Introduction

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What is computer vision?

"What does it mean, to see? The plain man's answer (and Aristotle's, too) would be, to know what is where by looking."

-- David Marr, Vision (1982)

- Automatic understanding of images and video
 - Computing properties of the 3D world from visual data (measurement).
 - Algorithms and representations to allow a machine to recognize objects, people, scenes, and activities (perception and interpretation).

Why study computer vision?

- As image sources multiply, so do applications
 - Relieve humans of boring, easy tasks
 - Enhance human abilities: human-computer interaction, visualization
 - Perception for robotics / autonomous agents
 - Organize and give access to visual content
- Goals of vision research:
 - Give machines the ability to understand scenes.
 - Aid understanding and modeling of human vision.
 - Automate visual operations.

Adapted from Trevor Darrell, UC Berkeley

Why study computer vision?





Personal photo albums



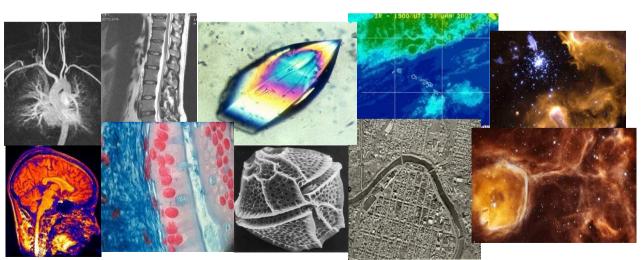
Picasa, flicki websh ts picsearch





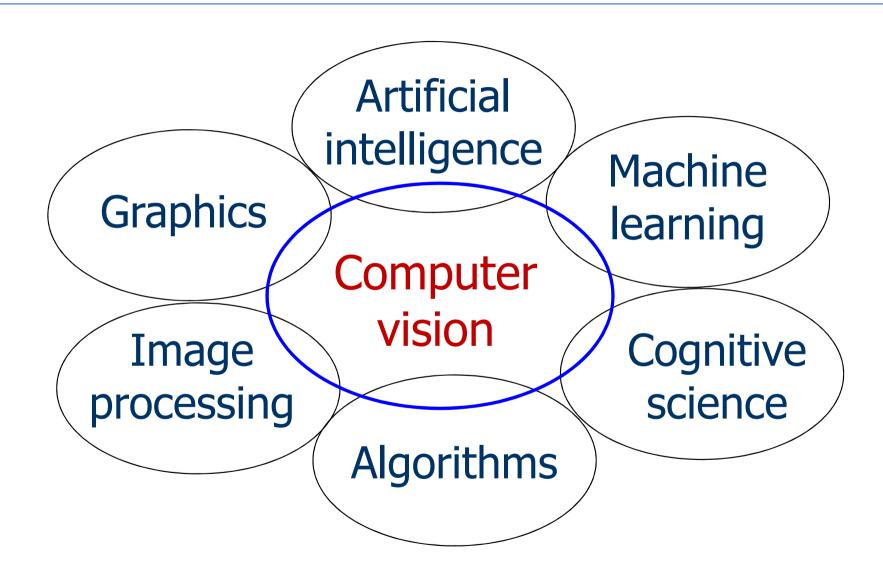


Surveillance and security CS 484, Fall 2012



Medical and scientific images

Related disciplines



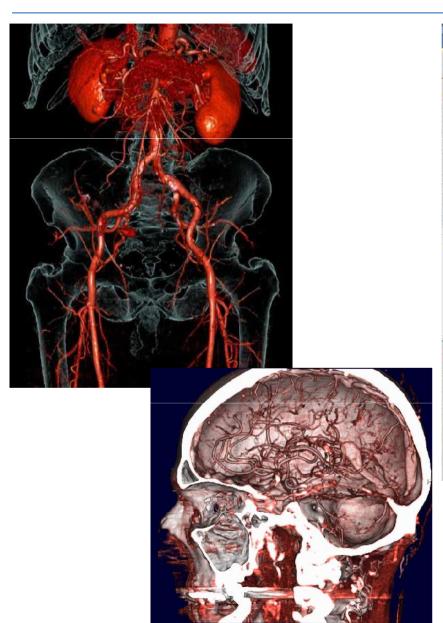
Applications

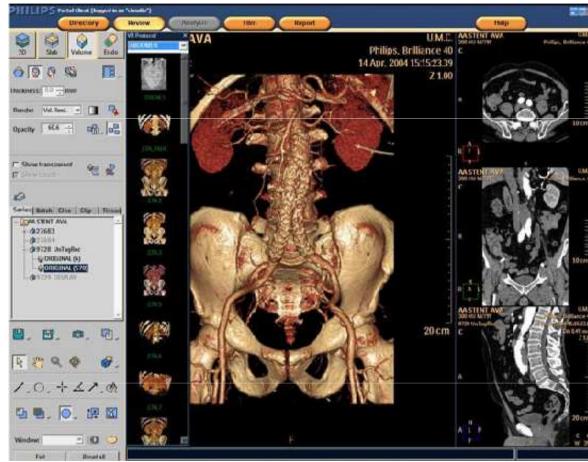
- Medical image analysis
- Security
 - Biometrics
 - Surveillance
 - Tracking
 - Target recognition
- Remote sensing
- Robotics

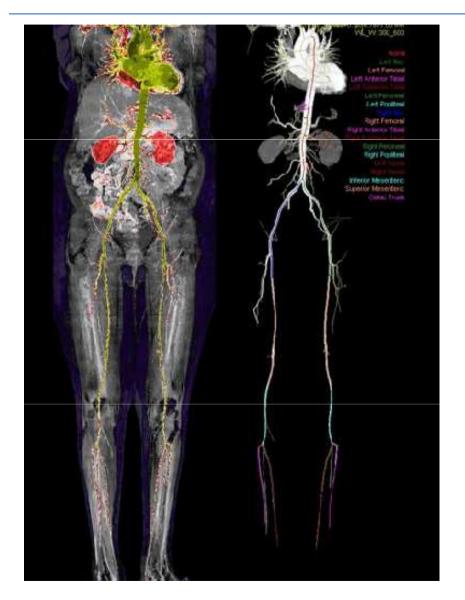
- Industrial inspection, quality control
- Document analysis
- Multimedia
- Assisted living
- Human-computer interfaces

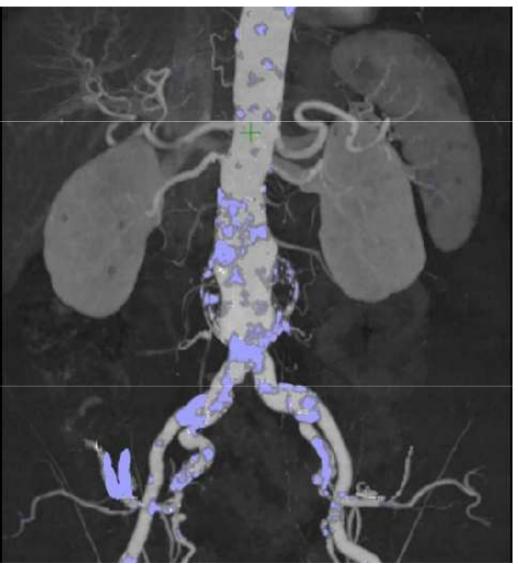
...



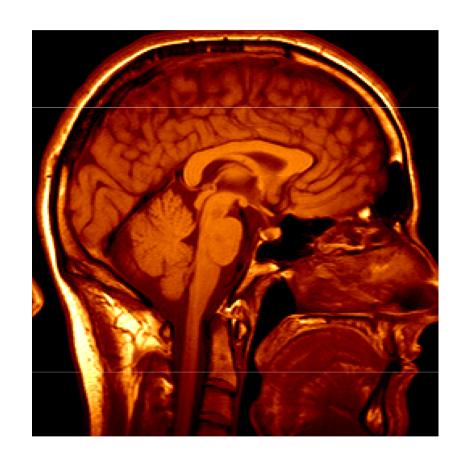








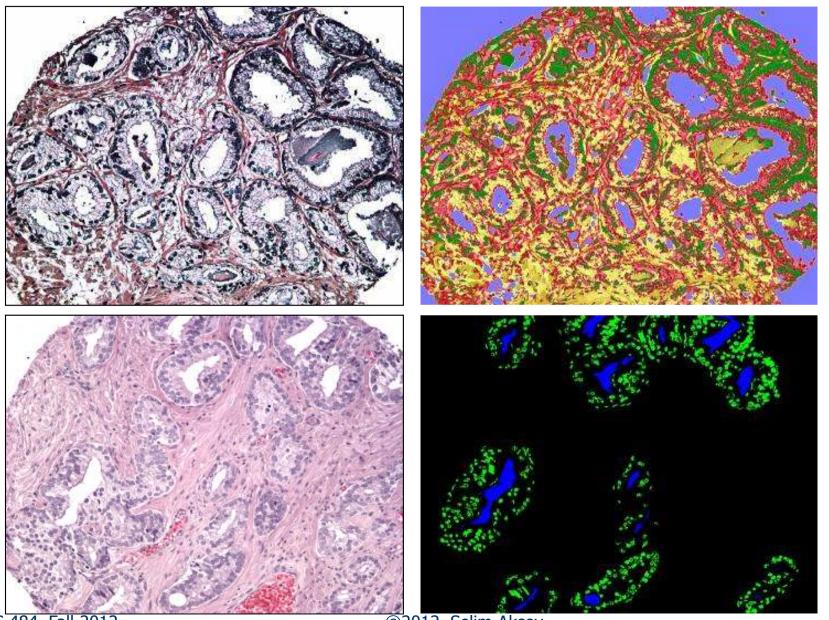
http://www.clarontech.com





3D imaging: MRI, CT

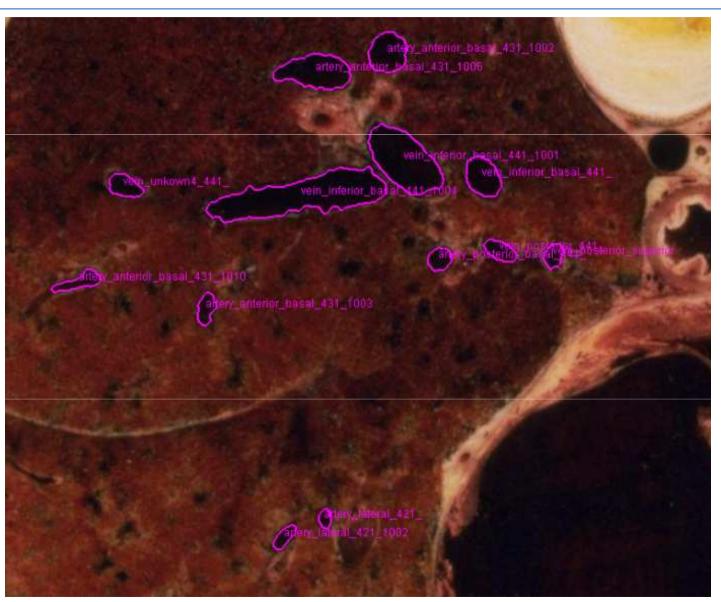
Image guided surgery Grimson et al., MIT



Cancer detection and grading

11

CS 484, Fall 2012 ©2012, Selim Aksoy



Slice of lung

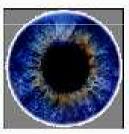
© 2000 Randy Glasbergen. www.glasbergen.com GLASBERGEN

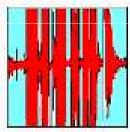
> "Your x-ray showed a broken rib, but we fixed it with Photoshop."

