Vision & Localization
"Seeing Where You Are"

METR 4202: Advanced Control & Robotics

Drs Surya Singh, Paul Pounds, and Hanna Kurniawati

Lecture # 8 September 10, 2012

(with Vision Material from Richard Szeliski, *Computer Vision: Algorithms and Applications*)

metr4202@itee.uq.edu.au

http://itee.uq.edu.au/~metr4202/

RoboticsCourseWare Contributor

NEW, NEW Schedule

Week	Date	Lecture (M: 12-1:30, 43-102)
1	23-Jul	Introduction
2	30-Jul	Representing Position & Orientation & State (Frames, Transformation Matrices & Affine Transformations)
3	6-Aug	Robot Kinematics and Dynamics
4	13-Aug	Robot Dynamics & Control
5	20-Aug	Obstacle Avoidance & Motion Planning
6	27-Aug	Sensors, Measurement and Perception
7	3-Sep	Perception (+ Prof. S. LaValle)
8	10-Sep	Computer Vision & Localization (SFM/SLAM)
9	17-Sep	State-Space Modelling (+ Prof. M. Srinivasan)
	24-Sep	*Study break*
10	1-Oct	*Public Holiday*
11	8-Oct	Localization and Navigation
12	15-Oct	Control/Planning Under Uncertainty
13	22-Oct	Vision-based control (Prof. P. Corke) & Course Review

Updates: Lab 2 → Free Extension to Oct 2

For Lab 2:

- Project description posted
- Uses a Kinect
  mostly as a "Camera"

- Submit code via **UQ eLearning**
  Report via Submission System

- Remember "extension" to **Tuesday, October 2 at 10am**
- Final Exam: 12/11/12 at 11:15 am

Quick Outline

1. **Perception II: Computer Vision → Localization**
   1. Feature extraction
   2. Stereopsis and depth

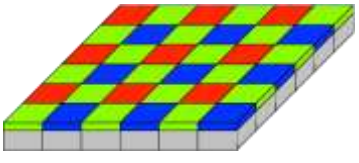
2. **Camera Calibration**

3. **Lab 2: Q & A**

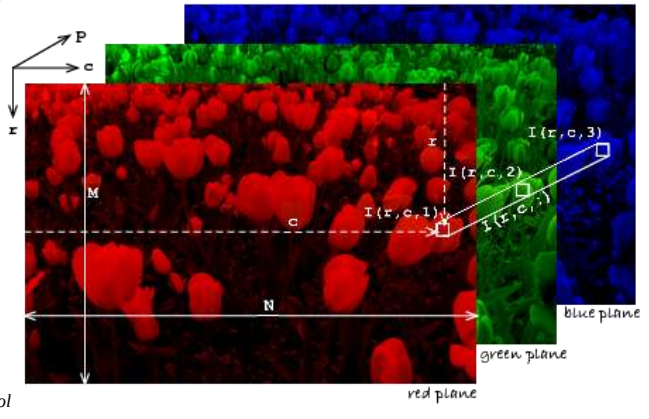
Features

- Dense:
  - Colour
  - Edges
  - Disparity
- Sparse:
  - Corners
  - Lines
  - Statistics on Edges: SIFT, SURF

Features -- Colour Features



Bayer Patterns



Ch. 10, *Robotics Vision and Control*

Edge Detection

- Canny edge detector:
  - Pepsi Sequence:

Image Data: http://www.cs.brown.edu/~black/mixtureOF.html and Szeliski, CS223B-L9
See also: Use of Temporal information to aid segmentation:
http://www.cs.toronto.edu/~babalex/SpatiotemporalClosure/supplementary_material.html

Why extract features?

- **Object detection**
- Robot Navigation
- Scene Recognition

- Steps:
  - Extract Features
  - Match Features

Adopted drom S. Lazebnik, Gang Hua (CS 558)

Why extract features? [2]

- Panorama stitching…
  → Step 3: Align images
  (see: Hartley & Zisserman, *Multiple View Geometry*)

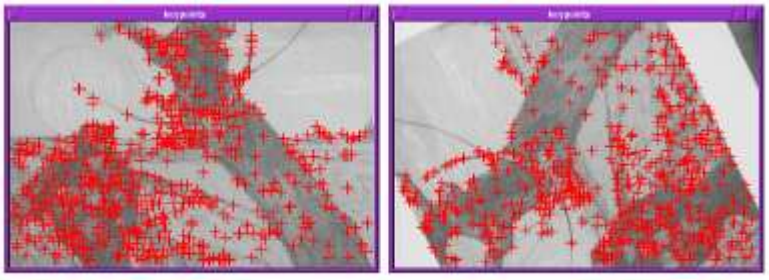
Adopted from S. Lazebnik, Gang Hua (CS 558)

