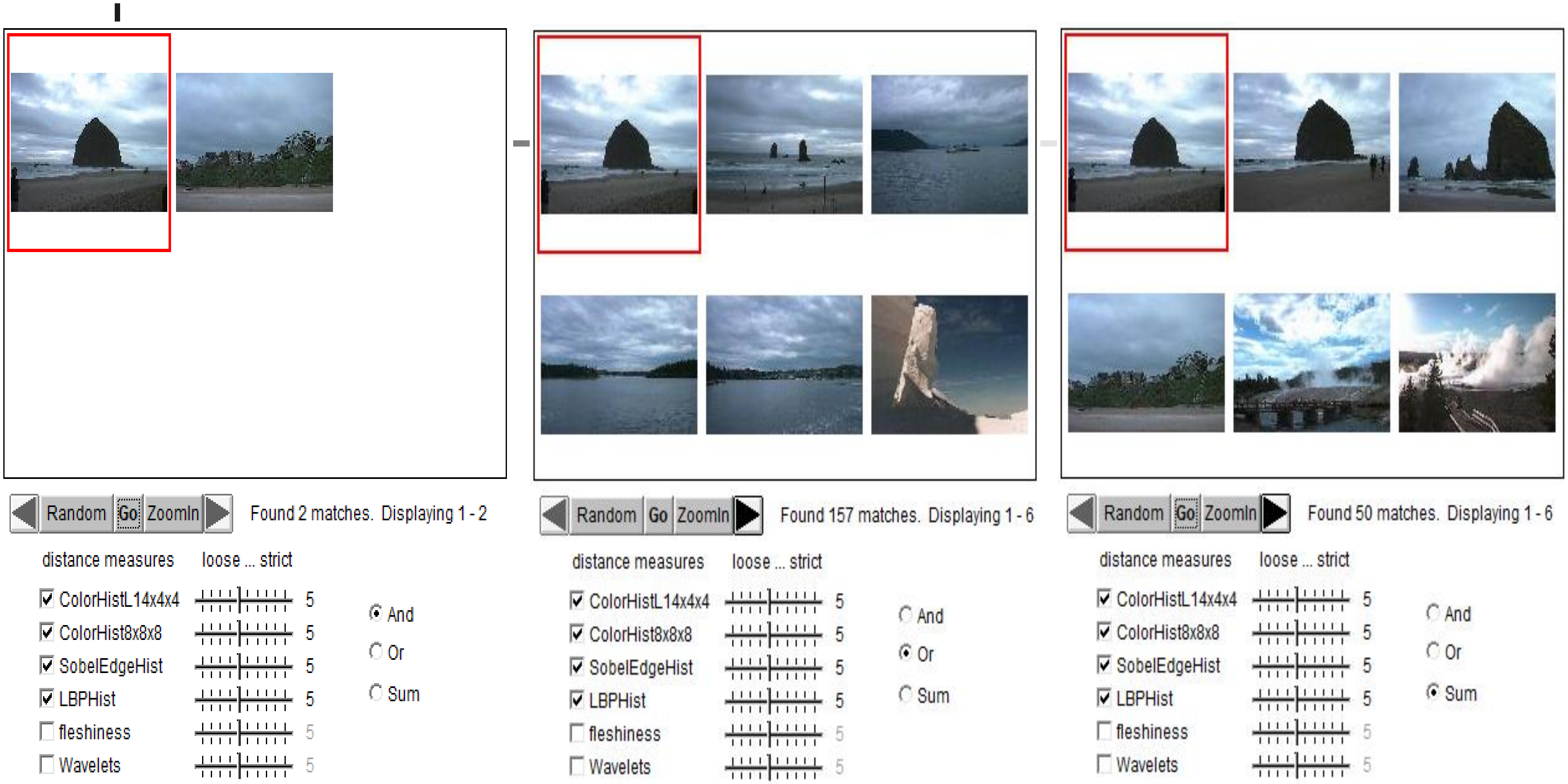
Another example: different features



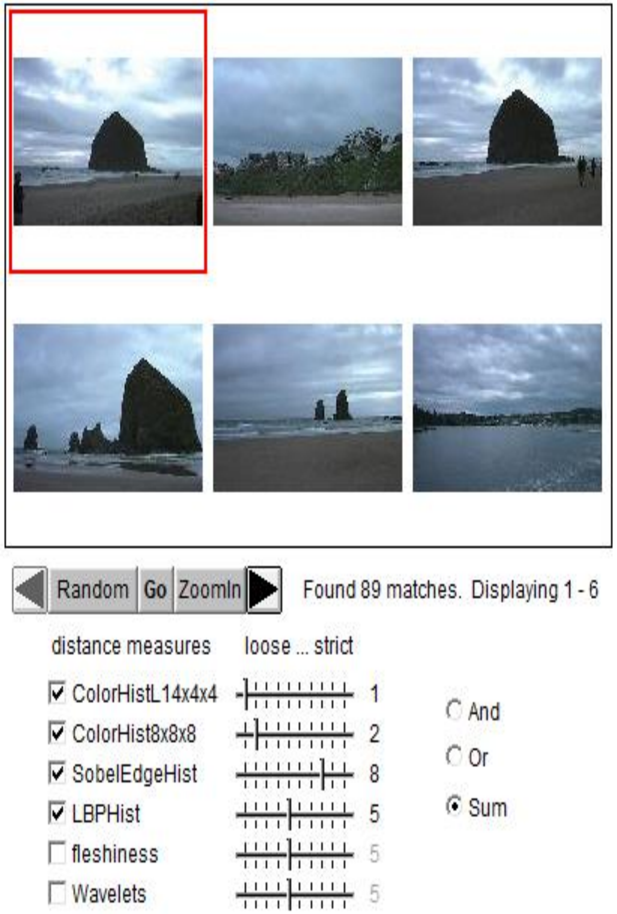




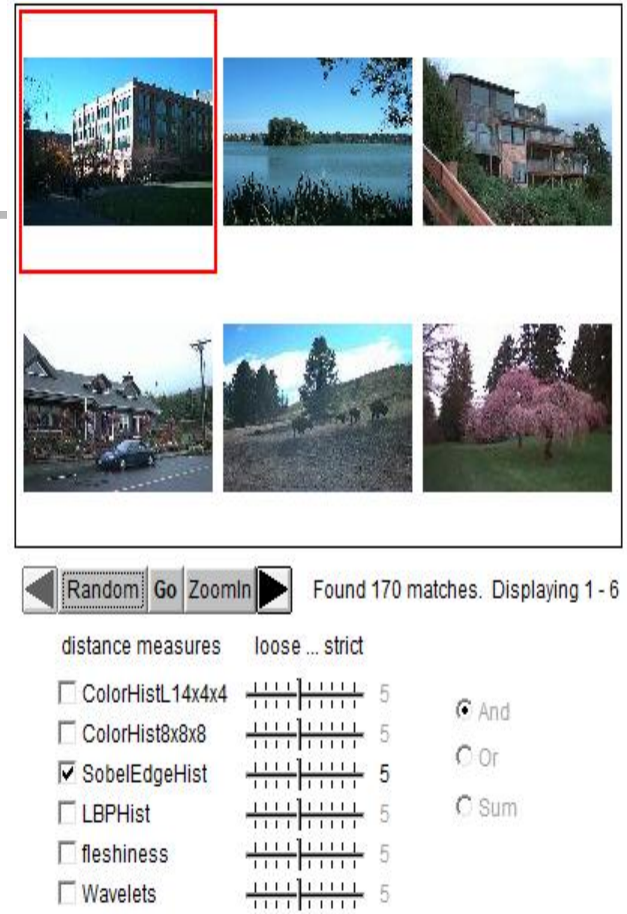
Different ways for combination



Different weights on features




