

# Content-Based Image Retrieval



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



# Content-based Image Retrieval (CBIR)

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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

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- 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?

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- 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

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- 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

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- Google Images

<http://www.google.com/imghp>

Try the camera icon.

The logo graphic consists of three overlapping squares: a yellow one at the top left, a red one at the bottom left, and a blue one at the bottom right. A black crosshair is centered over the intersection of the squares.

# Microsoft Bing

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- <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







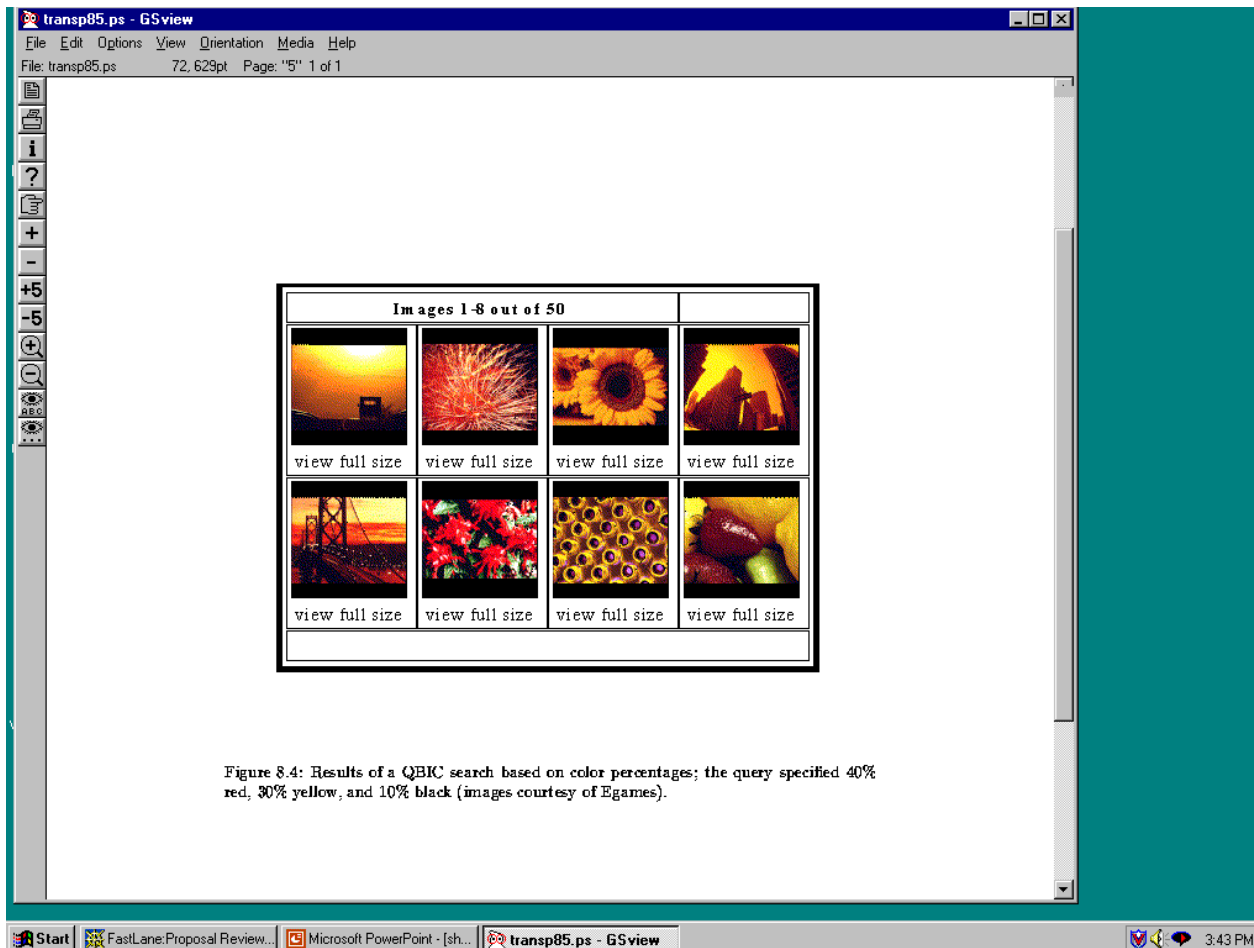
# Features

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- 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

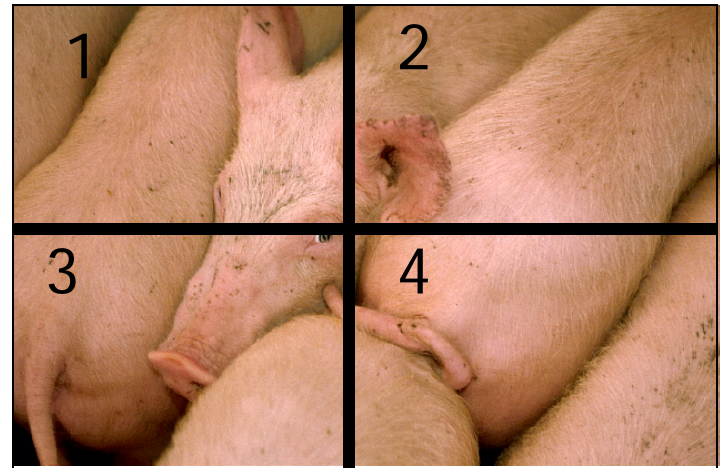
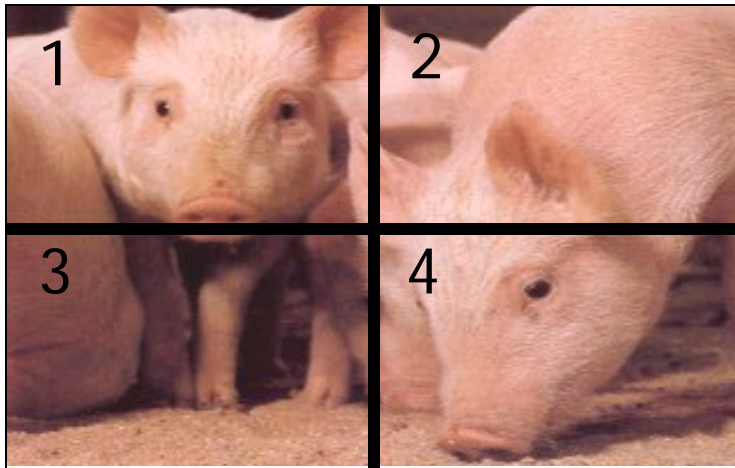
This is the most powerful, but you have to be able to recognize the objects!