Biometrics











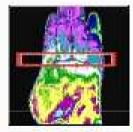












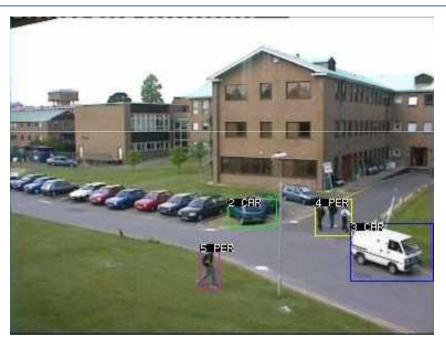


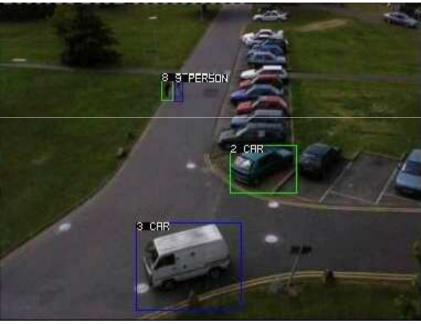




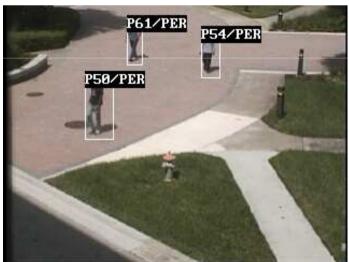








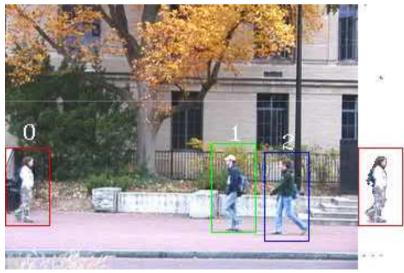


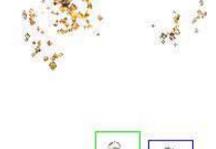


University of Central Florida, Computer Vision Lab







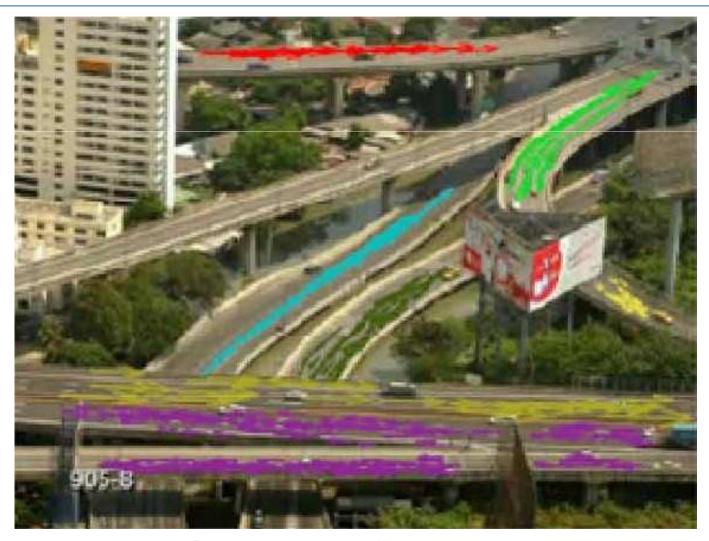




Adapted from Octavia Camps, Penn State



Adapted from Martial Hebert, CMU



Generating traffic patterns







Tracking in UAV videos

Adapted from Martial Hebert, CMU, and Masaharu Kobashi, U of Washington

Smart cars



Vehicle and pedestrian protection





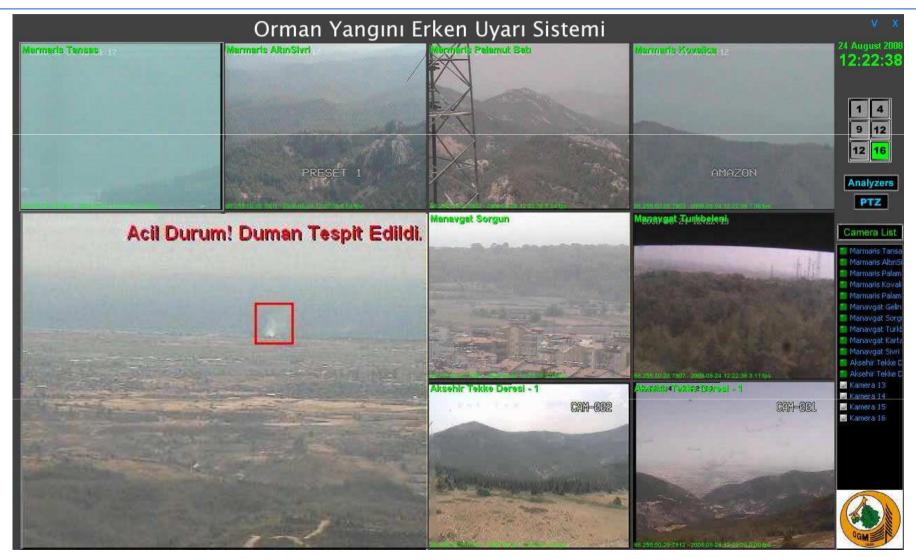






Lane departure warning, collision warning, traffic sign recognition, pedestrian recognition, blind spot warning

Forest fire monitoring system

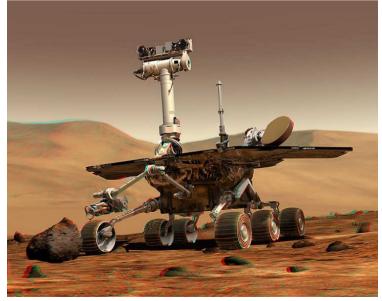


Early warning of forest fires

Robotics

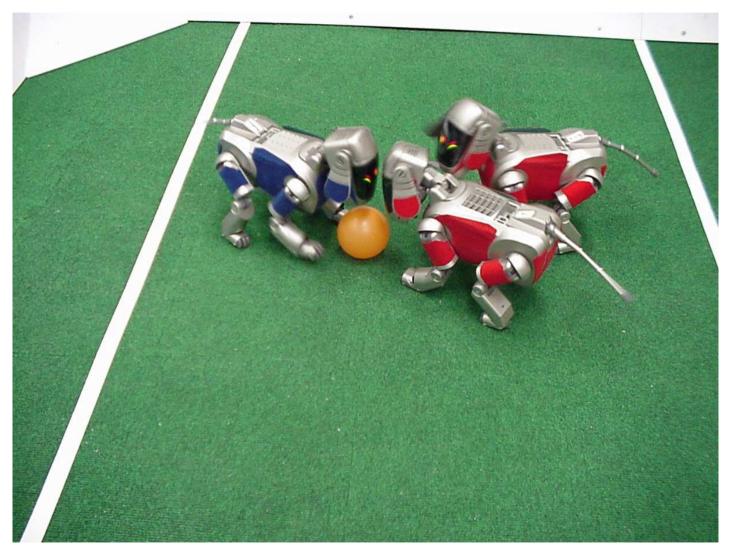






Adapted from CSE 455, U of Washington

Robotics



Adapted from Steven Seitz, U of Washington

Autonomous navigation



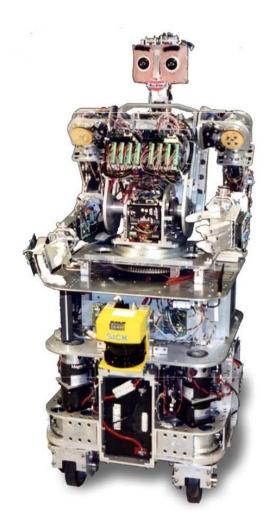






http://www.darpa.mil/grandchallenge/index.asp http://en.wikipedia.org/wiki/DARPA_Grand_Challenge