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


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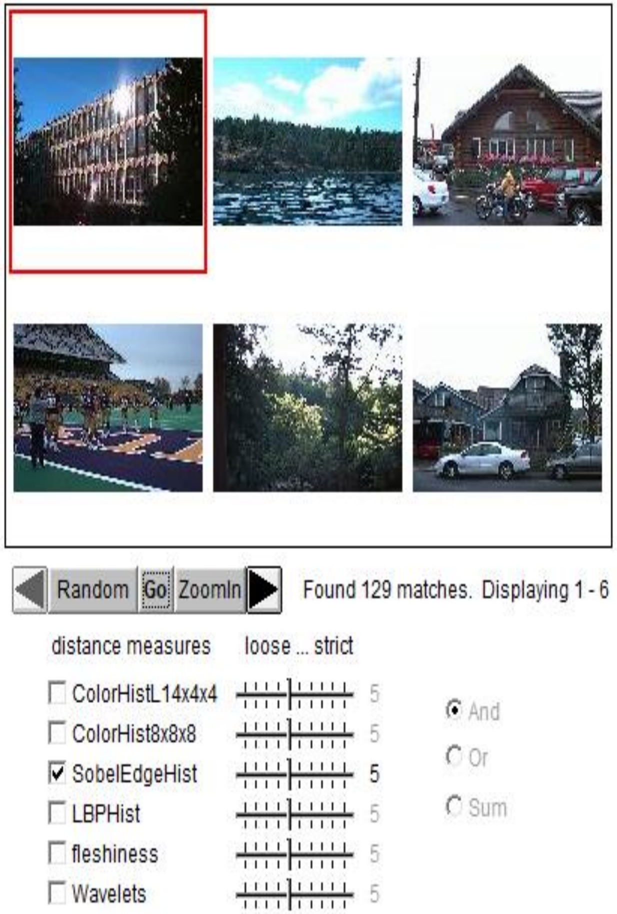
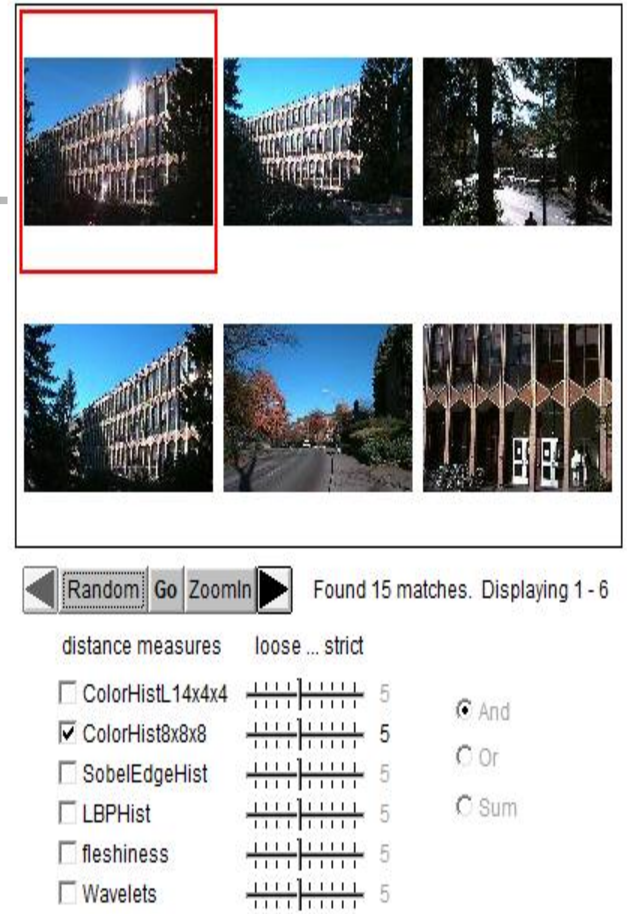