# 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)

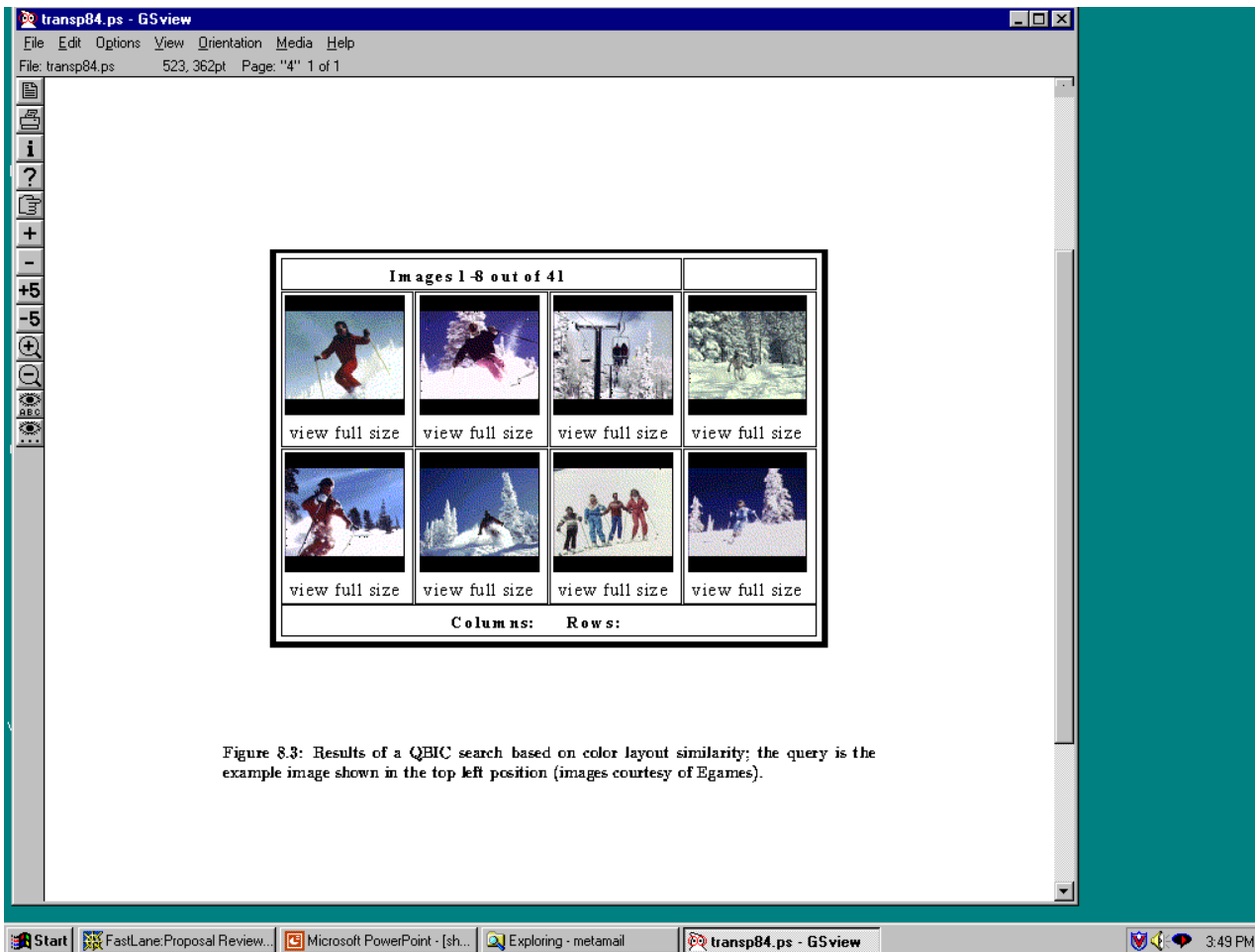


Figure 8.3: Results of a QBIC search based on color layout similarity; the query is the example image shown in the top left position (images courtesy of Egames).