Autonomous navigation



Michigan State University



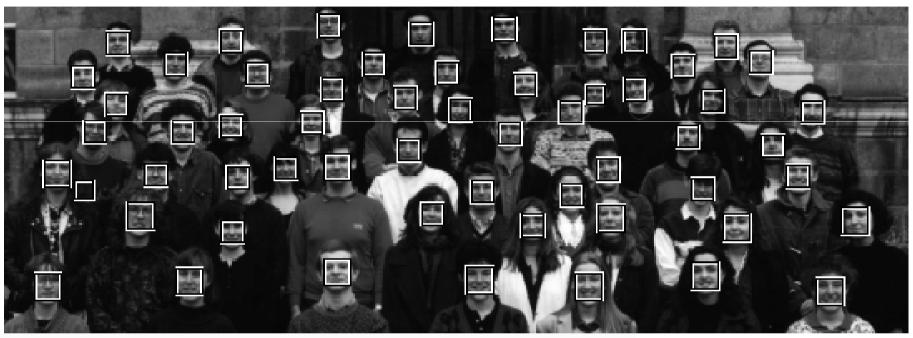






General Dynamics Robotics Systems http://www.gdrs.com

Face detection and recognition







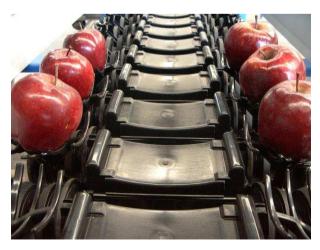
Adapted from CSE 455, U of Washington

CS 484, Fall 2012

Industrial automation



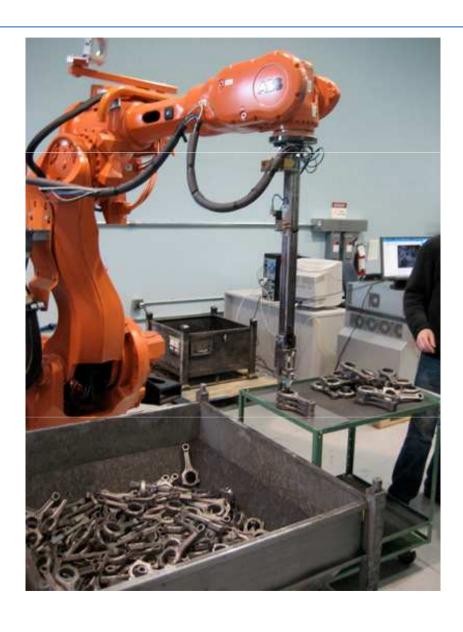




Automatic fruit sorting

Color Vision Systems http://www.cvs.com.au

Industrial automation



Industrial robotics; bin picking

http://www.braintech.com

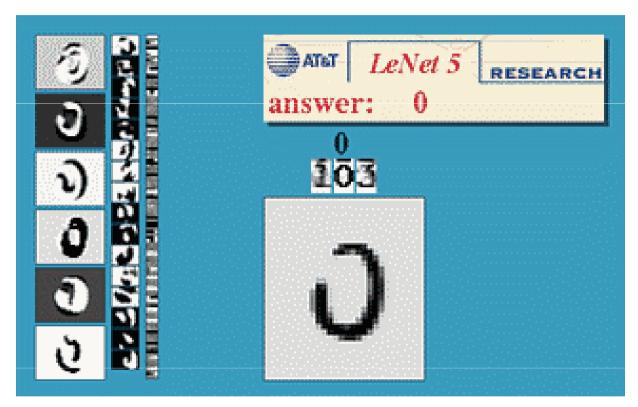
Postal service automation





General Dynamics Robotics Systems http://www.gdrs.com

Optical character recognition



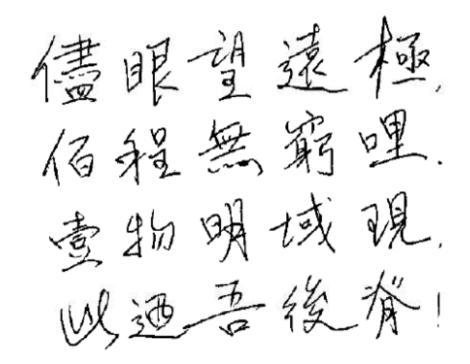


Digit recognition, AT&T labs http://www.research.att.com/~yann

License place recognition

Adapted from Steven Seitz, U of Washington

Document analysis

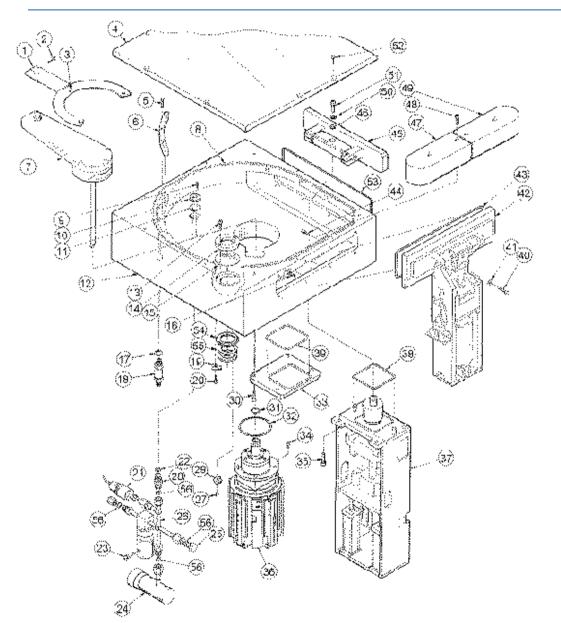


I looked as hard as I could see, beyond 100 plus infinity an object of bright intensity – it was the back of me!

Figure 1.5: (Left) Chinese characters and (right) English equivalent. Is it possible that a machine could automatically translate one into the other? Chinese characters and poem courtesy of John Weng.

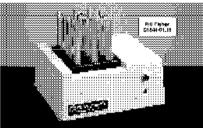
Adapted from Shapiro and Stockman

Document analysis





Blood Bank /Dylmbans



Model 145 Isotemp* Dry Bath Incubator

Holds 1 to 4 heating blocks with choice of 11 well sizes

limansions: 91 imes 15 $W imes 4^{\circ}$ H (28 imes 28) imes 13 cm). With line core andd or Healing blocks sold senerals

Rectical Requirements						
1980 (1980) He (20120) (1980 approved)						
2409/.50/80 Hz (8009/						

Average deviator Leminorani et 3/10 Prizmajera Madel

Incu-Block* Partial Immersion Thermometers

For all standard heat, no blocks and water baths. Orbical temperatures (25 ft 36°, 37°, 58° C) are marked with arrows. Available with shatter-

Panga 10	ΠM _. 3C	Tellers France	Cos Mo	Red
26,57	0.54	Ne	14-992.	45.89
25.57	0.51	Yes	14-963	45.15
•				

More Thermometers

For more thermometers, including digital types, see page 952

Model 147 isotemp* Dry Bath Holds single heating block with choice of 11 well sizes

indicator amp, line core and bit of and instructions. Dimensions: 8 t. ≥ 80. W × 2 TT 115 × 17 × 2 cm). CSA approved. Healing, blocks and

Redded Begulements	C
190V 50/90 Hz, 120N	i i

Interchangeable Heating Blocks for Isotemp* Dry Baths

For Mode & 145 and 147 Due elzed glumiaum glievo (Chemic



well block is similar to the other block with 10 mm holes. Not semble well blodes are 1591 been 14.4 cm.)

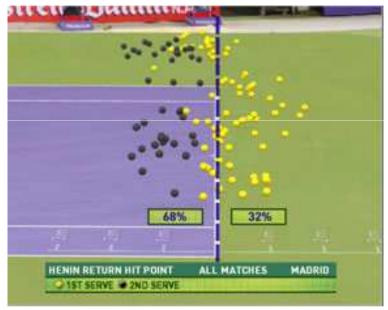
Har, mm	Welletings	Cert Mr.	Even
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12	12	11-715-109	71.18
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13	12	11-715-111	71 12
15	12	11-715-113	71 18
161	Н	11-715-123	71.5
18	12	11-715-115	71 12
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21	5	11-715-119	71 15
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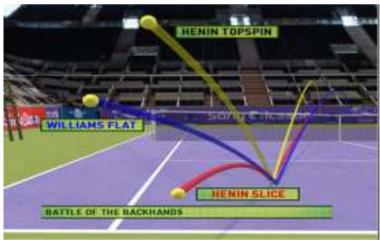
Adapted from Linda Shapiro, U of Washington

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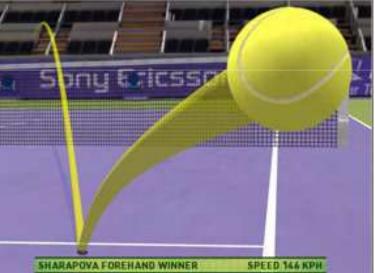
Sports video analysis