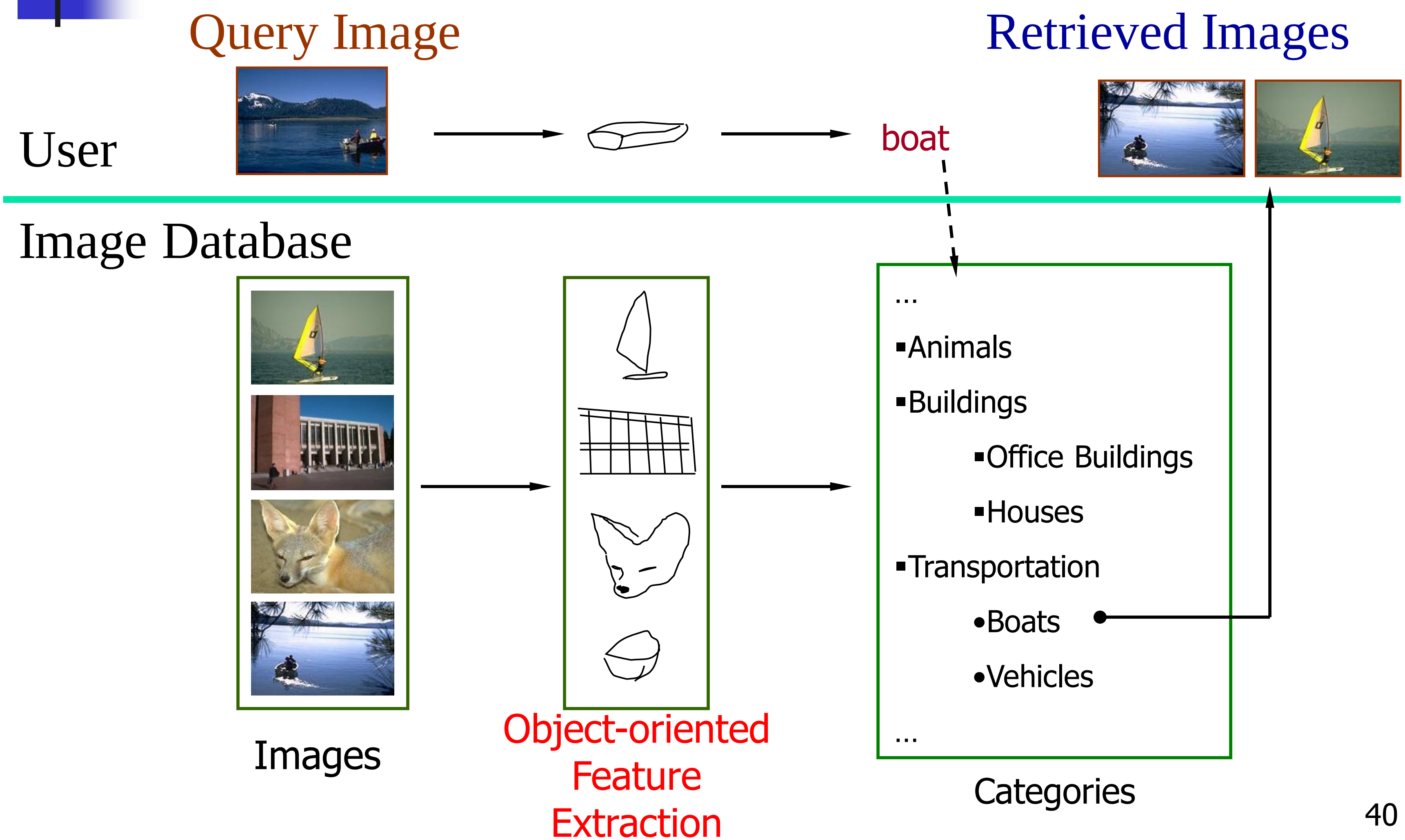

Random
Go
ZoomIn
Found 129 matches. Displaying 1 - 6
distance measures
loose ... strict
ColorHistL14x4x4 5
ColorHist8x8x8 5
SobelEdgeHist 5
LBPHist 5
fleshiness 5
Wavelets 5
And
Or
Sum