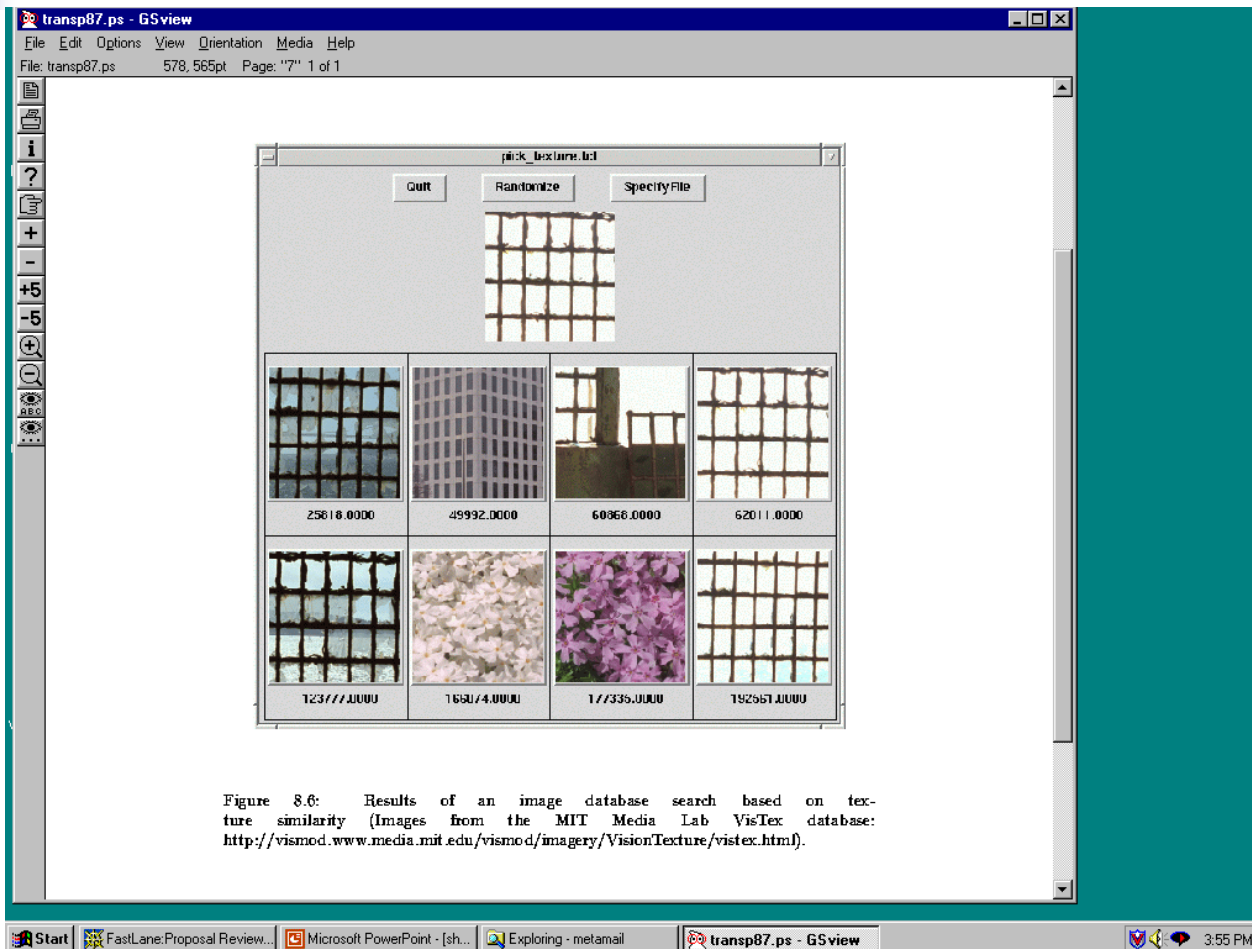


# Texture Distances

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- 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



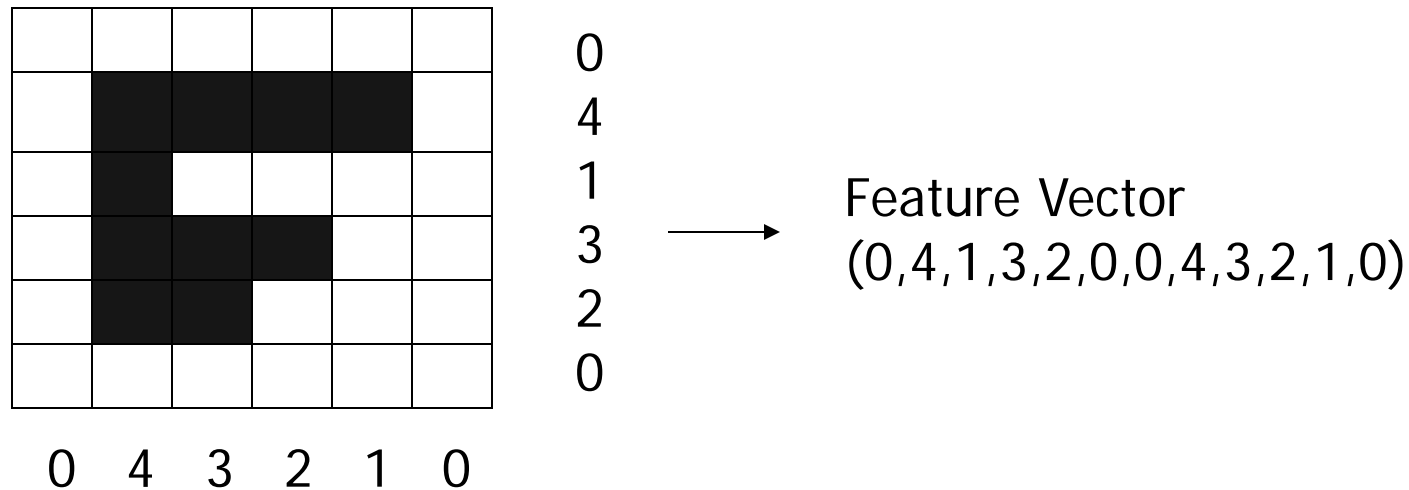


# Shape Distances

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- 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

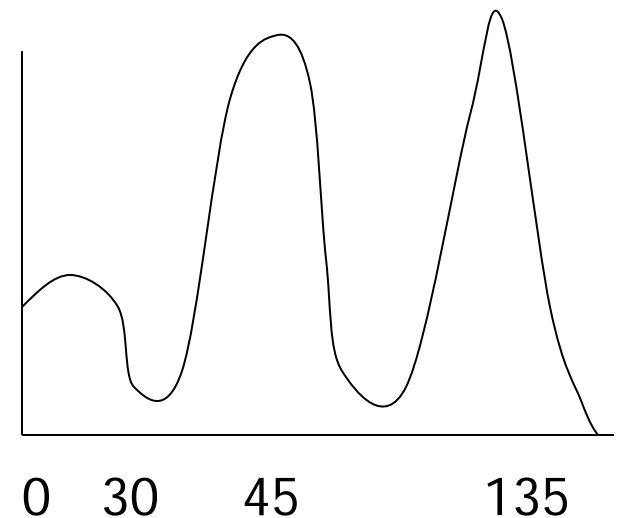
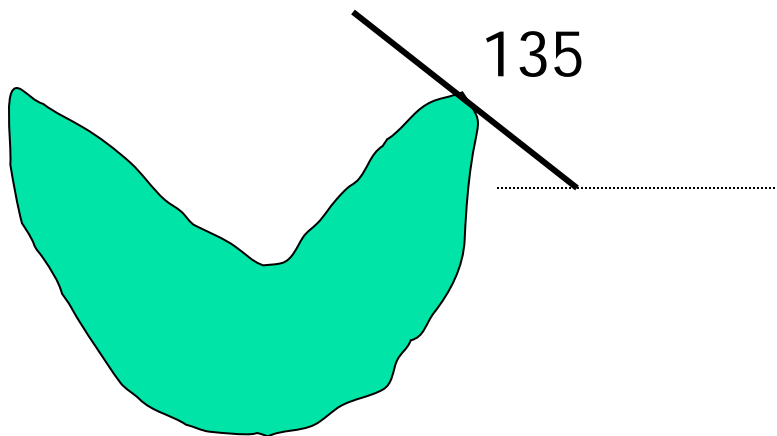


In projection matching, the horizontal and vertical projections form a histogram.

