Course Outline

- Image Processing Basics
  - Image Formation
  - Binary Image Processing
  - Linear Filters
  - Edge & Structure Extraction (remainders)
  - Color
- Recognition (Global Models)
- Segmentation
- Local Features & Matching
- Object Recognition and Categorization
- 3D Reconstruction
- Motion and Tracking

Recap: Canny Edge Detector

1. Filter image with derivative of Gaussian
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   - Thin multi-pixel-wide “ridges” down to single pixel width
4. Linking and thresholding (hysteresis):
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves and the low threshold to continue them

MATLAB:

```matlab
>> edge(image,'canny');
>> help edge
```

Recap: Edges vs. Boundaries

Edges useful signal to indicate occluding boundaries, shape.

...but quite often boundaries of interest are fragmented, and we have extra “clutter” edge points.

Recap: Chamfer Matching

- Chamfer Distance
  - Average distance to nearest feature
  \[
  D_{\text{chamfer}}(T, I) = \frac{1}{|T|} \sum_{t \in T} d_I(t) \]
  - This can be computed efficiently by correlating the edge template with the distance-transformed image
Recap: Fitting and Hough Transform

Given a model of interest, we can overcome some of the missing and noisy edges using fitting techniques.

With voting methods like the Hough transform, detected points vote on possible model parameters.

Recap: Hough Transform

- How can we use this to find the most likely parameters \((m,b)\) for the most prominent line in the image space?
  - Let each edge point in image space vote for a set of possible parameters in Hough space.
  - Accumulate votes in discrete set of bins; parameters with the most votes indicate line in image space.

Hough Transform for Circles

- Circle: center \((a,b)\) and radius \(r\)
  \[(x-a)^2 + (y-b)^2 = r^2\]

  - For a fixed radius \(r\), unknown gradient direction

Hough Transform for Circles

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Hough Transform for Circles

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For every edge pixel \((x, y)\):
  For each possible radius value \(r\):
    For each possible gradient direction \(\theta\):
      \[a = x - r \cos(\theta)\]
      \[b = y + r \sin(\theta)\]
      \[H[a, b, r] += 1\]
  end
end

Example: Detecting Circles with Hough

Crosshair indicates results of Hough transform, bounding box found via motion differencing.

Note: a different Hough transform (with separate accumulators) was used for each circle radius (quarters vs. penny).
Voting: Practical Tips

- Minimize irrelevant tokens first (take edge points with significant gradient magnitude)
- Choose a good grid / discretization
  - Too coarse: large votes obtained when too many different lines correspond to a single bucket
  - Too fine: miss lines because some points that are not exactly collinear cast votes for different buckets
- Vote for neighbors, also (smoothing in accumulator array)
- Utilize direction of edge to reduce free parameters by 1
- To read back which points voted for “winning” peaks, keep tags on the votes.

Hough Transform: Pros and Cons

Pros

- All points are processed independently, so can cope with occlusion
- Some robustness to noise: noise points unlikely to contribute consistently to any single bin
- Can detect multiple instances of a model in a single pass

Cons

- Complexity of search time increases exponentially with the number of model parameters
- Non-target shapes can produce spurious peaks in parameter space
- Quantization: hard to pick a good grid size

Generalized Hough Transform

- What if want to detect arbitrary shapes defined by boundary points and a reference point?

At each boundary point, compute displacement vector: \( r = a - p_i \).

For a given model shape: store these vectors in a table indexed by gradient orientation \( \theta \).

Example: Generalized Hough Transform

Say we’ve already stored a table of displacement vectors as a function of edge orientation for this model shape.

Example: Generalized Hough Transform

Now we want to look at some edge points detected in a new image, and vote on the position of that shape.
Application in Recognition

- Instead of indexing displacements by gradient orientation, index by “visual codeword”.


Topics of This Lecture: Color

- Measuring color
  - Spectral power distributions
  - Color mixing
- Perception of color
  - Human photoreceptors
  - Environmental effects, adaptation
  - Color matching experiments
- Using color in machine vision systems
  - Color spaces
  - Color for recognition

What Is Color?

- Color is a psychological property of our visual experiences when we look at objects and lights, not a physical property of those objects or lights (S. Palmer, Vision Science: Photons to Phenomenology)
- Color is the result of interaction between physical light in the environment and our visual system

Electromagnetic Spectrum

- Why do we see light at these wavelengths?
  - Because that’s where the sun radiates electromagnetic energy.

The Physics of Light

Any source of light can be completely described physically by its spectrum: the amount of energy emitted (per time unit) at each wavelength 400 - 700 nm.