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

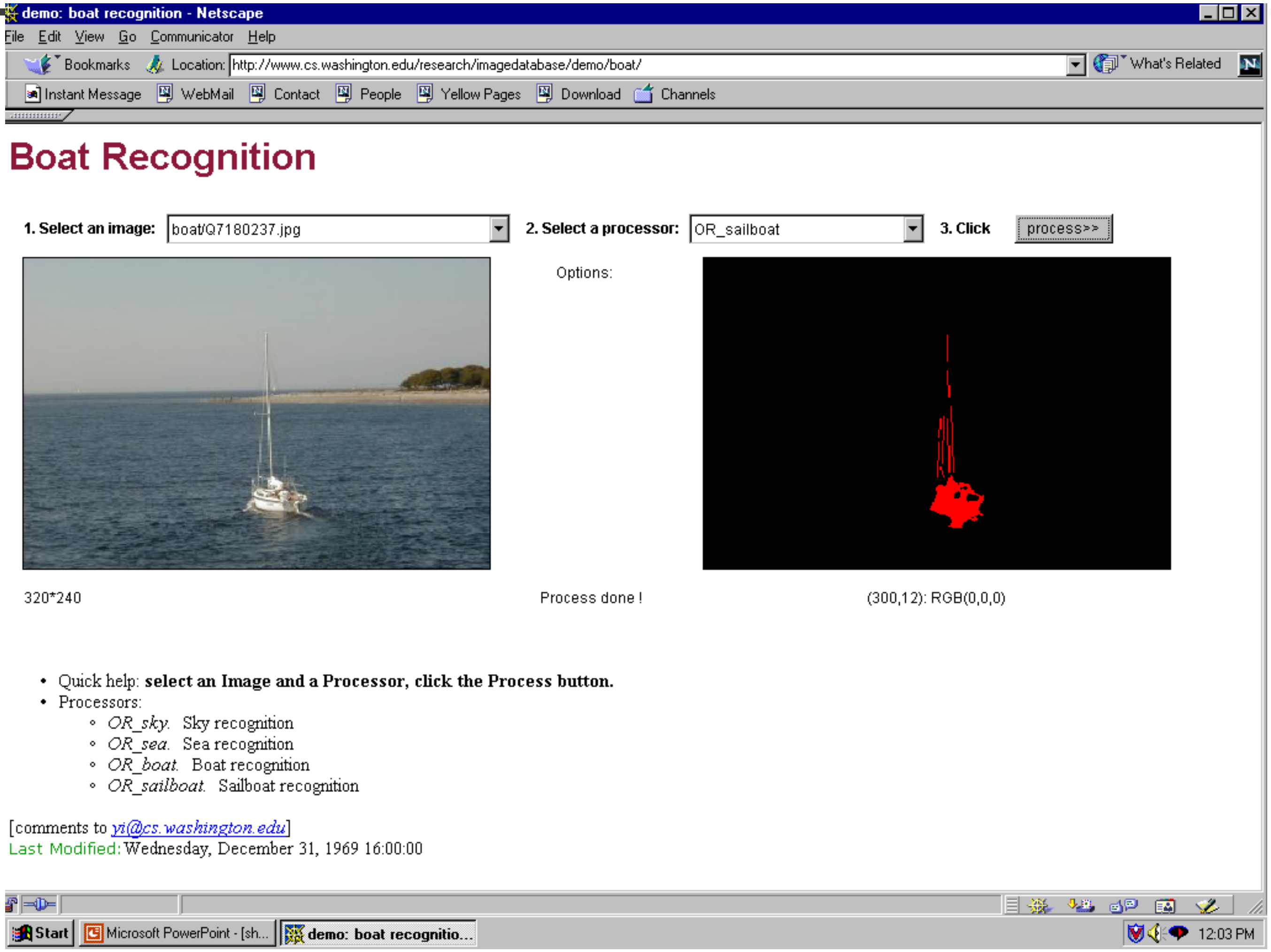
Research Objective



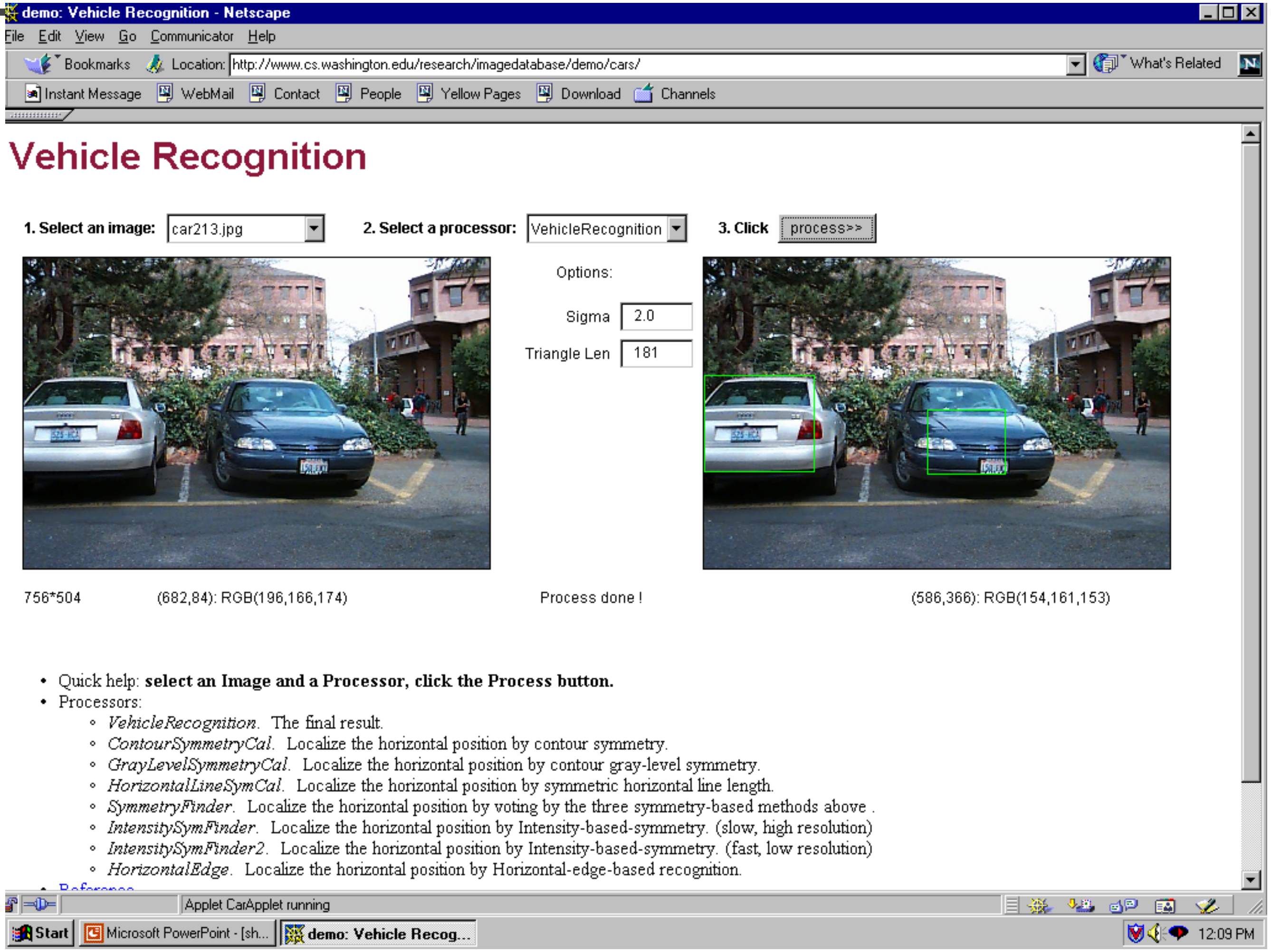
Overall Approach

