

## Lecture 2: CS677

Aug 24, 2017

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## Review

- Previous class
  - Course requirements
  - Assignments, grading
  - Adding more students to the class
  - Topics to be studied in class
  - Some problems of vision
- **TODAY ONLY: office hours 1-2PM**
- Today's objective
  - Some example state-of-art apps
  - Human visual system (very briefly)
  - Image formation

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## Why is Vision Hard?

- Seems easy to us, no conscious effort is needed by human viewers
- Small variations in human population's ability to see/perceive
  - Does not require training/education for everyday tasks
- Can't we just recognize objects based on "how they look"?
  - Isn't a pen (a chair) a pen (chair) because it looks like a pen (chair)?
  - What does a pen (chair) look like?
  - Do we memorize images of pens or extract some more abstract representations (such as thin, mostly cylindrical objects with a conical section narrowing to a small circle at the end)?
  - We also need to detect/segment objects from others

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## Find Objects in this Image



- Where is the object of interest? (Figure-ground problem)
- Do we need to know we are looking for a bicycle?
- How do we know if the object is a bicycle?
  - Do we need to know bikes have two wheels, handlebar etc
  - If so, how do we find the wheels and the other parts?

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### Find Objects



- What is figure, what is ground?
- Different shape of bicycle, with a rider
- What color is the backpack of the rider?
- How far is the fence from the biker?

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### Additional Complexities



- Harder to segment figure from ground
- If we draw a box around bicycle, image will also have a car in it. Do we need to separate the two before we can recognize or do we recognize first and then separate?
- How far is the car from the bicycle?

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### More Problems of Vision

- Recovery of 3-D
- Variations in pose, illumination, camera properties..
- Dealing with occlusion
- Inference of surface properties (material)
- Dynamic scene analysis
- ...

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### Mathematics or Machine\_Learning?

- All vision problems can be stated as learning a function between input and output, say  $\mathbf{y} = f(\mathbf{x})$
- If  $f$  can be described (or well approximated) by an analytical function, say a polynomial in case of scalar values, the task reduces to find the parameters of the function
- If the form of  $f$  can not be derived by analysis, then we can try to fit a complex, generic function with many degrees of freedom
  - Illustrate by example (fit curves to set of points)
  - This is the approach taken by machine learning, in particular deep learning
- Which is better?
  - If  $f$  is indeed a simple, derivable function, we can be confident of the solution; otherwise, it may “underfit” the data
  - Deep learning is susceptible to “overfitting” and requires huge amounts of training data
  - Transparency, ease of human interaction

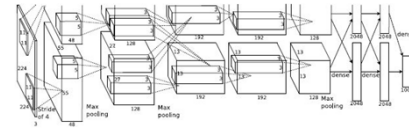
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### Evolution of Computer Vision Approaches

- Early methods used representations based on intuition
  - “Hand-designed” descriptors and classification rules
- Later methods incorporated sophisticated mathematical models
  - These turned out to be very effective for recovering 3-D geometry from multiple images as problem is well posed mathematically
  - Less effective for semantic analysis such as object segmentation and recognition
    - Trend was to use hand-designed features but machine learned classifiers
- Current trend
  - Let machine learn the complete pipeline though structure of the pipe is still defined by designers
  - Achieves much higher accuracies when sufficient training data is available but methods are not transparent; hard to find source of errors

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### “Alexnet”



- First deep learning network that achieved high object classification performance (2012)
- Large number of parameters (~100M)
- Intermediate layers are “hidden” (we don’t know what the right values are, they may not represent any recognizable entities such as parts)

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### What are we going to Study?

- A combination of mathematical and learning methods
- More emphasis on mathematical methods in first part of the course as the geometry problems are relatively well-defined
- More emphasis on machine learning (deep learning) in second half as problems are not easy to describe in precise math terms
- Anticipation that future systems will use a combination of techniques so best to learn basic principles of both.

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### Current state of the art

- The following slides show some examples of what current vision systems can do
  - Many taken from class page of Prof. Seitz/Szeliski

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## Driving Scene



From Mobileye

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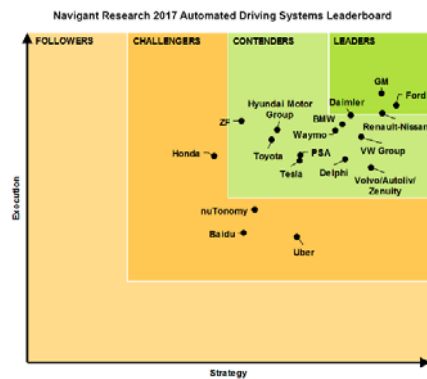
## Self-Driving Cars

- A short video showing some visual needs and capabilities
  - <https://www.youtube.com/watch?v=42rmGs0Rvtw>
- A long talk on status of self-driving cars (watch on your own)
  - <https://www.youtube.com/watch?v=GJ82mk99Agw>
- A business analysis of participants in self-driving technology
  - <http://www.businessinsider.com/the-companies-most-likely-to-get-driverless-cars-on-the-road-first-2017-4/#1-ford-18>

