Visual Hacks

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Outline

1. Introduction
2. Imaging Geometry
3. Features
4. Feature Description
5. Recognition
6. Wrap-up

Camera

- Most flexible sensory modality
- Complex sensory processing
- Not discussed in any detail
- Offers wide range
- Diverse tasking of sensor
- Relatively inexpensive
- Computationally demanding

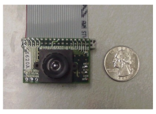
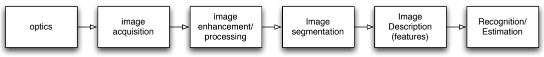


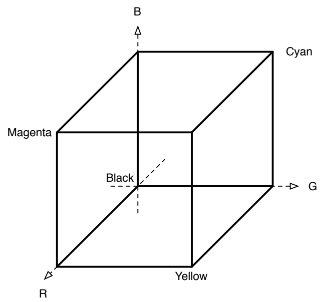
Image processing chain



Color Models

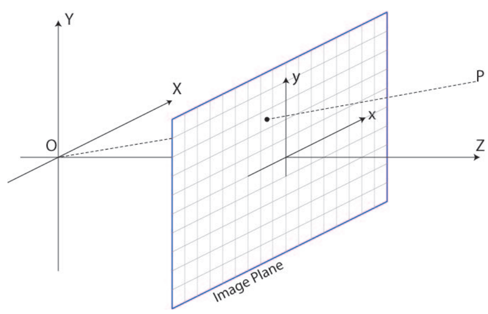
- There are quite a few image color models
  - RGB Red, Green, Blue
  - HSI Hue, Saturation, Intensity
  - CMY Cyan, Magenta, Yellow
- For this course RGB is adequate
- Check carefully on the selected / available color models

Color combinations



Outline

Pin-Hole Model



Pin-Hole Model

- The relations are then:

$$
\begin{aligned}
\frac{x}{\lambda} &= \frac{X}{Z} \\
\frac{y}{\lambda} &= \frac{Y}{Z} \\
&\Rightarrow \\
x &= \frac{\lambda X}{Z} \\
y &= \frac{\lambda Y}{Z}
\end{aligned}
$$

Pin-Hole Model

- Remember Homogeneous Coordinates?

$$
\vec{P} = \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}
$$

- Define the Perspective transform as

$$
\mathbf{T} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{1}{\lambda} & 0 \end{bmatrix}
$$

Camera models

- The pin-hole model is a fair approximation for medium focal lengths
- For extreme values of the focal length various kinds of distortion should be taken into account
- Calibration is usually required to ensure use of the camera for real-world tasks
- MATLAB has a great toolbox for image calibration
`http://www.vision.caltech.edu/bouguetj/calib_doc/`

Outline

Image Features

- Computer Vision has been studied for 4 decades. It might offer the biggest potential.
- Robustness is the major challenge
- SLAM is termed “Structure from motion” (SFM) in the vision literature.

Harris Features

- Detection of high curvature corner/edge points
- Standard in several image processing packages.
- Noise sensitive

$$M = \begin{pmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{pmatrix}$$

$$R = \det M - k(\mathrm{trace} M)^2$$

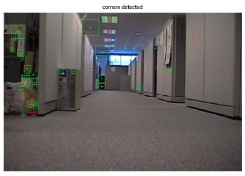
- Lukas-Tomasi-Kanade (condition number of M)

Harris

corners detected

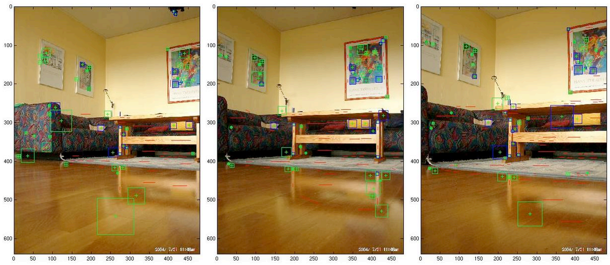
Harris example

SIFT features

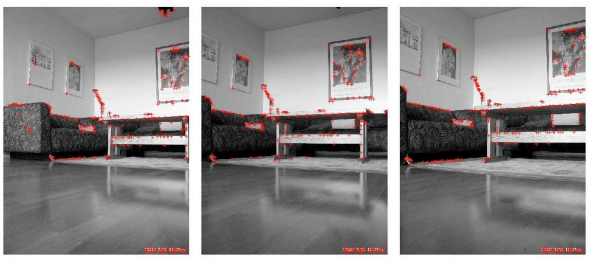


- (Lowe, 2004)
- Scale-space top-points
- Coding of local orientation at top-points
- Example code is available (linux) and several Matlab versions.