- 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

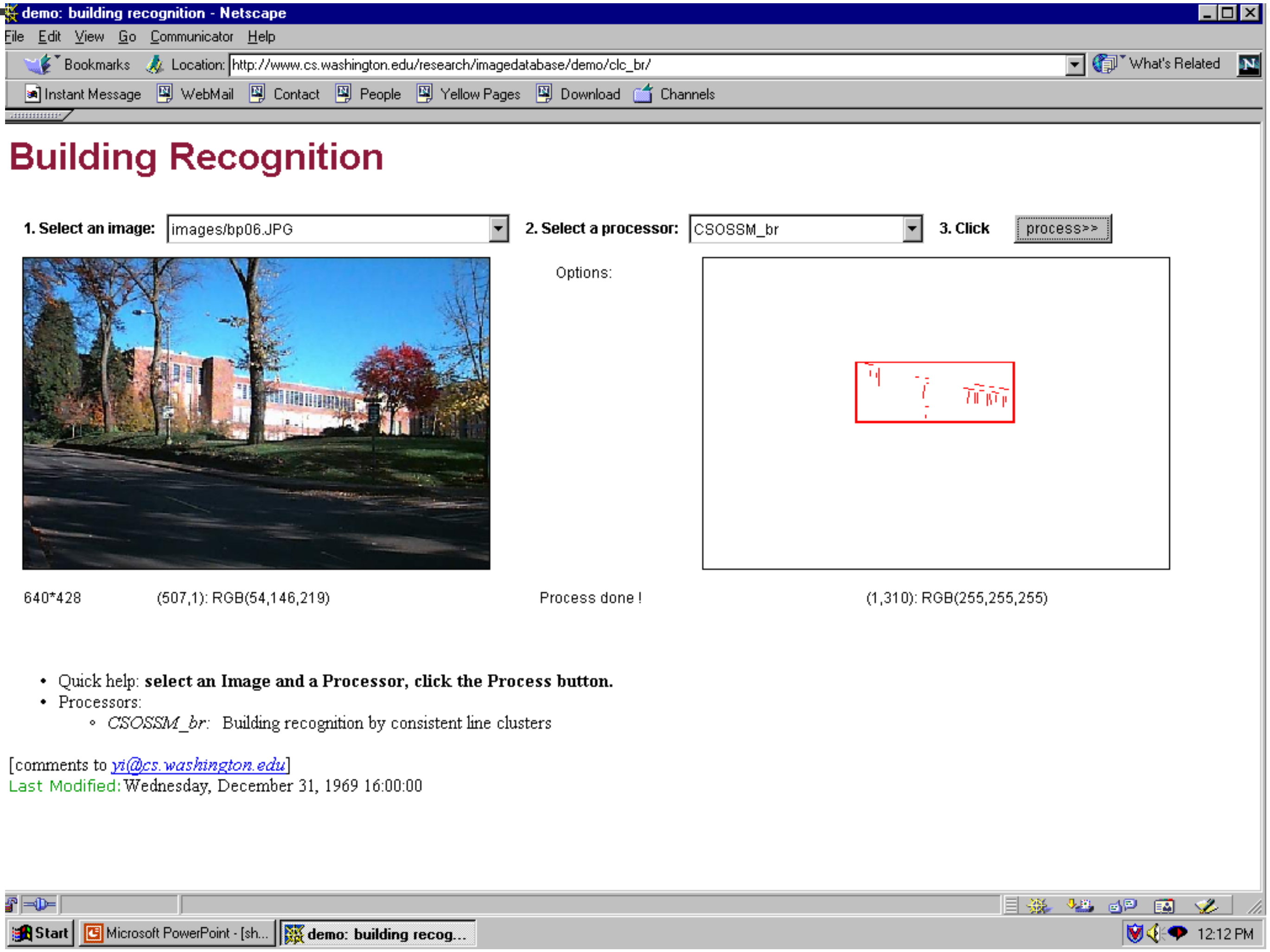
Boat Recognition



Vehicle Recognition



Building Recognition



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.