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

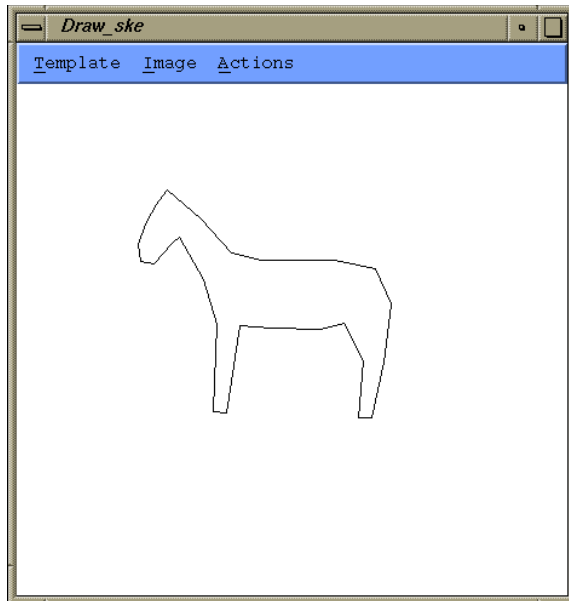
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- Fourier Descriptors
- Sides and Angles
- Elastic Matching

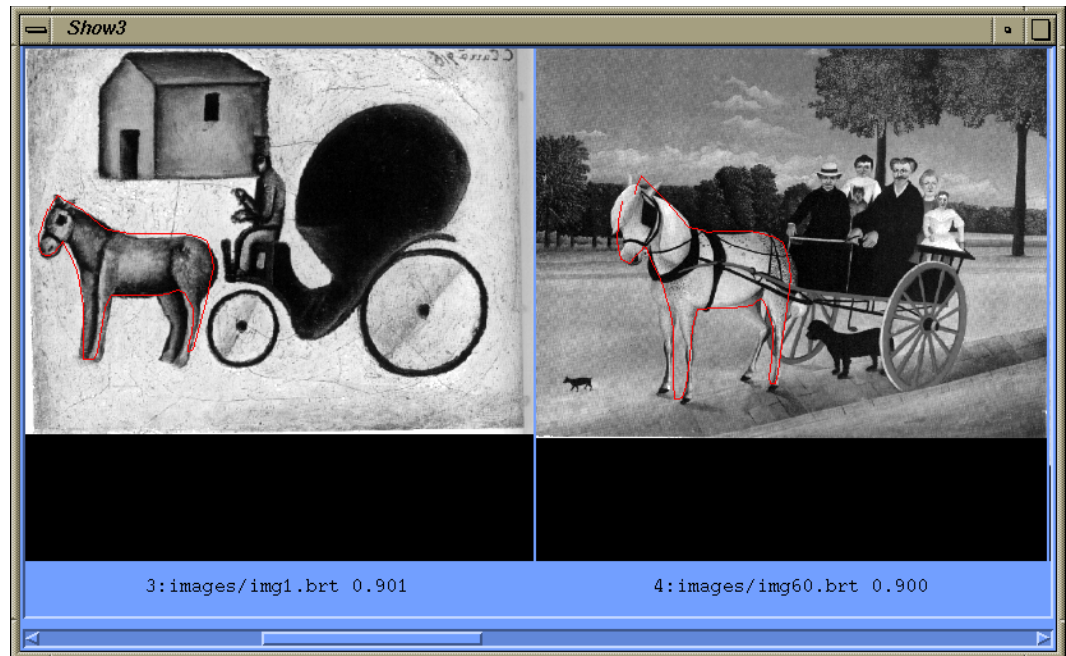
The distance between query shape and image shape has two components:

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

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- 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)

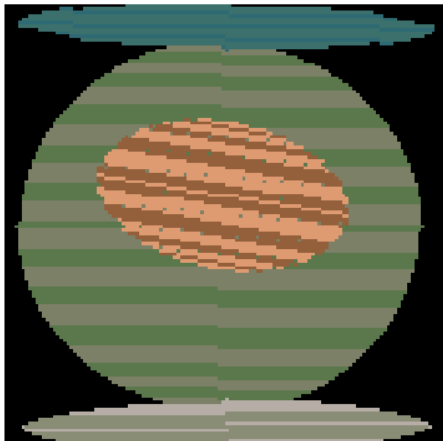


- Segmented the query (and all database images) using EM on color+texture
- Allowed users to select the most important region and what characteristics of it (color, texture, location)
- Asked users if the background was also important

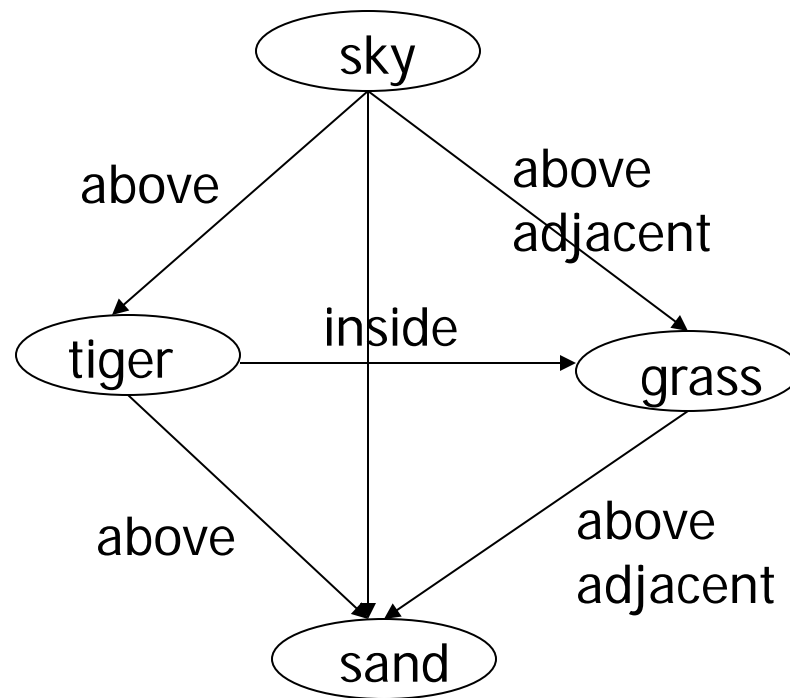
# Tiger Image as a Graph (motivated by Blobworld)



image



abstract regions



# Andy Berman's FIDS System

multiple distance measures

Boolean and linear combinations

efficient indexing using images as keys

**Fids demo**

Put In Cart  
Check Out

Random Go ZoomIn Found 51 matches. Displaying 1 - 6

distance measures loose ... strict

<input type="checkbox"/> ColorHistL14x4x4		5
<input checked="" type="checkbox"/> ColorHist8x8x8		5
<input type="checkbox"/> SobelEdgeHist		5
<input checked="" type="checkbox"/> LBPHist		5
<input type="checkbox"/> fleshiness		5
<input type="checkbox"/> Wavelets		5