Tennis review system

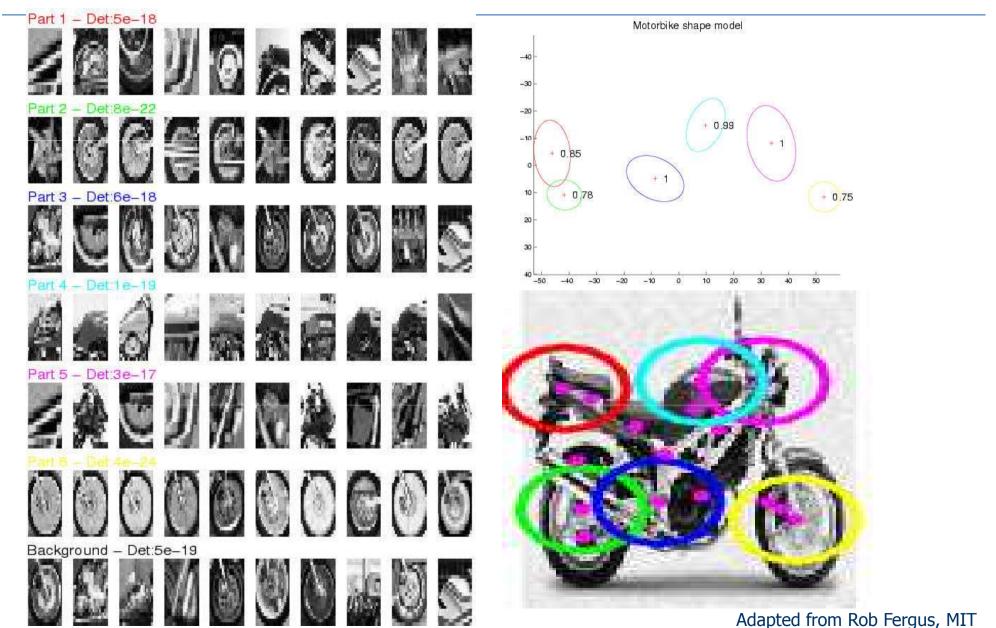




Scene classification



Object recognition



Object recognition



Lincoln, Microsoft Research



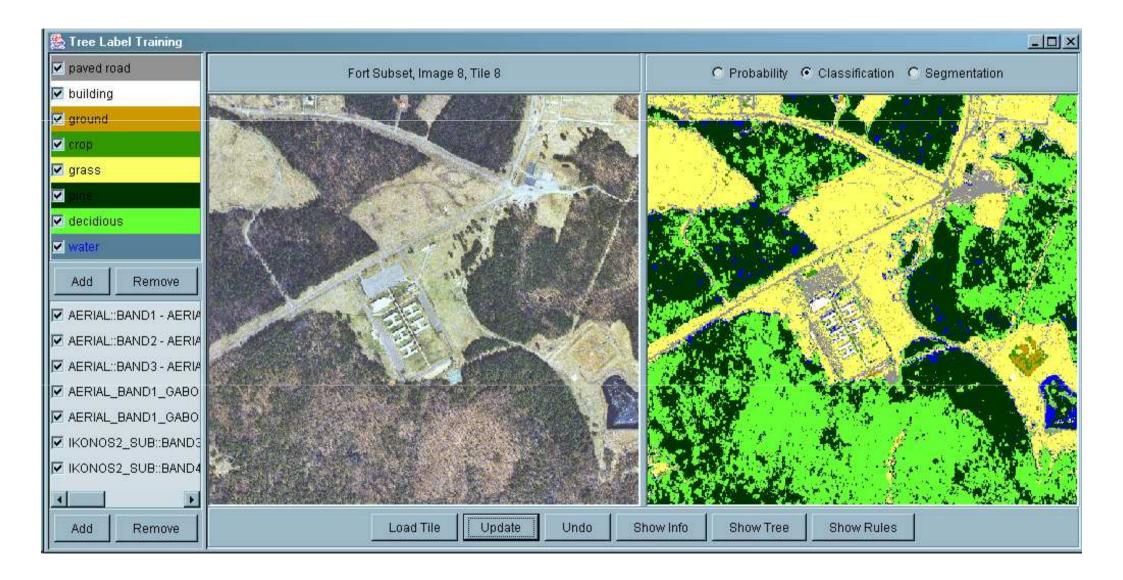
kooaba





Google Goggles
Bing Vision

Land cover classification



Land cover classification



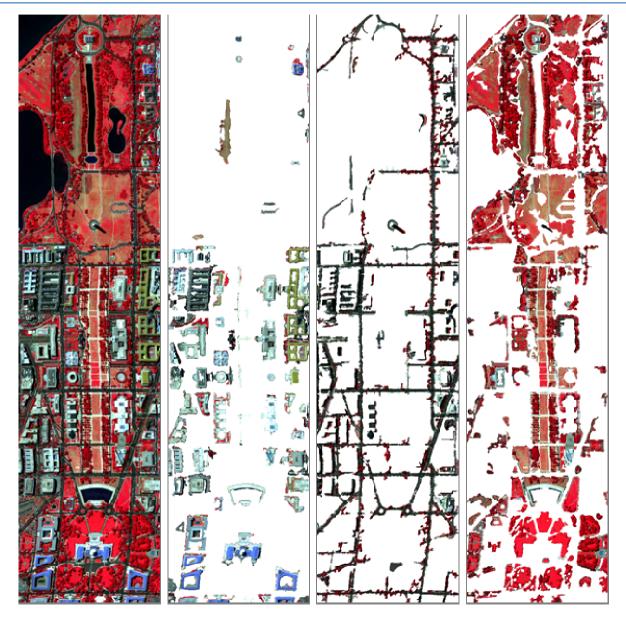






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Object recognition

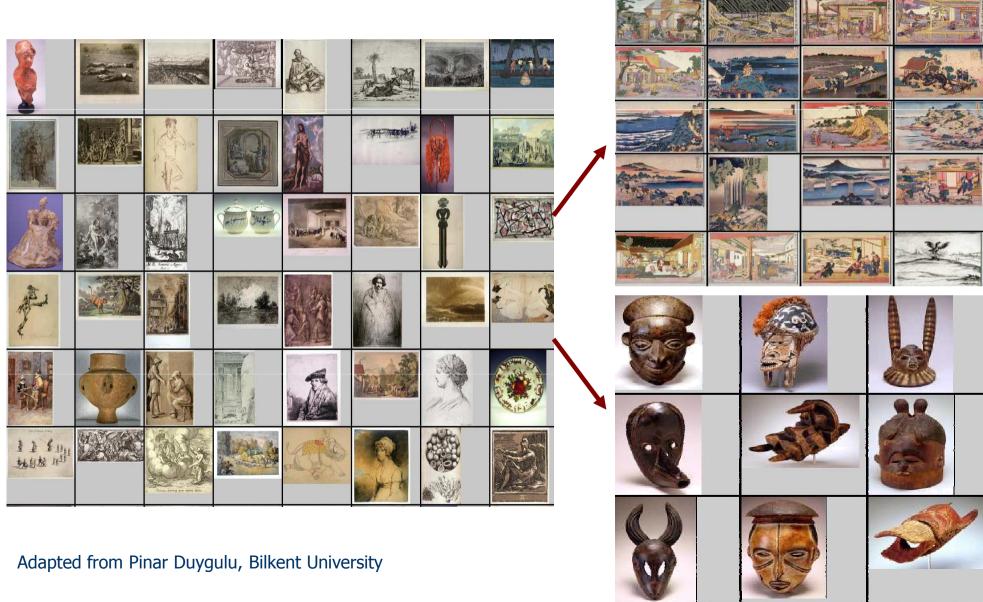


Object recognition



Recognition of buildings and building groups

Organizing image archives



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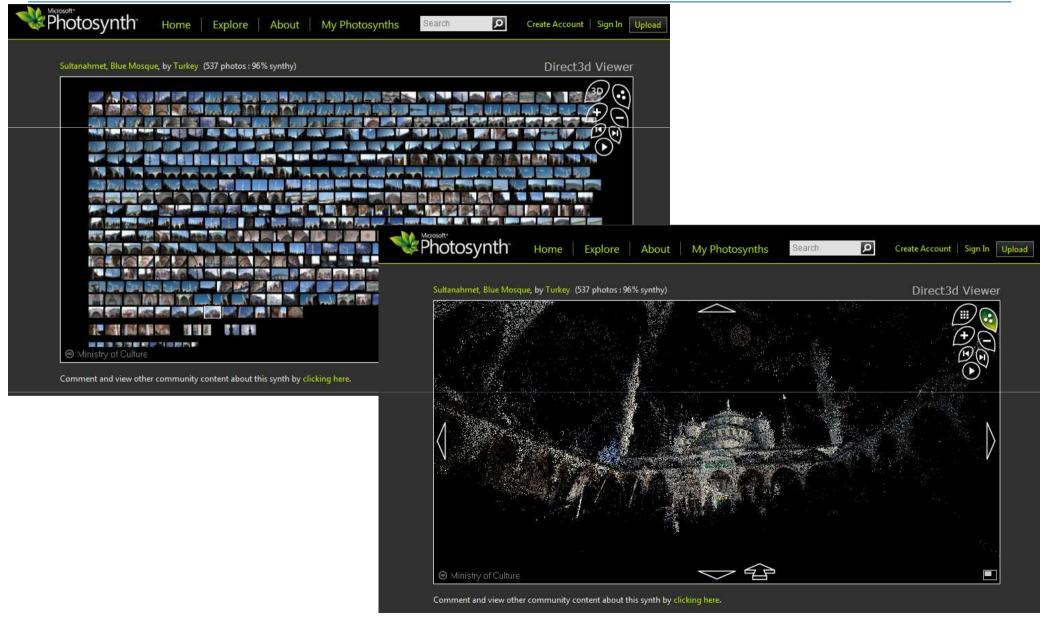
Photo tourism: exploring photo collections