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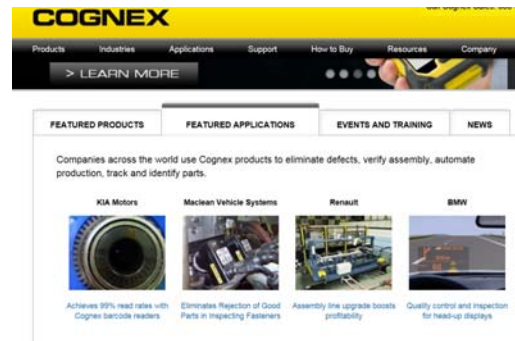
## Autonomous Driving Leaders



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## Manufacturing and Inspection



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## Earth viewers (3D modeling)



Image from Microsoft's [Virtual Earth](#)  
(see also: [Google Earth](#))

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## iPhone PANO Images



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**Photosynth**

- Try It
- What is Photosynth?
- Collections
- Team blog
- Videos
- System requirements
- About us
- FAQ

"What if your photo collection was an entry point into the world, like a wormhole that you could jump through and explore..."

Try the Tech Preview

The Photosynth Technology Preview is a taste of the newest - and, we hope, most exciting - way to view photos on a computer. Our software takes a large collection of photos of a place or an object, analyzes them for similarities, and then displays the photos in a reconstructed three-dimensional space, showing you how each one relates to the next.

<http://labs.live.com/photosynth/>

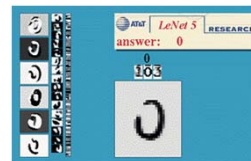
Based on [Photo Tourism technology](#)

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## Optical character recognition (OCR)

- Technology to convert scanned docs to text
  - If you have a scanner, it probably came with OCR software



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



License plate readers  
[http://en.wikipedia.org/wiki/Automatic\\_number\\_plate\\_recognition](http://en.wikipedia.org/wiki/Automatic_number_plate_recognition)

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### Face detection

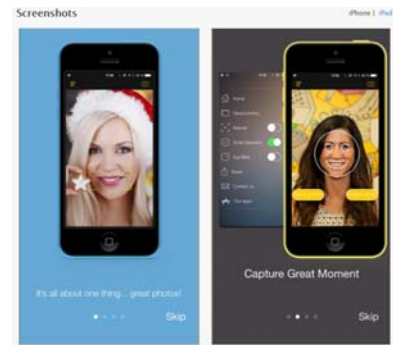


- Most new digital cameras now detect faces

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### Smile Detector (from Quanticapps)



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### SensibleVision



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### Cognitec Face Recognition

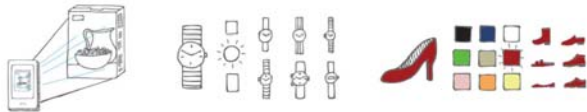


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## A9.com

Visual Search also develops computer vision solutions that support Amazon initiatives along the entire product delivery pipeline: from the time a new product is photographed and added to our catalog to the time an item is bought and shipped to the customer.



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## Amazon Go

- <https://www.youtube.com/watch?v=NrmMk1Myrxc>

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## Special Effects

- From movie "Avatar"; image from [www.rockying.com](http://www.rockying.com)



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## Sports



Sportvision first down line  
Nice [explanation](http://www.howstuffworks.com) on [www.howstuffworks.com](http://www.howstuffworks.com)

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## Vision-based interaction (and games)



Nintendo Wii has camera-based IR tracking built in.

Microsoft Kinect  
(no images here)



[Digimask](#): put your face on a 3D avatar.



*"Game turns moviegoers into Human Joysticks"*, CNET  
Camera tracking a crowd, based on [this work](#).

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## Microsoft Kinect



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## Vision in space



[NASA's Mars Exploration Rover Spirit](#) captured this westward view from atop a low plateau where Spirit spent the closing months of 2007.

- Vision systems (JPL) used for several tasks
  - Panorama stitching
  - 3D terrain modeling
  - Obstacle detection, position tracking

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## Robotics



NASA's Mars Spirit Rover  
[http://en.wikipedia.org/wiki/Spirit\\_rover](http://en.wikipedia.org/wiki/Spirit_rover)

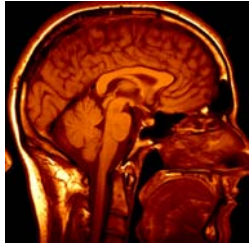


<http://www.robocup.org/>

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## Medical imaging



3D imaging  
MRI, CT

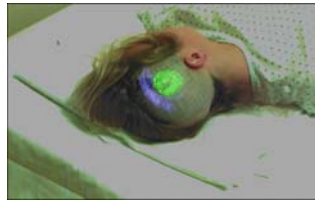


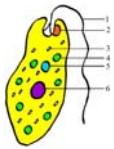
Image guided surgery  
[Grimson et al., MIT](#)