And  
 Or  
 Sum

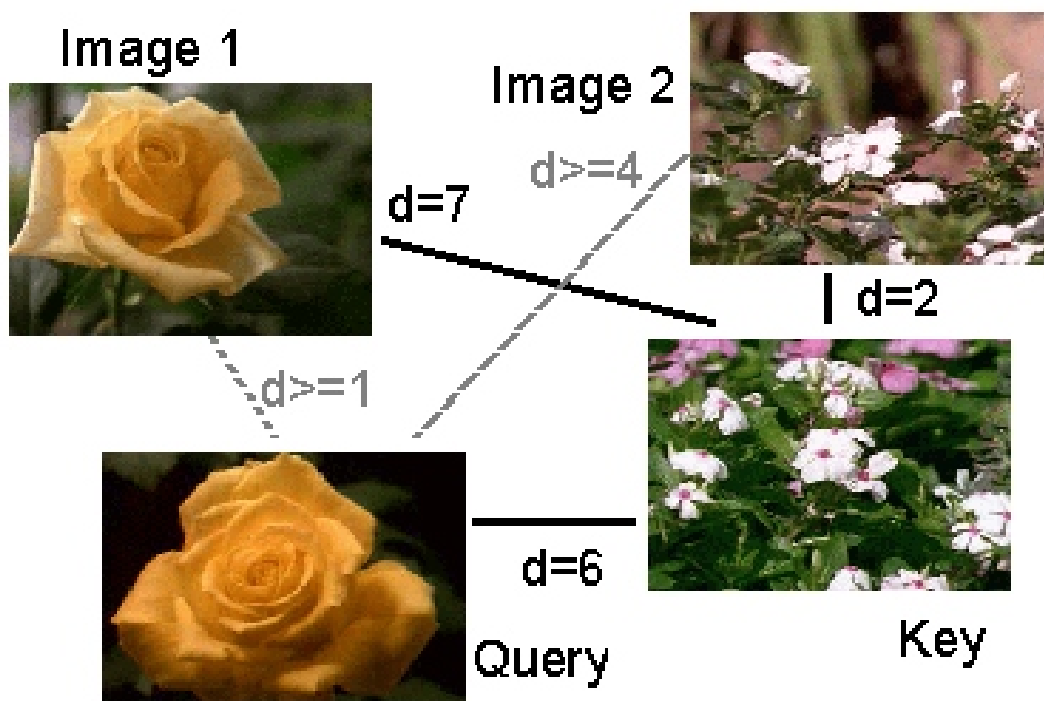
A double click on an image means:  
 Set query / Go  
 Zoom in

demo: Fids - Netscape

10:38 AM

## Andy Berman's FIDS System:

Use of **key images** and the **triangle inequality** for efficient retrieval.  $d(I,Q) \geq |d(I,K) - d(Q,K)|$





# Andy Berman's FIDS System:

## Bare-Bones Triangle Inequality Algorithm

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### 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

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### 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



# Demo of FIDS

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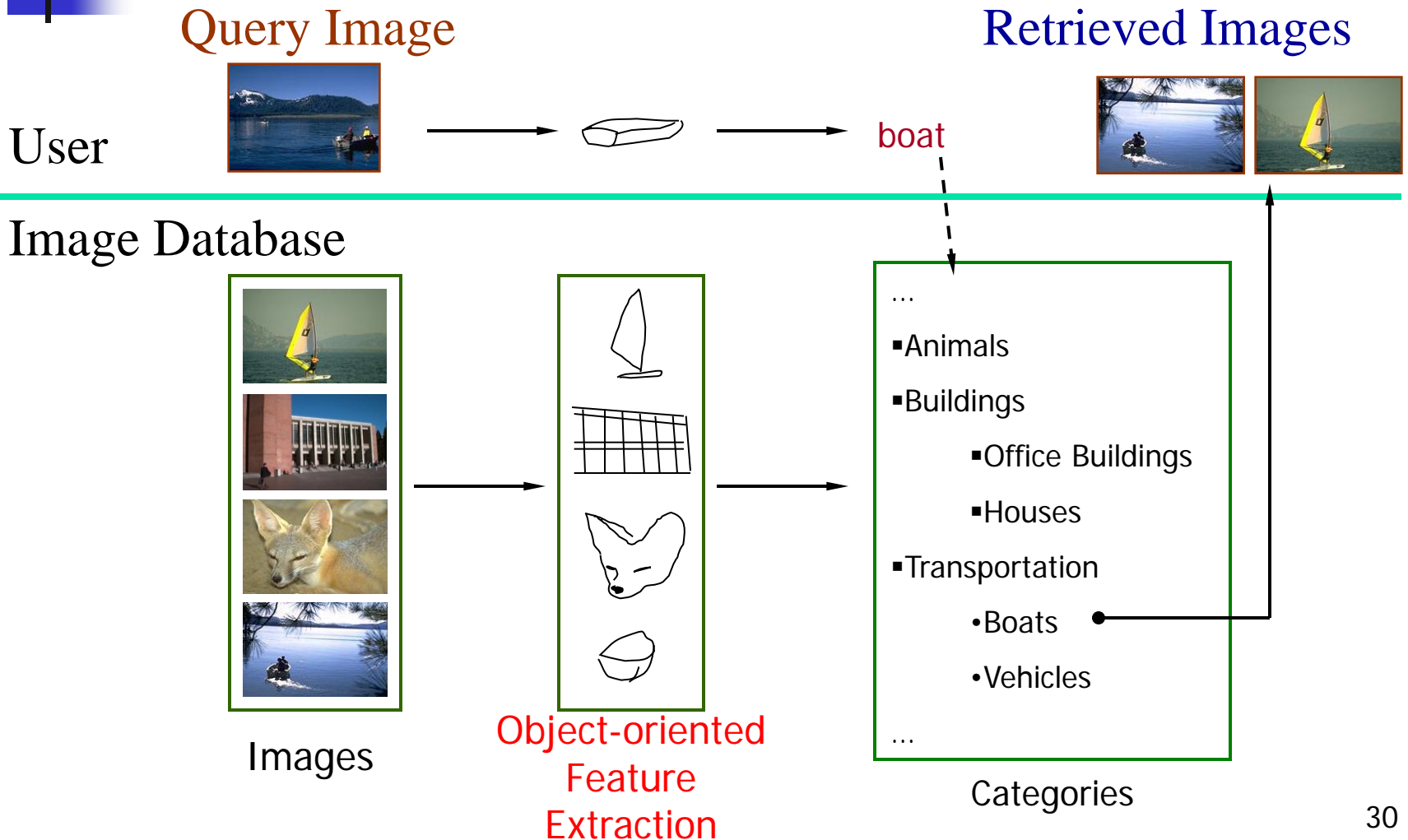
- <http://www.cs.washington.edu/research/imagedatabase/demo/>
- Try this and the other demos on the same page.
- First, in the Java control panel, add a site exception: <http://imagedatabase.cs.washington.edu/demo/fids/>
- Then make sure you are running 32 bit Firefox (or IE) with 32 bit Java (64 not tested)
- For IE, may have to enable Java plugins