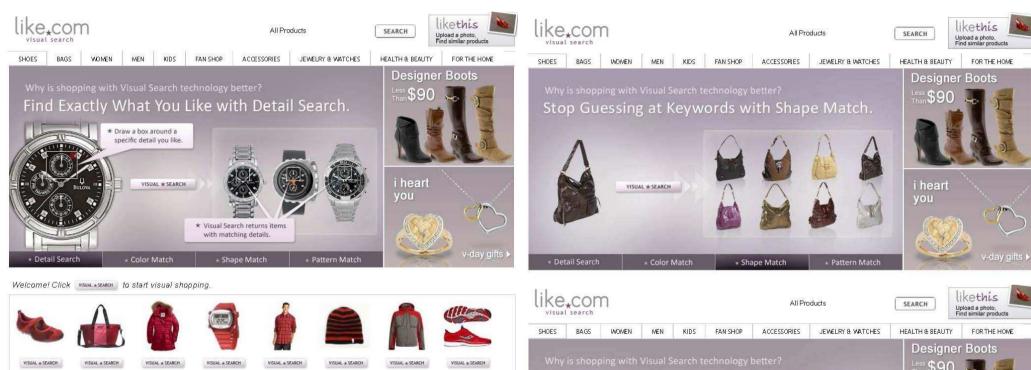


Building 3D scene models from individual photos

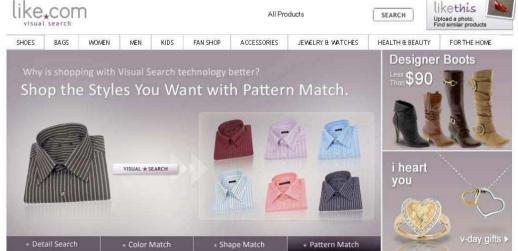
Photosynth



Content-based retrieval

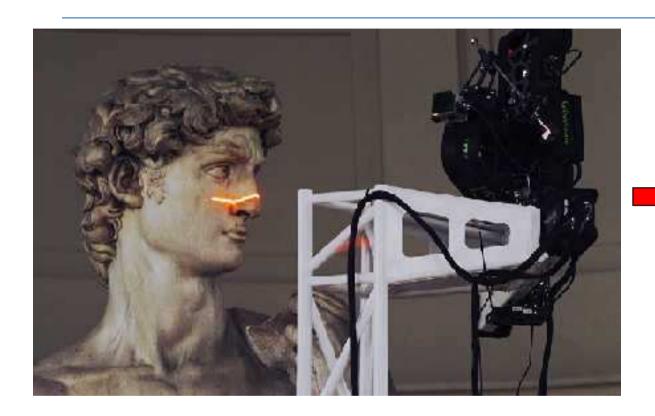


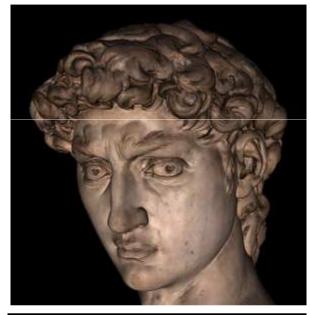
Online shopping catalog search



http://www.like.com

3D scanning and reconstruction

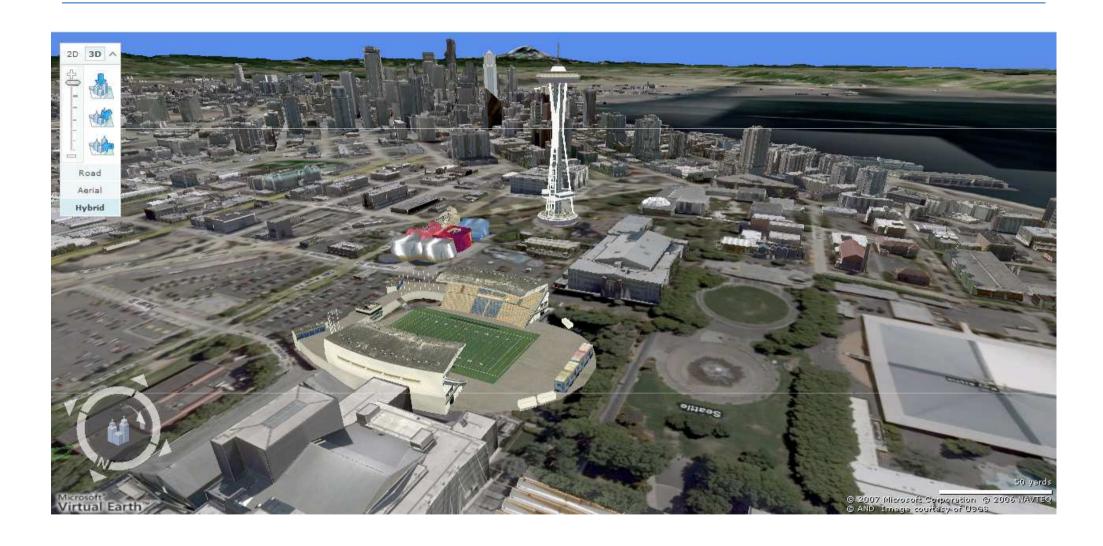






Adapted from Linda Shapiro, U of Washington

Earth viewers (3D modeling)



Motion capture



Adapted from Linda Shapiro, U of Washington

Visual effects



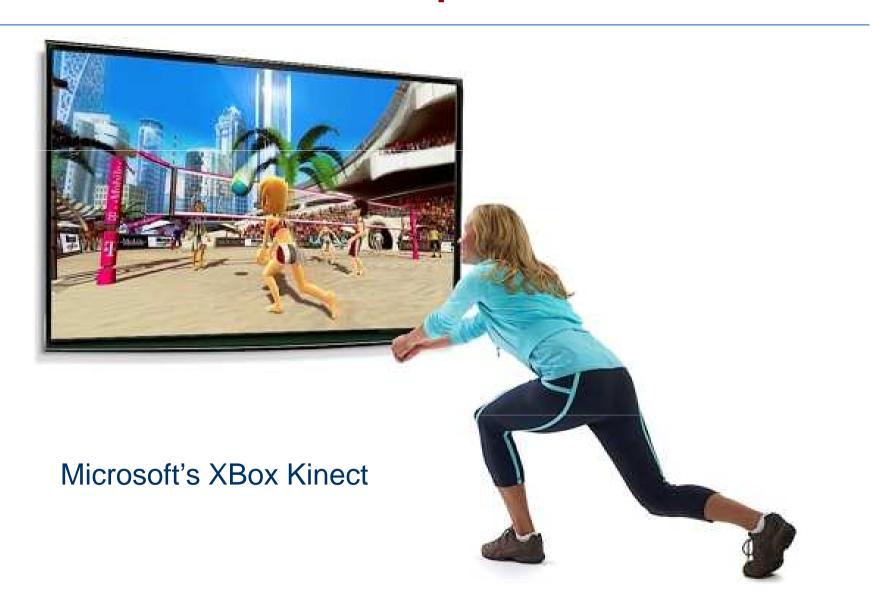








Motion capture



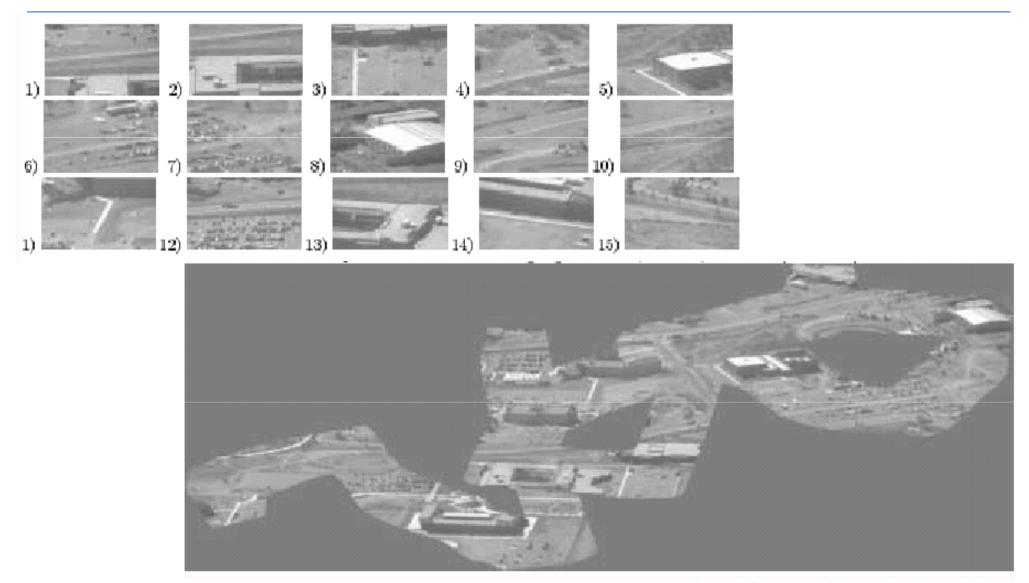
Mozaic





Adapted from David Forsyth, UC Berkeley

Mozaic



Adapted from David Forsyth, UC Berkeley

Critical issues

What information should be extracted?

How can it be extracted?

How should it be represented?

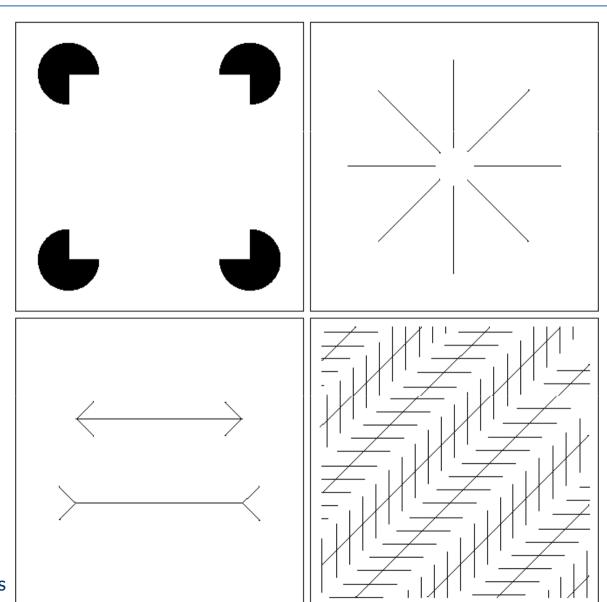
How can it be used to aid analysis and understanding?



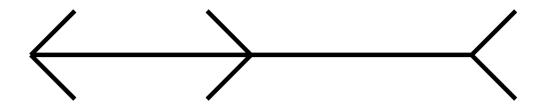
Subjective contours



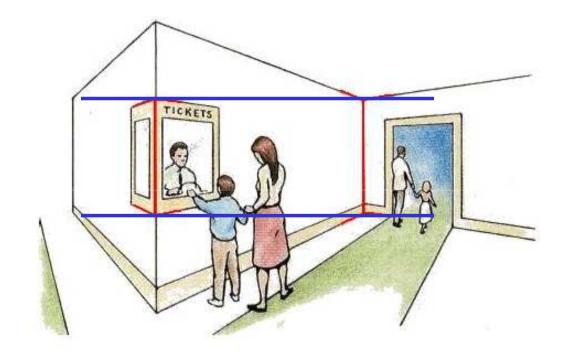
FIGURE 2.9 Some well-known optical illusions.