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The Physics of Light

Some examples of the spectra of light sources

A. Ruby Laser

B. Gallium Phosphide Crystal

C. Tungsten Lightbulb

D. Normal Daylight

Some examples of the reflectance spectra of surfaces

Red, Yellow, Blue, Purple

Interaction of Light and Surfaces

- Observed color is the result of interaction of light source spectrum with surface reflectance.
- Spectral radiometry: all definitions and units are now "per unit wavelength".
  - All terms are now "spectral"

The Psychophysical Correspondence

There is no simple functional description for the perceived color of all lights under all viewing conditions, but ......

A helpful constraint:
Consider only physical spectra with normal distributions

Mean ← Hue

Variance ← Saturation
The Psychophysical Correspondence

Area ↔ Brightness

# Photons vs. Wavelength

B. Leibe, Perceptual and Sensory Augmented Computing, Computer Vision WS 08/09

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Color Mixing

- Cartoon spectra for color names:
  - Red
  - Green
  - Blue
  - Yellow
  - Cyan

Additive Color Mixing

Colors combine by adding color spectra

Light adds to black.

Examples of Additive Color Systems

- CRT phosphors
- Multiple projectors

Superposition

• Additive mixing:
  The spectral power distribution of the mixture is the sum of the spectral power distributions of the components.
Subtractive Color Mixing

Colors combine by multiplying color spectra.

Pigments remove color from incident light (white).

Examples of Subtractive Color Systems

- Printing on paper
- Crayons
- Most photographic film

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The Eye

- The human eye is a camera!
- Iris - colored annulus with radial muscles
- Pupil - the hole (aperture) whose size is controlled by the iris
- Lens - changes shape by using ciliary muscles (to focus on objects at different distances)
- What's the "Film"?

Density of Rods and Cones in the Retina

- Rods and cones are non-uniformly distributed on the retina
- Rods responsible for intensity, cones responsible for color
- Fovea - small region (1 or 2°) at the center of the visual field containing the highest density of cones (and no rods).
- Less visual acuity in the periphery—many rods wired to the same neuron.

Rod/Cone Sensitivity

Dynamic range

- Consumer camera
- High dynamic range (HDR) camera
- Full human vision

- Dazzling light, bright sun on snow
- Outdoors in full sunlight
- Outdoors under a tree on a sunny day
- Comfortable indoor illumination; night sports events

- Threshold for perception of color
- Bright moonlight
- Threshold where dark-adapted
Three kinds of cones:
- Ratio of L to M to S cones: approx. 10:5:1
- Almost no S cones in the center of the fovea

Three kinds of cones:
- Green (M)
- Red (L)
- Blue (S)

Ratio of L to M to S cones: approx. 10:5:1
Almost no S cones in the center of the fovea

Brewster’s colors: evidence of interpolation from spatially offset color samples

Scale relative to human photoreceptor size: each line covers about 7 photoreceptors

Rods and cones act as filters on the spectrum
- To get the output of a filter, multiply its response curve by the spectrum, integrate over all wavelengths
  - Each cone yields one number
- How can we represent an entire spectrum with 3 numbers?
  - We can’t! Most of the information is lost.
  - Such spectra are known as metamers.

Spectra of some real-world surfaces

Metamers

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Environmental Effects & Adaptation

- **Chromatic adaptation**: we adapt to a particular illuminant
- **Assimilation, contrast effects, chromatic induction**: nearby colors affect what is perceived; receptor excitations interact across image and time
- **Afterimages**

  Color matching \(\approx\) color appearance  
  Physics of light \(\approx\) perception of light

Chromatic Adaptation

- If the visual system is exposed to a certain illuminant for a while, our color system starts to adapt / skew.

Brightness Perception

Edward Adelson

http://web.mit.edu/persci/people/adelson/illusions_demos.html

Color Illusions

Look at blue squares

Look at yellow squares

http://www.lottolab.org/articles/illusionsofflight.asp
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Contrast Effects
Afterimages

- Tired photoreceptors send out negative response after a strong stimulus

http://www.sandlotscience.com/Aftereffects/Andrus_Spiral.htm

Name that Color

Blue Red Green Cyan
Magenta Black Pink
Yellow Orange Violet
Brown Purple Cyan
Indigo Red Green Blue

High level interactions affect perception and processing.

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Standardizing Color Experience

- We would like to understand which spectra produce the same color sensation from people under similar viewing conditions
- Color matching experiments

Color Matching Experiment 1
The primary color amounts needed for a match:

$p_1$  $p_2$  $p_3$

We say a “negative” amount of $p_2$ was needed to make the match, because we added it to the test color’s side. The primary color amounts needed for a match:

$p_1$  $p_2$  $p_3$
Trichromacy
- Three numbers seem to be sufficient for encoding color.
- In color matching experiments, most people can match any given light with three primaries.
  - Exception: color blindness
- For the same light and same primaries, most people select the same weights.
- Trichromatic color theory dates back to 18th century (Thomas Young).