# Weakness of Low-level Features

- Can't capture the high-level concepts



# Research Objective





# Overall Approach

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- 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

demo: boat recognition - Netscape

File Edit View Go Communicator Help


Bookmarks Location: <http://www.cs.washington.edu/research/imagetdatabase/demo/boat/> What's Related

Instant Message WebMail Contact People Yellow Pages Download Channels

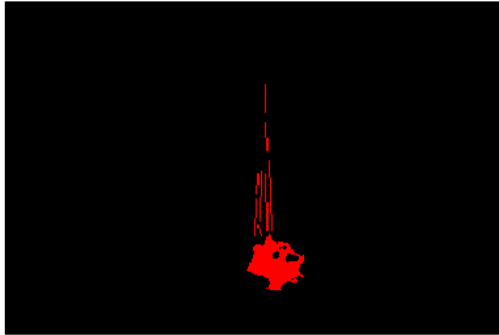
## Boat Recognition

1. Select an image:  2. Select a processor:  3. Click

Options:



320\*240



(300,12): RGB(0,0,0)

Process done !

- Quick help: **select an Image and a Processor, click the Process button.**
- Processors:
  - *OR\_sky*: Sky recognition
  - *OR\_sea*: Sea recognition
  - *OR\_boat*: Boat recognition
  - *OR\_sailboat*: Sailboat recognition

[comments to [yi@cs.washington.edu](mailto:yi@cs.washington.edu)]  
Last Modified: Wednesday, December 31, 1969 16:00:00

Start Microsoft PowerPoint - [sh...] demo: boat recognitio... 12:03 PM



# Vehicle Recognition

demo: Vehicle Recognition - Netscape

File Edit View Go Communicator Help

Location: <http://www.cs.washington.edu/research/imagetatabase/demo/cars/>

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## Vehicle Recognition

1. Select an image:  2. Select a processor:  3. Click

Options:

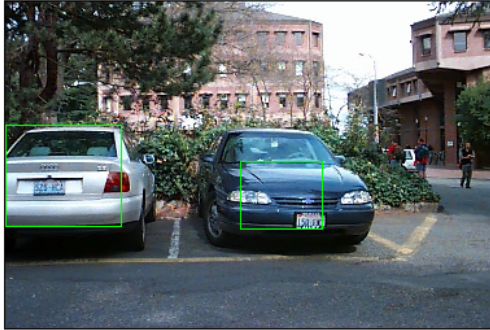
Sigma

Triangle Len



756\*504 (682,84): RGB(196,166,174)

Process done!



(586,366): RGB(154,161,153)

- Quick help: **select an Image and a Processor, click the Process button.**
- Processors:
  - *VehicleRecognition*. The final result.
  - *ContourSymmetryCal*. Localize the horizontal position by contour symmetry.
  - *GrayLevelSymmetryCal*. Localize the horizontal position by contour gray-level symmetry.
  - *HorizontalLineSymCal*. Localize the horizontal position by symmetric horizontal line length.
  - *SymmetryFinder*. Localize the horizontal position by voting by the three symmetry-based methods above.
  - *IntensitySymFinder*. Localize the horizontal position by Intensity-based-symmetry. (slow, high resolution)
  - *IntensitySymFinder2*. Localize the horizontal position by Intensity-based-symmetry. (fast, low resolution)
  - *HorizontalEdge*. Localize the horizontal position by Horizontal-edge-based recognition.

Applet CarApplet running

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# Building Recognition

demo: building recognition - Netscape


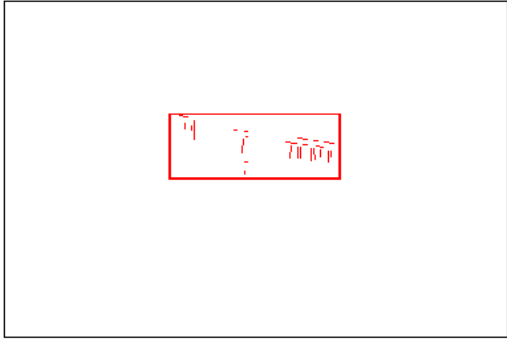
File Edit View Go Communicator Help

Location: [http://www.cs.washington.edu/research/imagedatabase/demo/clk\\_br/](http://www.cs.washington.edu/research/imagedatabase/demo/clk_br/)

Instant Message WebMail Contact People Yellow Pages Download Channels

## Building Recognition

1. Select an image:  2. Select a processor:  3. Click

 Options: 

640\*428 (507,1): RGB(54,146,219) Process done! (1,310): 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

[comments to [yi@cs.washington.edu](mailto:yi@cs.washington.edu)]  
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Start Microsoft PowerPoint - [sh...] demo: building recog... 12:12 PM



# Building Features: Consistent Line Clusters (CLC)

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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.