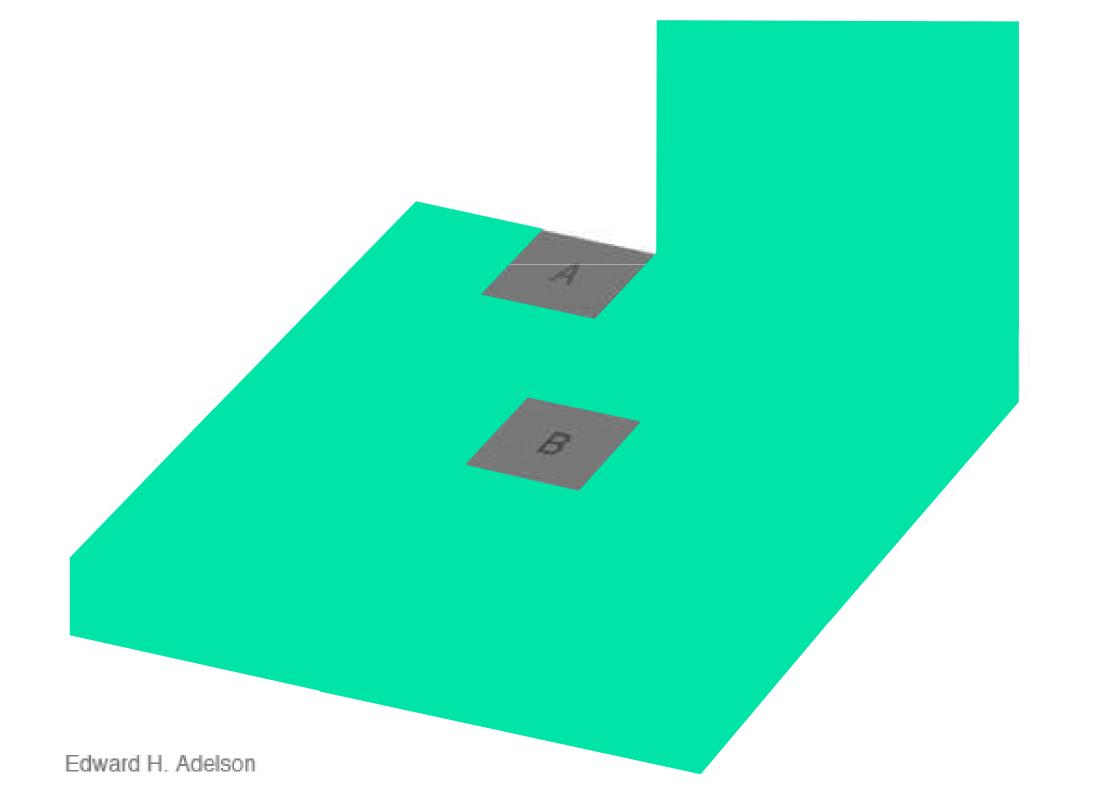


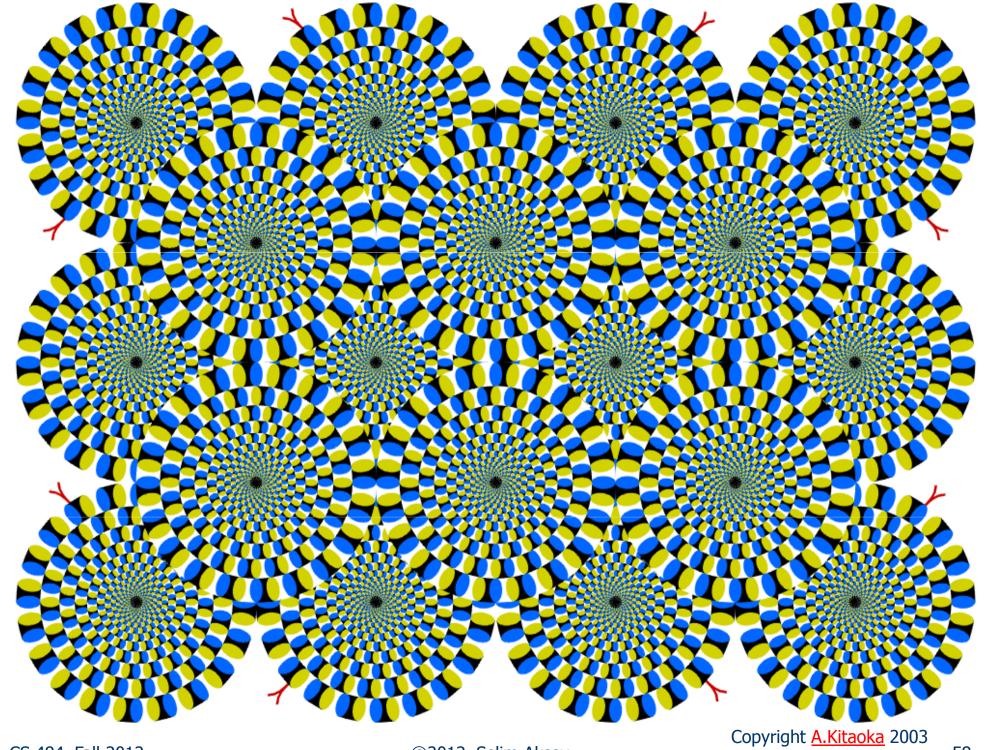
Adapted from Gonzales and Woods

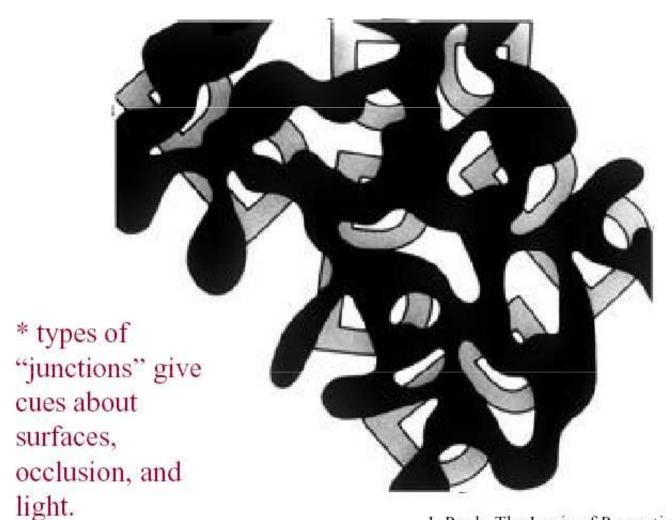


Müller-Lyer Illusion









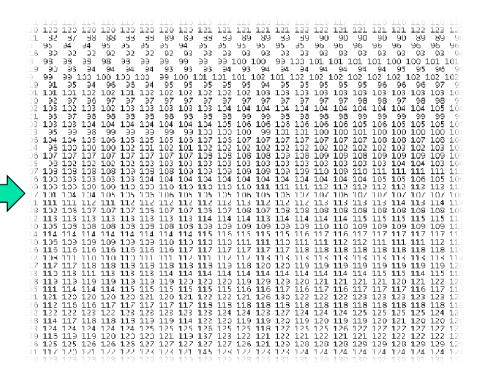
Occlusion

I. Rock, The Logic of Perception, 1983.

Adapted from Michael Black, Brown University

What the computer gets





Challenges 1: view point variation

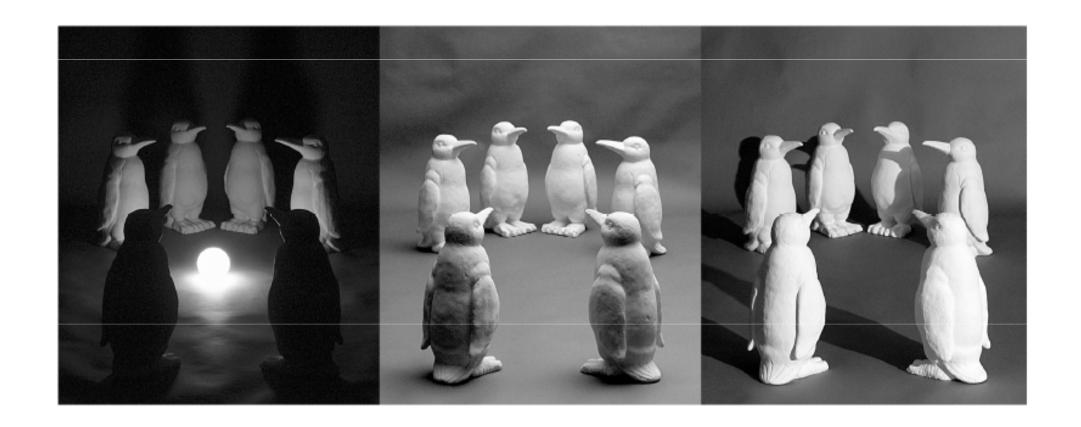






Adapted from L. Fei-Fei, R. Fergus, A. Torralba

Challenges 2: illumination



Challenges 3: occlusion

Magritte, 1957



Adapted from L. Fei-Fei, R. Fergus, A. Torralba

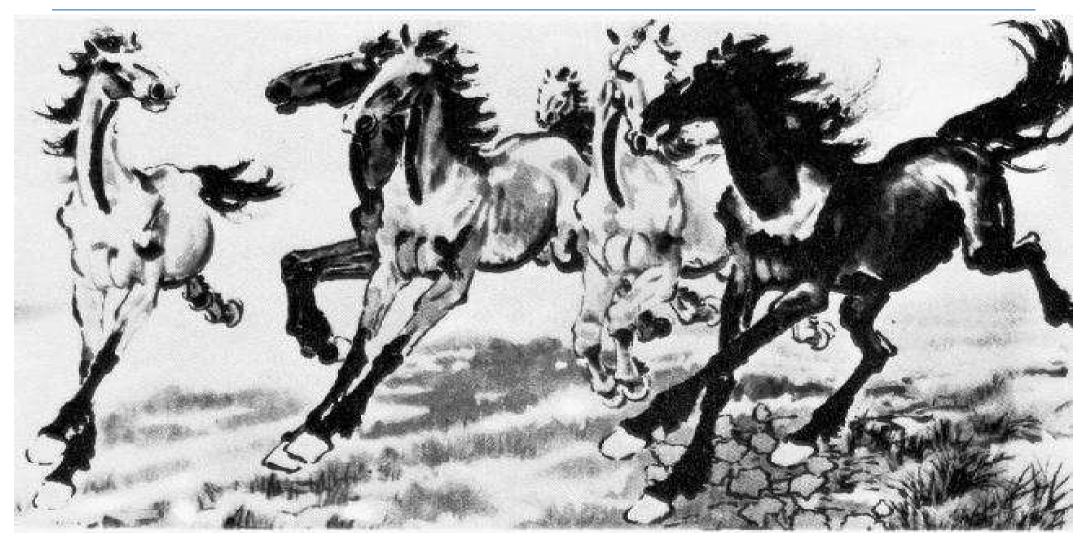
CS 484, Fall 2012

Challenges 4: scale



Adapted from L. Fei-Fei, R. Fergus, A. Torralba

Challenges 5: deformation

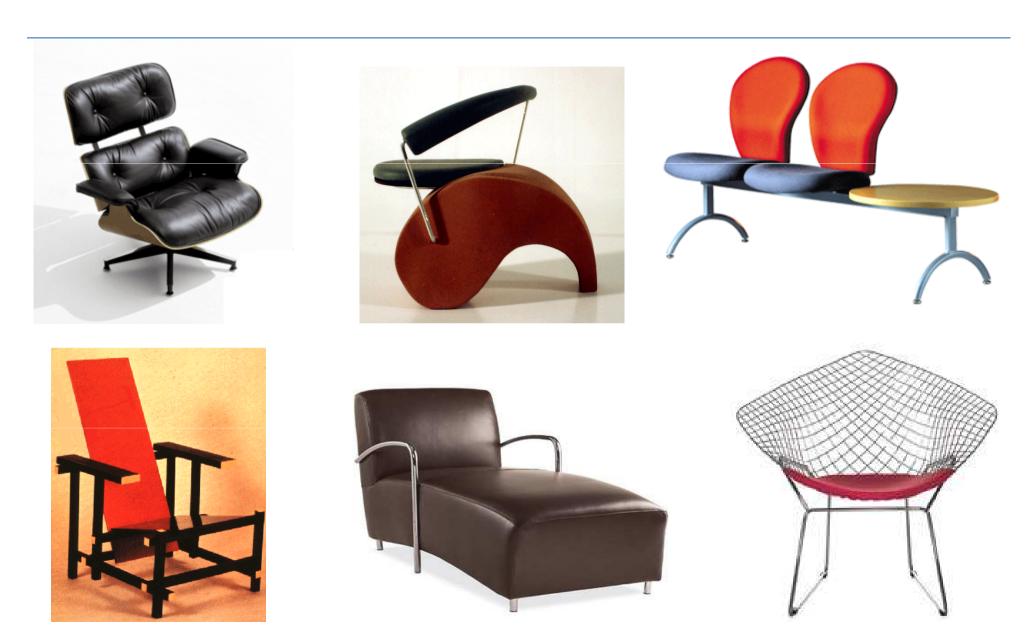


Xu, Beihong 1943

Challenges 6: background clutter



Challenges 7: intra-class variation

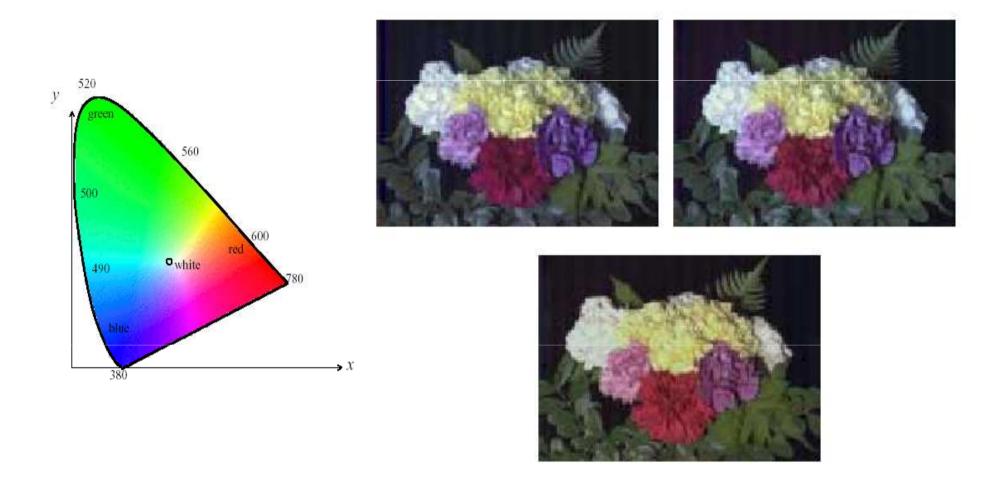


Adapted from L. Fei-Fei, R. Fergus, A. Torralba 67

Recognition

- How can different cues such as color, texture, shape, motion, etc., can be used for recognition?