SIFT Example



Harris Example



Outline

Feature Detection

- Covered in more detail in future lectures
- Basics of feature detection to get started
- The idea is to condense regions into a compact representation.

Example features

- Euler Number / #holes in a region
- Ellipse approximation (major/minor axes)
- Line parameters
- Compactness
- Perimeter length

Feature / Region Description

- Description of two different types of regions
  1. Contour based
  2. Region based
- Advantages / Disadvantages?

Contour descriptors

- Chain codes
- Signatures (polar)
- Polygonal approximation

Moments

- Statistical moments are in general defined as:

$$m_n = \sum_{i=0}^{L-1} x_i^n g(x_i)$$

- The mean is then

$$m_1 = \sum_{i=0}^{L-1} x_i g(x_i)$$

- Central moments are defined as

$$\mu_n = \sum_{i=0}^{L-1} (x_i - m_1)^n g(x_i)$$

- In two dimensions

$$\mu_{mn} \sum_{i=0}^{L-1} \sum_{j=0}^{K-1} (x_i - m_{10})^m (y_j - m_{01})^n g(x_i, y_j)$$

Well-known moments

- Standard deviation

$$\sigma = \sqrt{\mu_2} = \sqrt{\sum_{i=0}^{L-1} (x_i - m_1)^2 g(x_i)}$$

- Skewness - μ_3 - indicates the symmetry of the distribution, value 0 = perfect symmetry
- Normalized central moments of order (p+q)

$$\nu_{pq} = \frac{\mu_{pq}}{m_{pq}^{\gamma}}$$

  where $\gamma = \frac{p+q}{2} + 1$
- Moments are widely used for characterization of regions and for standard tasks

Least Square Line Fitting

- Assume g(x,y) = 1 where we have the line elements
- If we have computed $\mu_{20}, \mu_{11}, \mu_{02}, \mu_{10}, \mu_{01}, \mu_{00}$
- We want to estimate a line of the form

$$y = a + bx$$

- The regressions can be computed as

$$b = \frac{\mu_{11}}{\mu_{20}}$$

$$a = \mu_{01} - b\mu_{10}$$

- Quality of fit defined as r^2

$$r^2 = \frac{\mu_{11}^2}{\mu_{02}\mu_{20}}$$

Other use of moments

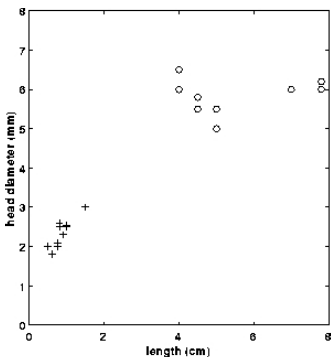
- Characterization of image texture
- Variance, Cross correlation, ... allow pattern matching
- Ellipse matching - major / minor axes of a region
- A rich and easy to use descriptor

Outline

Recognition

- Supervised recognition
- A prior database of samples has been recorded and processed
- Strategy
  1. Compute a set of descriptors
  2. Determine how well the "features" match against prototypes
  3. Choose the best fit

Example - Bolts or Needles



Minimum distance classification

- Suppose we have computed the mean value for each of the classes
- $m_{needle} = [0.86, 2.34]^T$ and $m_{bolt} = [5.74, 5, 85]^T$
- We can then compute the minimum distance

$$d_j(x) = ||x - m_j||$$

- $argmin_i d_i(x)$ is the best fit
- Decision functions can be derived

Bolts / Needle Decision Functions

Needle $d_{needle}(x) = 0.86x_1 + 2.34x_2 - 3.10$

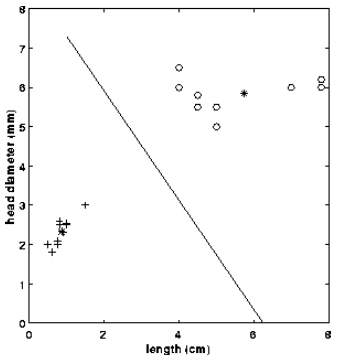
Bolt $d_{bolt}(x) = 5.74x_1 + 5.85x_2 - 33.59$

Decision boundary

$$d_i(x) - d_j(x) = 0$$

$$d_{needle/bolt}(x) = -4.88x_1 - 3.51x_2 + 30.49$$

Example decision surface



Nearest neighbor

- Assume you have a set of prototypes (f_i) that are classified
- Estimate distance to prototypes: $d_i(x) = ||x - f_i||$
- Assign the label that corresponds to the closest prototype
- Easy to implement, can often be pre-processed or simplified

Outline

Wrap-up

- Select tools to fit your task
- Quick tour of vision 101
- Think about color spaces
- Use off-the-shelf calibration
- Consider simple robust features
- This is not a project about recognition ....