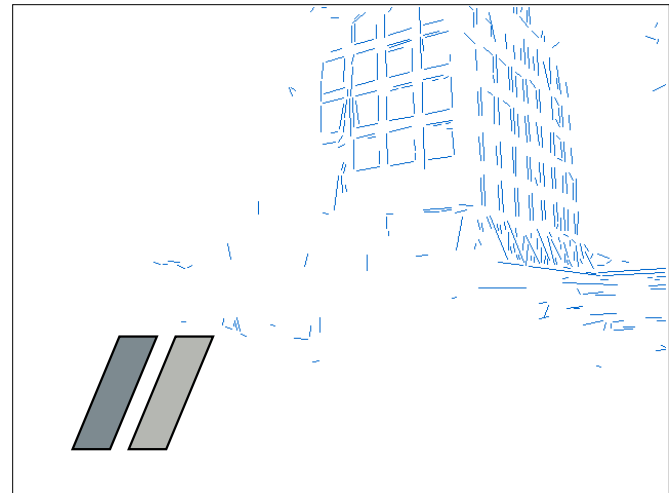


# Color-CLC

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- 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

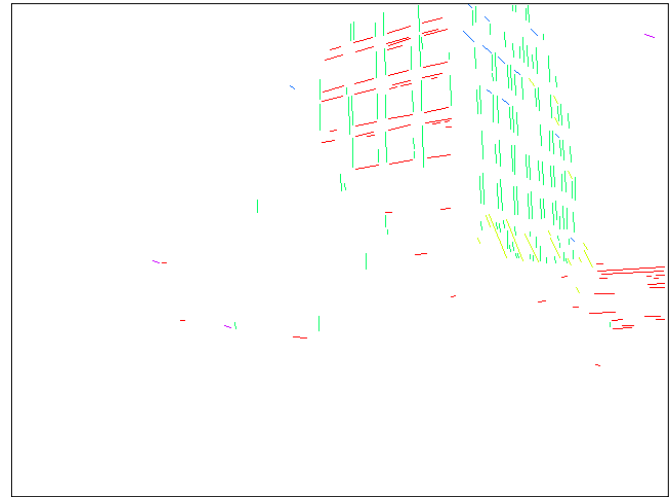
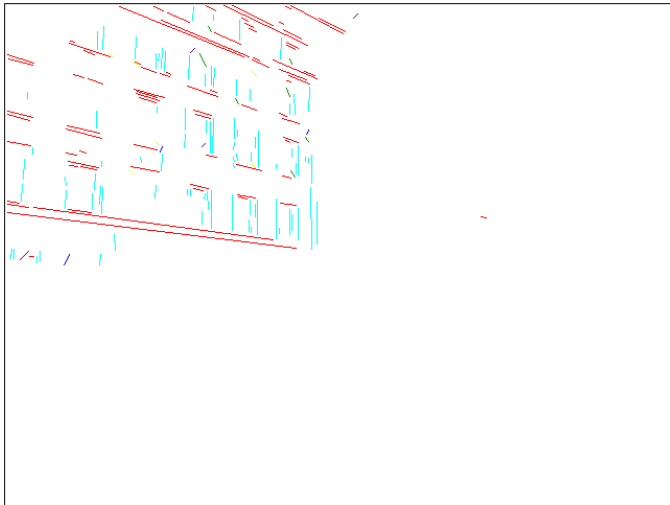
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- The lines in an Orientation-CLC are parallel to each other in the 3D world
- The parallel lines of an object in a 2D image can be:
  - Parallel in 2D
  - Converging to a vanishing point (perspective)



# Orientation-CLC

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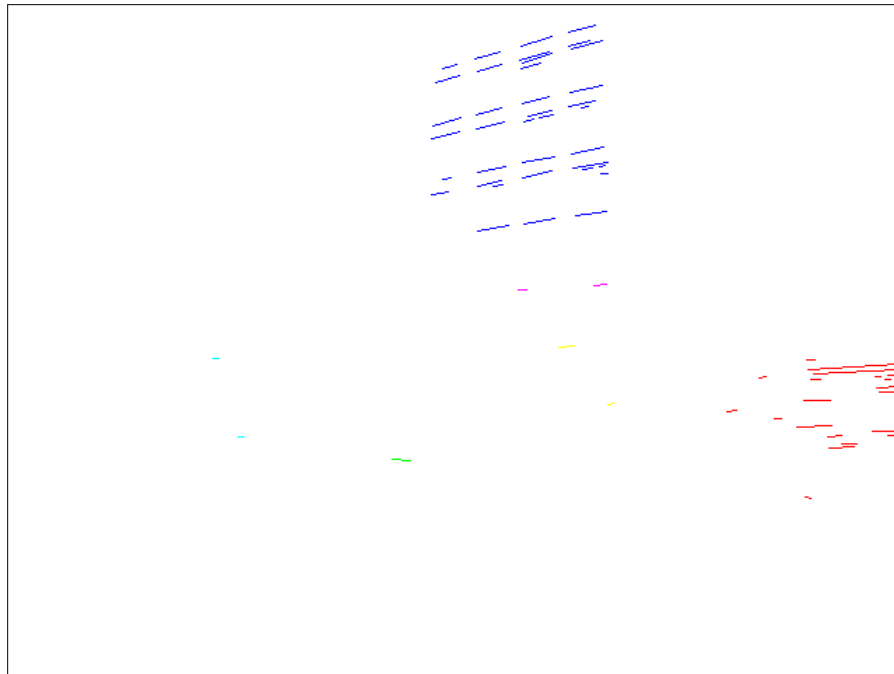




# Spatially-CLC

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- Vertical position clustering
- Horizontal position clustering