 - Which parts of image should be recognized together?
 - How can objects be recognized without focusing on detail?
 - How can objects with many free parameters be recognized?
 - How do we structure very large model bases?

Color



Adapted from Martial Hebert, CMU

Texture



Adapted from David Forsyth, UC Berkeley

Color, texture, and proximity

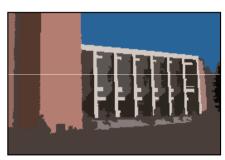


Segmentation

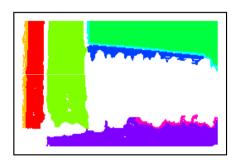
Original Images



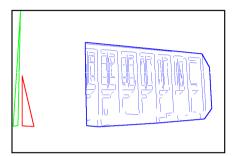
Color Regions



Texture Regions



Line Clusters

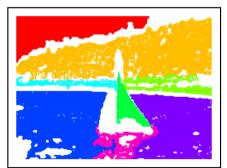




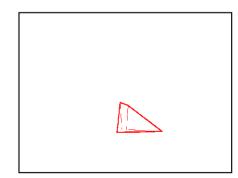






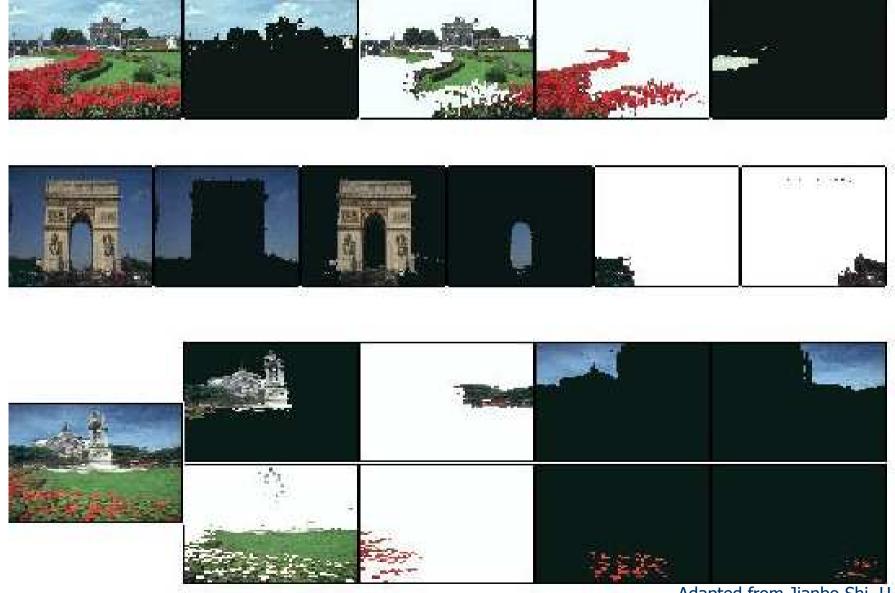




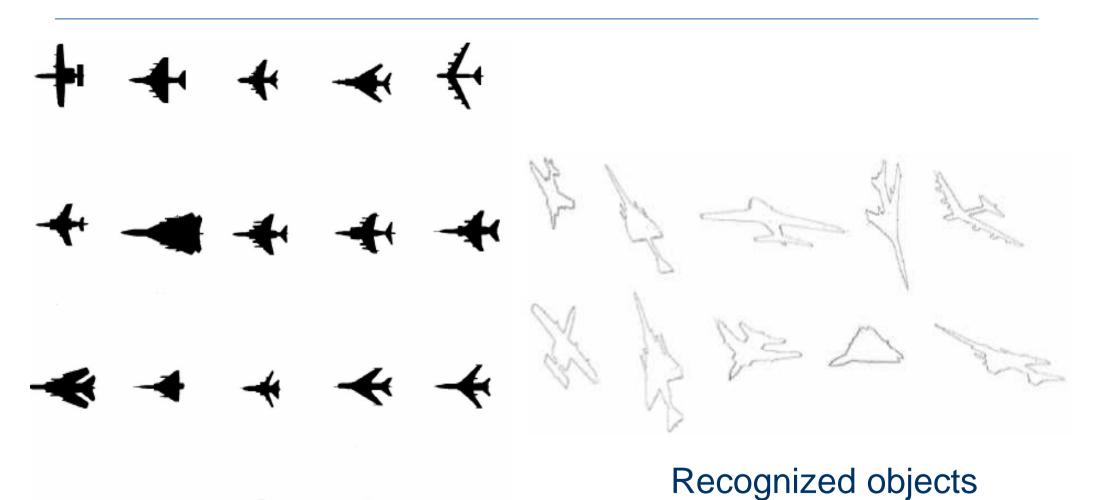


Adapted from Linda Shapiro, U of Washington

Segmentation



Shape





Model database

Adapted from Enis Cetin, Bilkent University

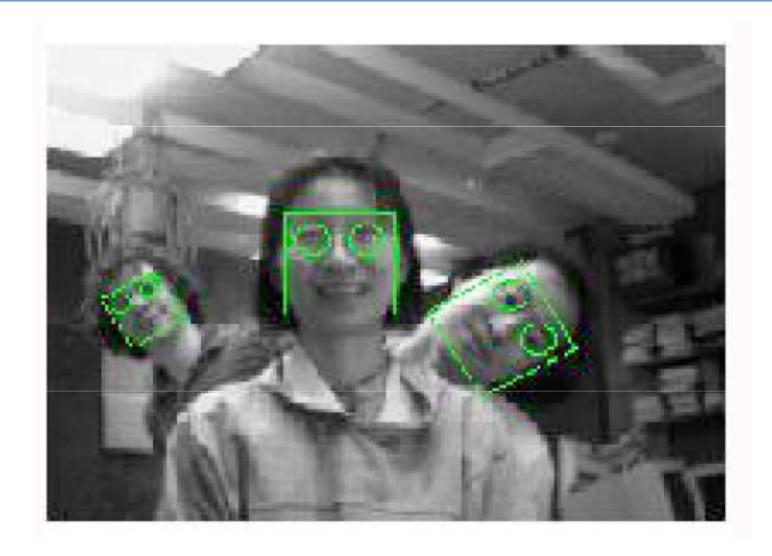
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Motion



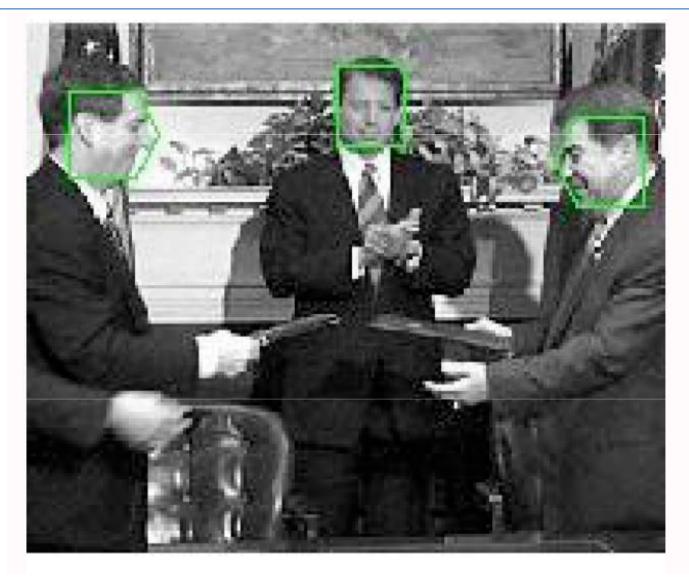
Adapted from Michael Black, Brown University