Grassman’s Laws
- If two test lights can be matched with the same set of weights, then they match each other:
  - Suppose \( A = u_i P_i + u_2 P_2 + u_3 P_3 \)
  - and \( B = u_i P_i + u_2 P_2 + u_3 P_3 \).
  - Then \( A = B \).
- If we scale the test light, then the matches get scaled by the same amount:
  - Suppose \( A = k u_i P_i + k u_2 P_2 + k u_3 P_3 \).
  - Then \( k A = (k u_i) P_i + (k u_2) P_2 + (k u_3) P_3 \).
- If we mix two test lights, then mixing the matches will match the result (superposition):
  - Suppose \( A = u_i P_i + u_2 P_2 + u_3 P_3 \)
  - and \( B = v_i P_i + v_2 P_2 + v_3 P_3 \).
  - Then \( A + B = (u_i + v_i) P_i + (u_2 + v_2) P_2 + (u_3 + v_3) P_3 \).
  - Here “=” means “matches”.

Linear Color Spaces
- Defined by a choice of three primaries.
- The coordinates of a color are given by the weights of the primaries used to match it.
- Matching functions: weights required to match single-wavelength light sources.

Computing Color Matches
- How do we compute the weights that will yield a perceptual match for any test light using a given set of primaries?
  1. Select primaries.
  2. Estimate their color matching functions: observer matches series of monochromatic lights, one at each wavelength.
  3. Multiply matching functions and test light.

\[
C = \begin{pmatrix}
  c_i(\lambda_i) \\
  c_j(\lambda_j) \\
  c_k(\lambda_k)
\end{pmatrix}
\]

Computing Color Matches
- \( \lambda_i \) matches \( c_i(\lambda_i), c_j(\lambda_j), c_k(\lambda_k) \)
- Now have matching functions for all monochromatic light sources, so we know how to match a unit of each wavelength.
  - Arbitrary new spectral signal is a linear combination of the monochromatic sources.

\[
t = \begin{pmatrix}
  t(\lambda_1) \\
  \vdots \\
  t(\lambda_N)
\end{pmatrix}
\]
Computing Color Matches

- So, given any set of primaries and their associated matching functions \( C \), we can compute weights \( e \) needed on each primary to give a perceptual match to any test light \( t \) (spectral signal).

\[
e = Ct
\]

We estimate the matrix \( C \) (photopic color matching functions).

Fig from B. Wandell, 1996

Slide credit: Kristen Grauman

Why is computing the color match for any color signal for a given set of primaries useful?

- Want to paint a carton of Kodak film with the Kodak yellow color.
- Want to match skin color of a person in a photograph printed on an ink jet printer to their true skin color.
- Want the colors in the world, on a monitor, and in a print format to all look the same.

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Standard Color Spaces

- Use a common set of primaries/color matching functions
- Linear color space examples
  - RGB
  - CIE XYZ
- Non-linear color space
  - HSV

Linear Color Spaces: RGB

- Primaries are monochromatic lights (for monitors, they correspond to the three types of phosphors)
- Subtractive matching required for some wavelengths

RGB matching functions

- Good for devices, but not for perception...

Linear Color Spaces: CIE XYZ

- Established in 1931 by the International Commission on Illumination
- Primaries are imaginary, but matching functions are everywhere positive
- 2D visualization: draw \((x, y)\), where

\[
x = X/(X+Y+Z), \quad y = Y/(X+Y+Z)
\]

Matching functions
HSV Color Space

- Hue, Saturation, Value (Brightness)
- Nonlinear - reflects topology of colors by coding hue as an angle.
- Matlab: hsv2rgb, rgb2hsv.

Distances in Color Space

- Are distances between points in a color space perceptually meaningful?

Uniform Color Spaces

- Attempt to correct this limitation by remapping color space so that just-noticeable differences are contained by circles.
  ⇒ Distances are more perceptually meaningful.
- Examples:
  - CIE u'v'
  - CIE Lab

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Color as Low-Level Cue

- For recognition
- For content-based image retrieval (CBIR)
**Color as Low-Level Cue for CBIR**

- Color histograms: Use distribution of colors to describe image
- No spatial information - invariant to translation, rotation, scale

*More about this in the lecture 8...*

**Color-Based Image Retrieval**

**Example database**

**Color-Based Skin Detection**

- Used 18,696 images to build a general color model.
- Histogram representation

**Color-Based Segmentation for Robot Soccer**

- Automatic color model learning from a color-coded map of the environment

**Coming Up Next...**

- Image Processing Basics
- Segmentation
- Object Recognition
- Local Features & Matching
- Object Categorization
- 3D Reconstruction
- Motion and Tracking
References and Further Reading

- Background information on color can be found in Chapter 6 of
  Prentice Hall, 2003

- Perceptual illusions
  - http://www.sandlotscience.com/Aftereffects/Andrus_Spiral.htm