Color-CLC

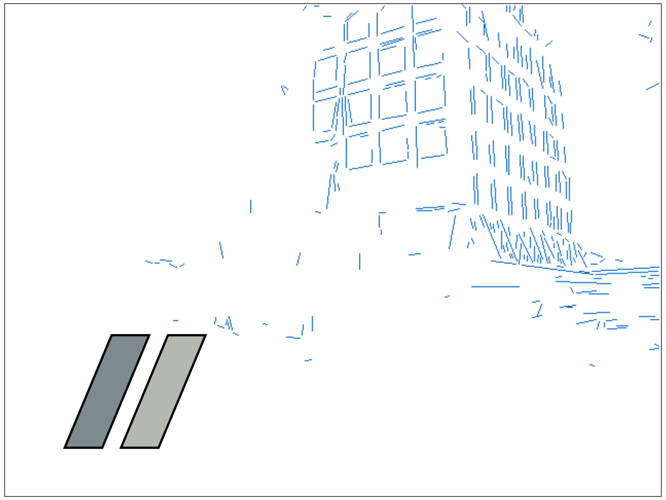
- Color feature of lines: color pair (c_1,c_2)
- Color pair space:

  RGB (256^3*256^3) Too big!

  Dominant colors (20*20)
- Finding the color pairs:

  One line $\rightarrow$ Several color pairs
- Constructing Color-CLC: use clustering

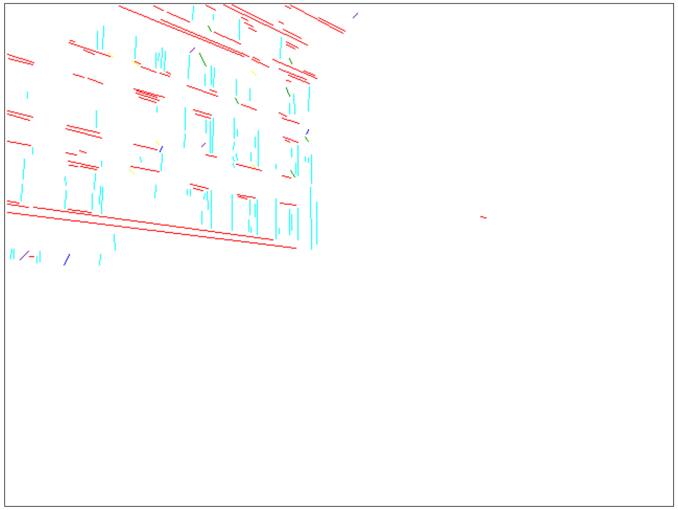
Color-CLC

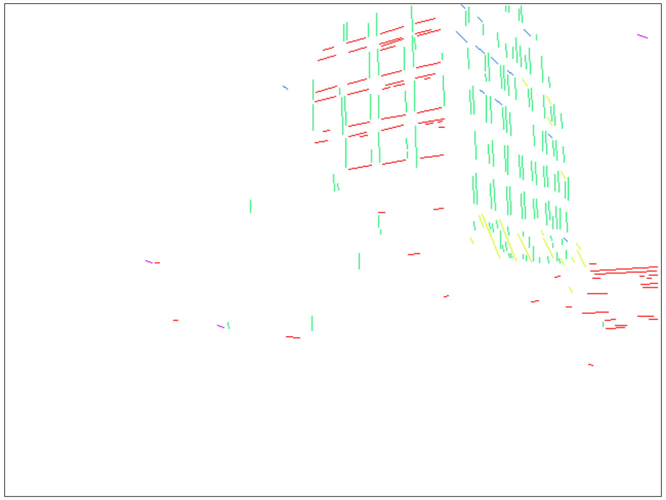


Orientation-CLC

- The lines in an Orientation-CLC are parallel to each other in the 3D world
- The parallel lines of an object in a 2D image can be:
  - Parallel in 2D
  - Converging to a vanishing point (perspective)

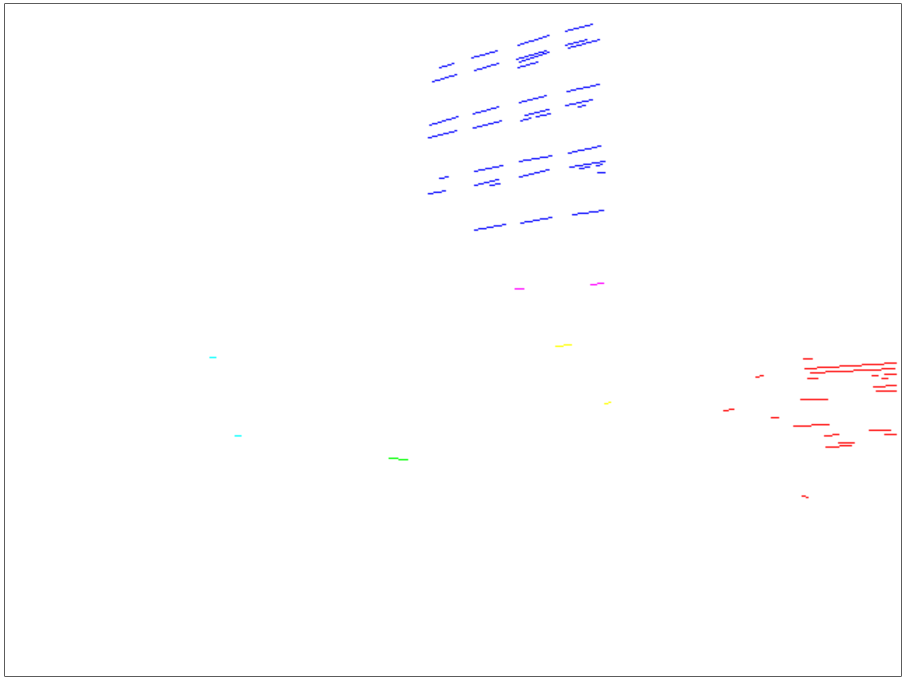
Orientation-CLC





Spatially-CLC

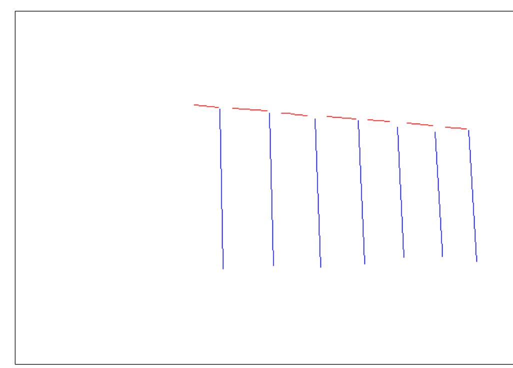
- Vertical position clustering
- Horizontal position clustering