Detection



Adapted from David Forsyth, UC Berkeley

Detection

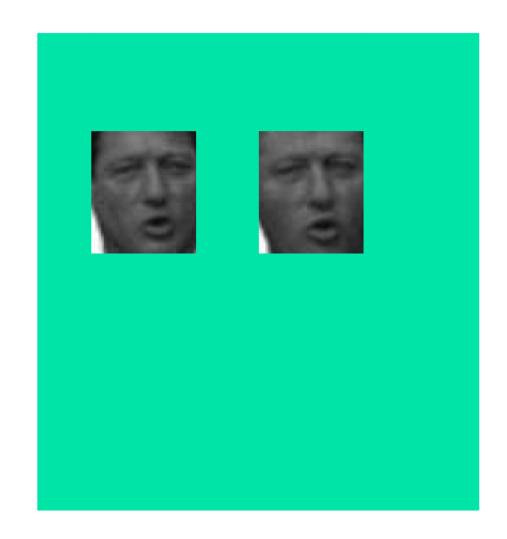


Adapted from David Forsyth, UC Berkeley

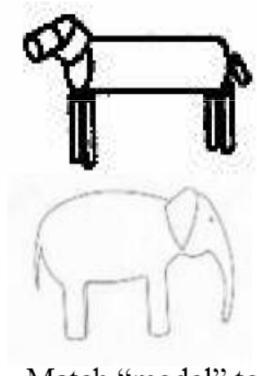
Detection

What are our "models"?

How good are they?



Recognition

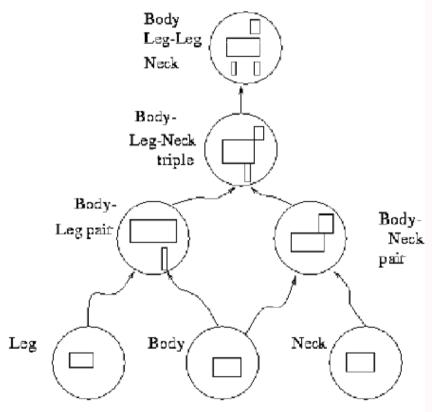


Match "model" to measurements?



Adapted from Michael Black, Brown University

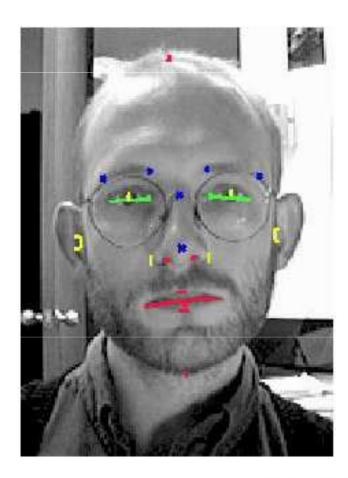
Recognition



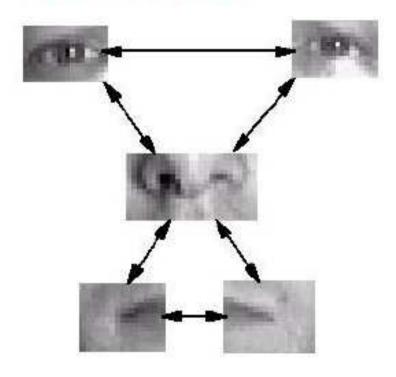


Adapted from David Forsyth, UC Berkeley

Parts and relations



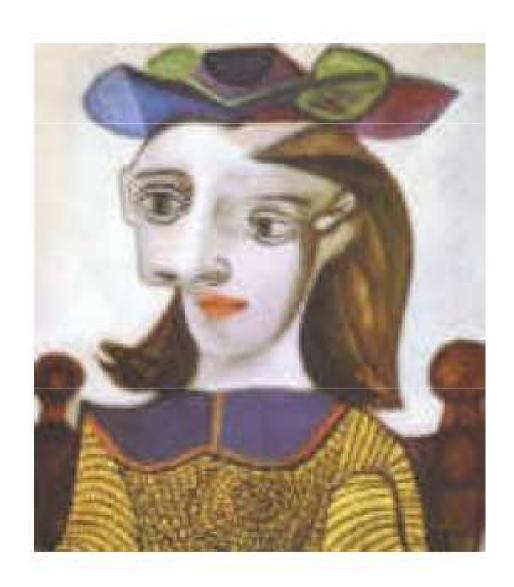
Patch Model



http://www.research.ibm.com/ecvg/biom/facereco.html

Adapted from Michael Black, Brown University

Parts and relations



How flexible are the spatial relations of the parts?

Adapted from Michael Black, Brown University

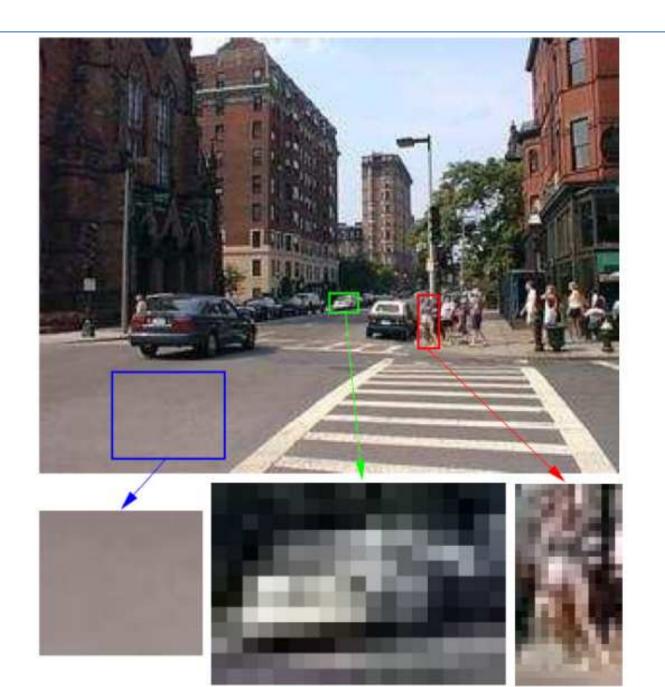












Adapted from Derek Hoiem, CMU

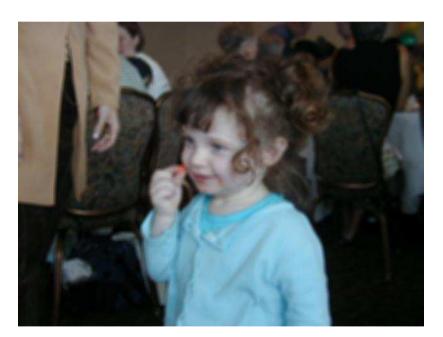
Stages of computer vision

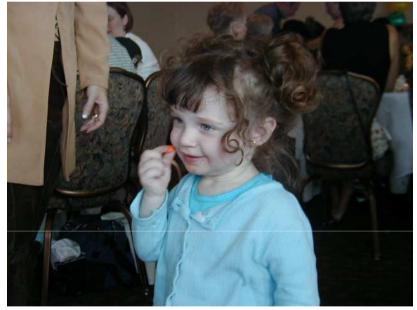
■ Low-level image → image

- Mid-level
 - image → features / attributesImage analysis / image understanding
- High-level features → "making sense", recognition

Low-level

sharpening





blurring

Adapted from Linda Shapiro, U of Washington

Low-level



Canny

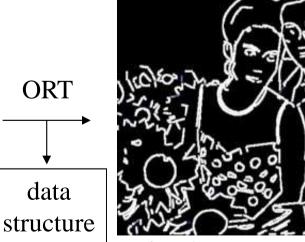


edge image Mid-level

original image



edge image



circular arcs and line segments

Adapted from Linda Shapiro, U of Washington

ORT

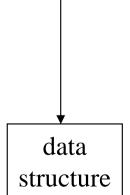
data

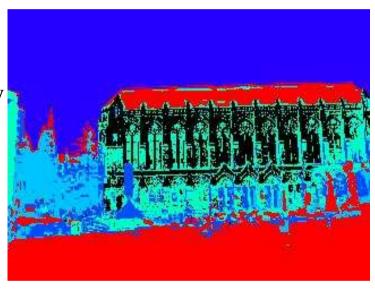
Mid-level



original color image

K-means clustering
(followed by connected component analysis)

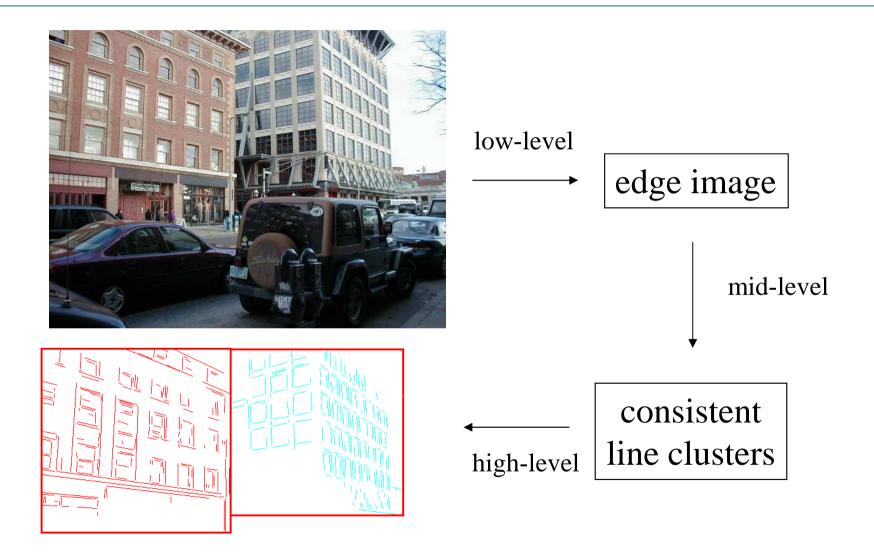




regions of homogeneous color

Adapted from Linda Shapiro, U of Washington

Low-level to high-level



Adapted from Linda Shapiro, U of Washington