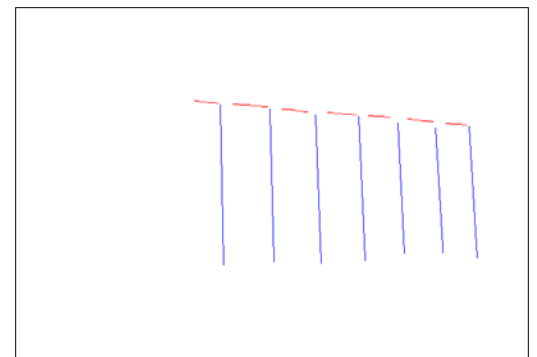




# Building Recognition by CLC

Two types of buildings → Two criteria

- Inter-relationship criterion
- Intra-relationship criterion





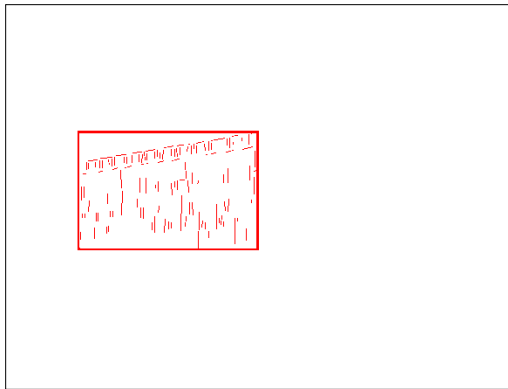
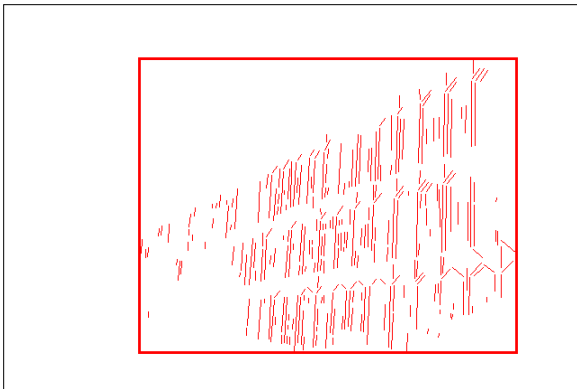
# Experimental Evaluation

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- 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

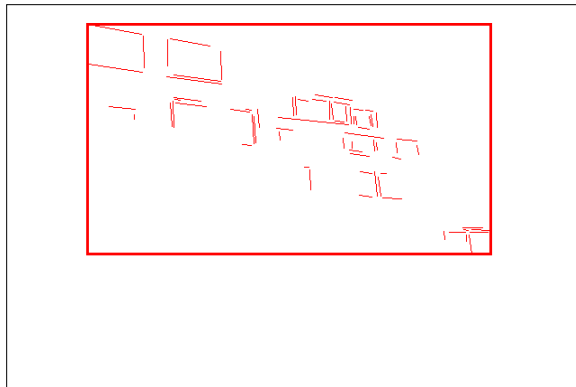
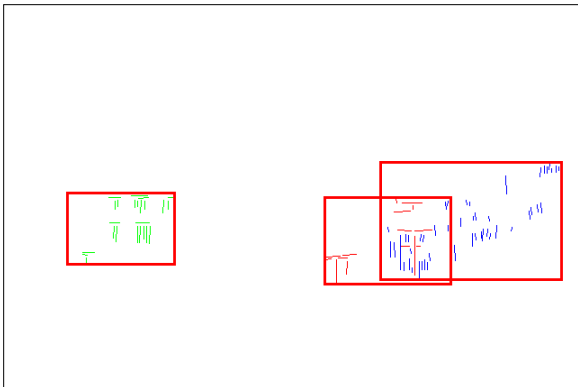
# Experimental Evaluation

## Well-Patterned Buildings



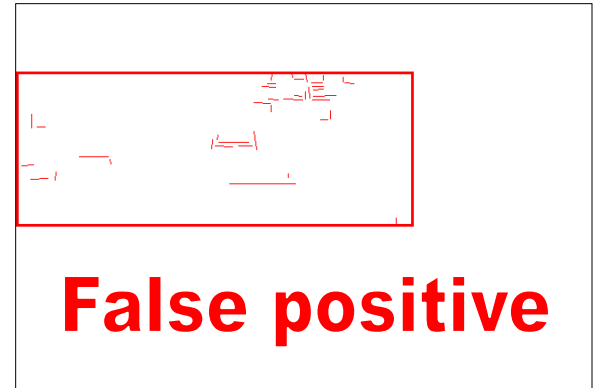
# Experimental Evaluation

## Non-Well-Patterned Buildings



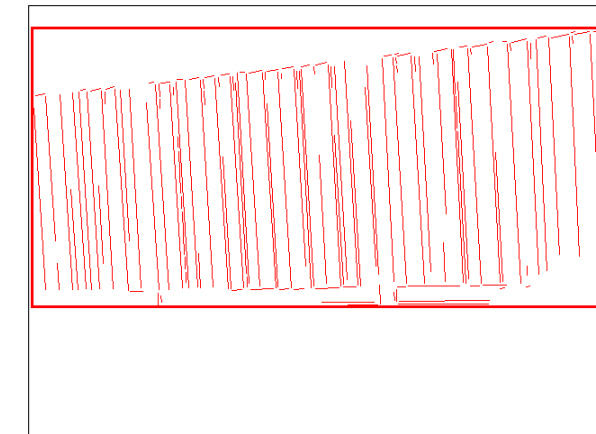
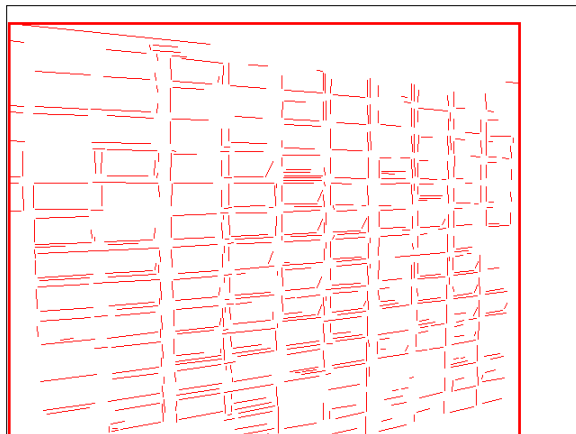
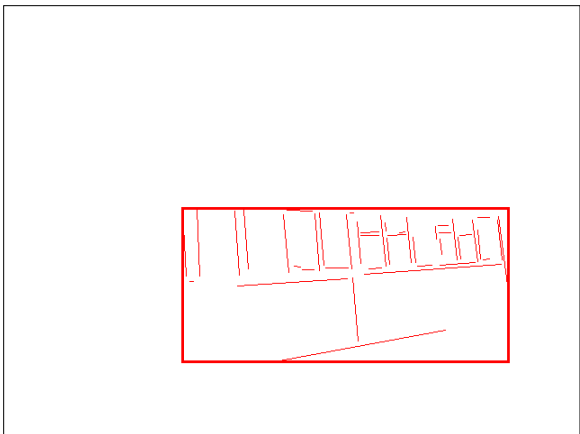
# Experimental Evaluation

## 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