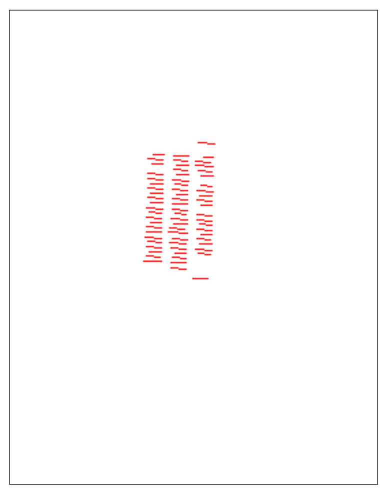


Building Recognition by CLC

Two types of buildings → Two criteria

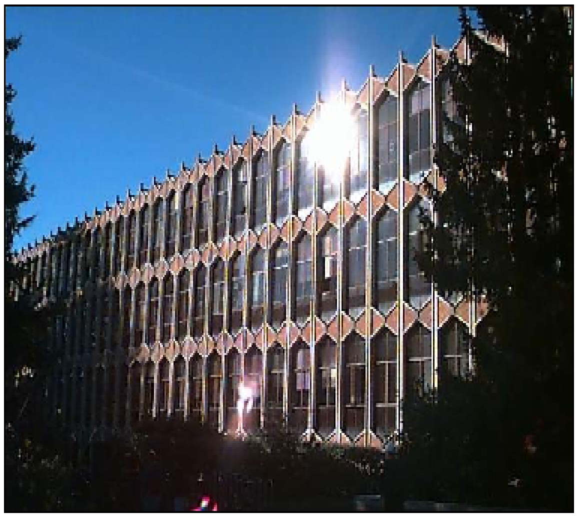
- Inter-relationship criterion
- Intra-relationship criterion



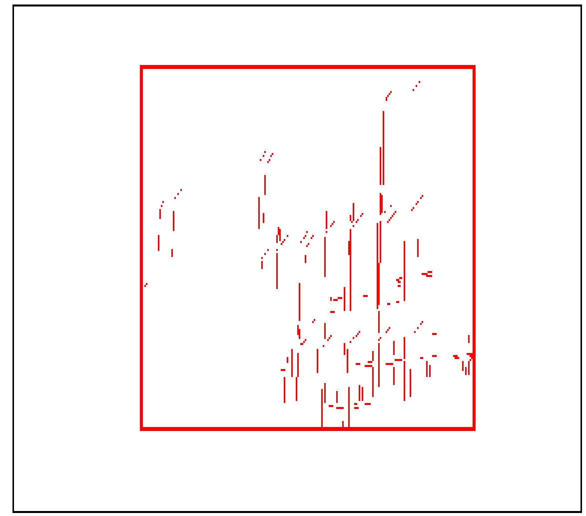


Building Recognition

1. Select an image: images/bp11.JPG 2. Select a processor: CSOSSM_br 3. Click process>>



Options:



640*428 (616,0): RGB(29,30,24) Process done ! (386,402): RGB(255,255,255)

- Quick help: **select an Image and a Processor, click the Process button.**
- Processors:
  - *CSOSSM_br:* Building recognition by consistent line clusters

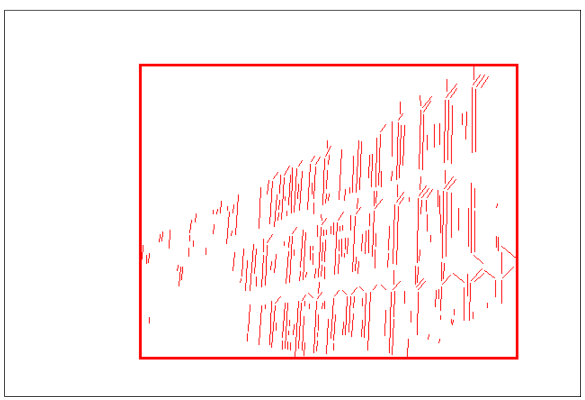
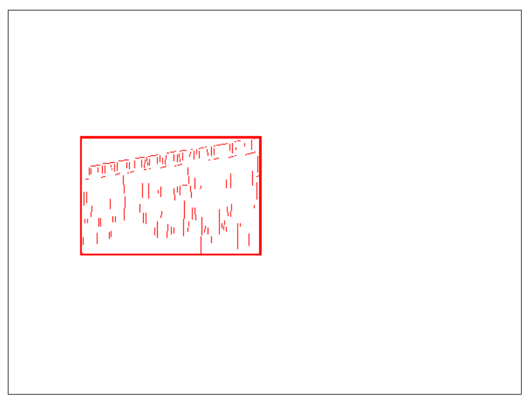
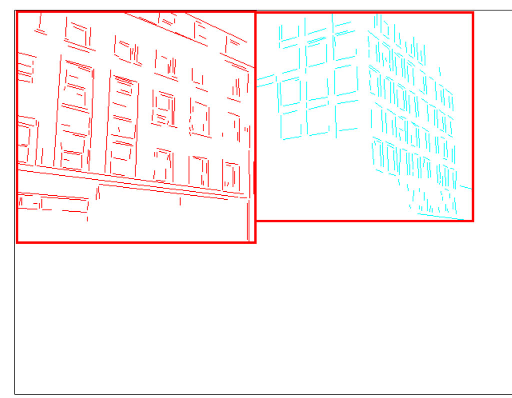
Experimental Evaluation