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## 5-Minute Break

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## Simple Eyes



Single cell organism, can sense  
presence/absence of light only  
[http://www.wikiwand.com/en/Evolution\\_of\\_the\\_eye](http://www.wikiwand.com/en/Evolution_of_the_eye)



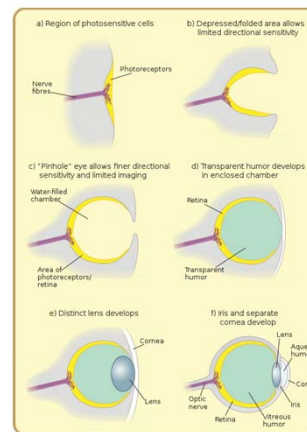
Holes provide some directional sensitivity.  
From Alessandro: wikipedia



Nautilus Eye: like a pin hole camera  
From Hillewaert: wikipedia

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## Evolution of Eyes

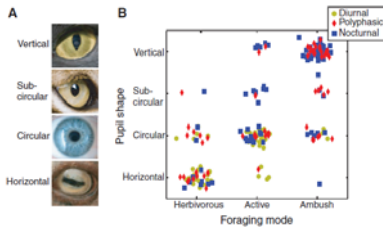


From Matticus: Wikipedia

Also,  
[http://www.wikiwand.com/en/Evolution\\_of\\_the\\_eye](http://www.wikiwand.com/en/Evolution_of_the_eye)

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## Pupil Shape

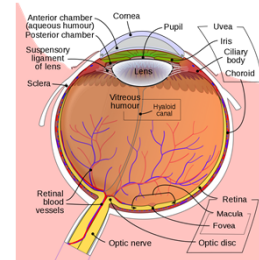


From Banks *et al.*: “Why do animal eyes have pupils of different shapes?”, in Science Advances, August 2015

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## Human Eye

- Like a camera
  - Lens, pupil (iris), focus by *accommodation*
- Image formed on back of eye (retina)
- Optic nerve sends *data* to brain (cortex)
  - Blind spot (where optic nerve comes out)



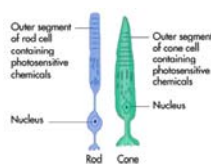
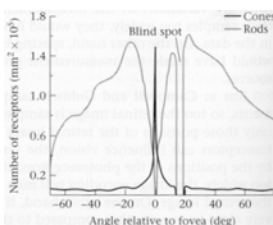
From Wikipedia

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## Retina

- Two types of photoreceptors
  - Rods: highly sensitive to light, not used for color vision, ~ 100M rods
  - Cones: 3 different types with different spectral sensitivities, less sensitive to light, ~ 5M cones
    - Explains why *color* is not seen at night
- Distribution is not uniform
  - High concentration of cones in fovea (0.5 minute visual angle)
  - Fixation (*foveation*) to get high resolution everywhere



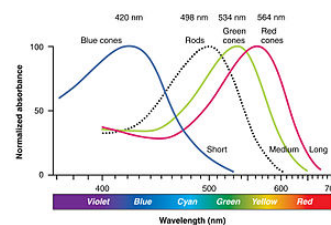
<http://ionabio.weebly.com/>

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## Color Sensor Response

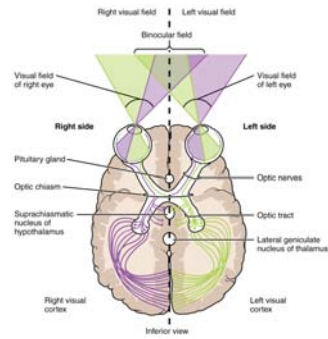
- Eyes do not have built in color spectrometer
- Rather, we have 3 sensors with different responses to lights of different color
- Perceived color depends on relative responses of three sensors



[https://en.wikipedia.org/wiki/Photoreceptor\\_cell](https://en.wikipedia.org/wiki/Photoreceptor_cell)

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### Cortex schematic



From [lindsayoptometric.com](http://lindsayoptometric.com)

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Optical nerve carries signals from retina to cortex  
~100:1 ratio of nerve fibers to receptors: some processing performed at this level

Optical *chiasma*: optic nerve fibers split to two halves of the brain

Many functional areas (V1, V2,...): knowledge about them is limited

### Image Formation

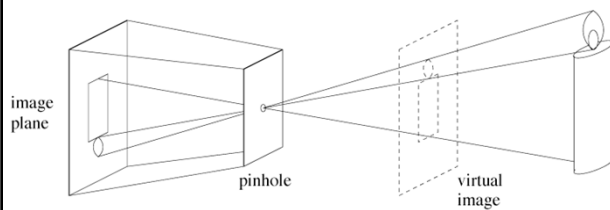
- Geometry
  - Where is the image of a point formed?
- Photometry/Colorimetry
  - How bright is the point?
  - What is its *color*?
- Ideal camera models
- Real lenses

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### Pinhole cameras

- Abstract camera model - box with a small hole in it
- Note inverted image
- Pinhole cameras work in practice, ignoring diffraction



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### Next Class

- FP: Sections 1.3, 2.1, 2.3.4, 2.4

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