- 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

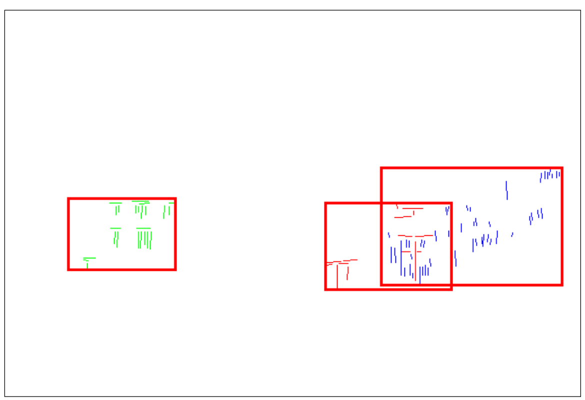
Well-Patterned Buildings

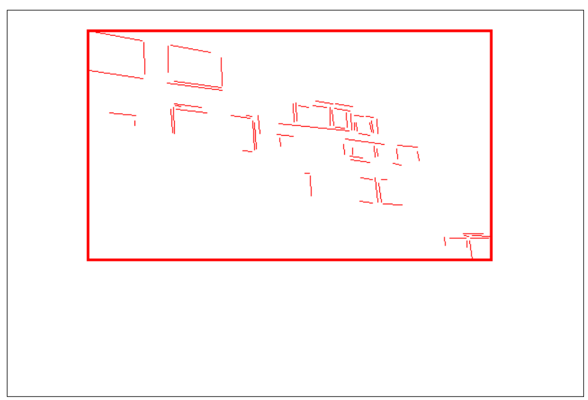


Experimental Evaluation

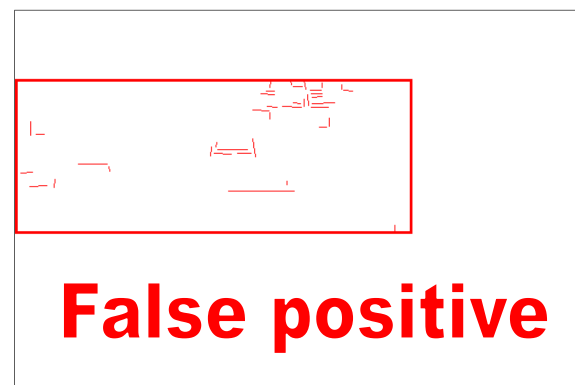
Non-Well-Patterned Buildings





Experimental Evaluation

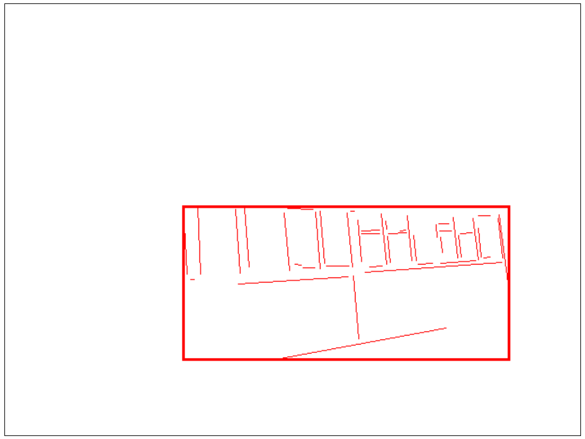
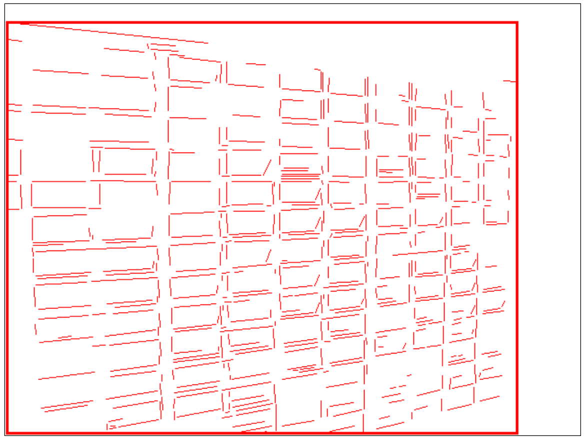
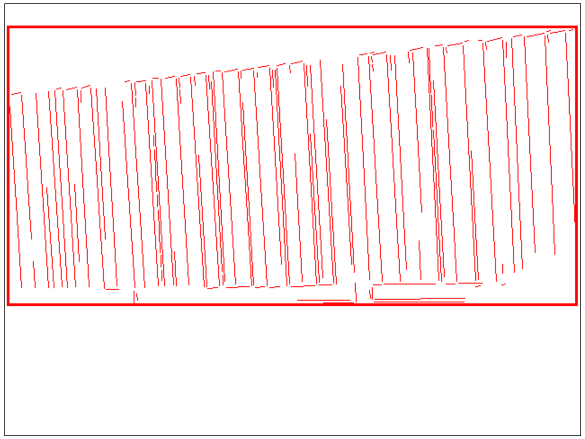
Non-Well-Patterned Non-Buildings



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