Characteristics of good features

- Repeatability
  - The same feature can be found in several images despite geometric and photometric transformations
- Saliency
  - Each feature is distinctive
- Compactness and efficiency
  - Many fewer features than image pixels
- Locality
  - A feature occupies a relatively small area of the image; robust to clutter and occlusion

Adopted from S. Lazebnik, Gang Hua (CS 558)

Finding Corners



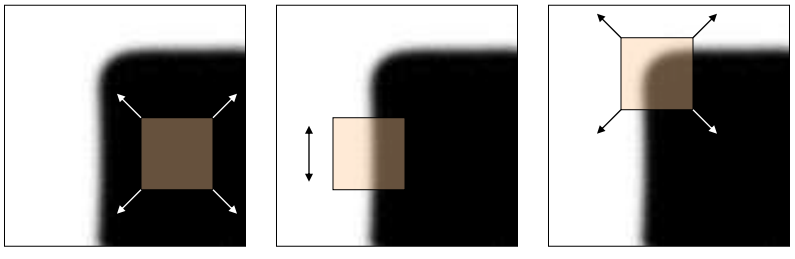
- Key property: in the region around a corner, image gradient has two or more dominant directions
- Corners are repeatable and distinctive

C.Harris and M.Stephens. "A Combined Corner and Edge Detector." *Proceedings of the 4th Alvey Vision Conference*: pages 147—151, 1988.

Adopted from S. Lazebnik, Gang Hua (CS 558)

Corner Detection: Basic Idea

- Look through a window
- Shifting a window in any direction should give a large change in intensity



"flat" region: no change in all directions

"edge": no change along the edge direction

"corner": significant change in all directions

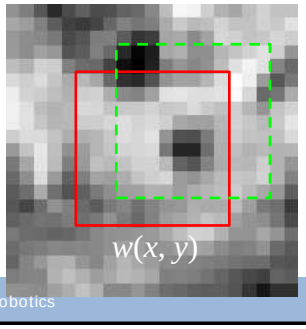
Source: A. Efros

Corner Detection: Mathematics

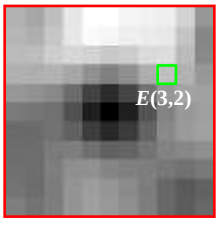
Change in appearance of window $w(x,y)$
for the shift $[u,v]$:

$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2$$

$I(x, y)$



$E(u, v)$



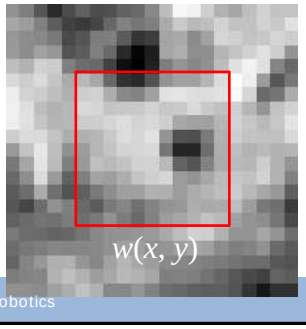
Adopted from
S. Lazebnik,
Gang Hua (CS 558)

Corner Detection: Mathematics

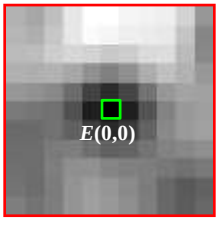
Change in appearance of window $w(x,y)$
for the shift $[u,v]$:

$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2$$

$I(x, y)$



$E(u, v)$



Adopted from
S. Lazebnik,
Gang Hua (CS 558)

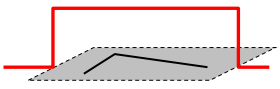
Corner Detection: Mathematics

Change in appearance of window $w(x,y)$
for the shift $[u,v]$:

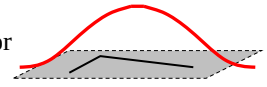
$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u,y+v) - I(x,y)\right]^2$$

Window function | Shifted intensity | Intensity

Window function $w(x,y)$ =



or



1 in window, 0 outside

Gaussian

Adopted from
S. Lazebnik,
Gang Hua (CS 558)

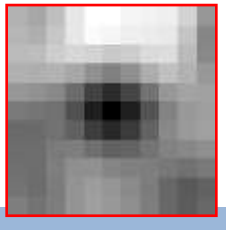
Corner Detection: Mathematics

Change in appearance of window $w(x,y)$
for the shift $[u,v]$:

$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u,y+v) - I(x,y)\right]^2$$

We want to find out how this function behaves for small shifts

$E(u, v)$



Adopted from
S. Lazebnik,
Gang Hua (CS 558)

Corner Detection: Mathematics

Change in appearance of window $w(x,y)$ for the shift $[u,v]$:

$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u,y+v) - I(x,y)\right]^2$$

We want to find out how this function behaves for small shifts

$$E(u,v) \approx E(0,0) + \begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} E_u(0,0) \\ E_v(0,0) \end{bmatrix} + \frac{1}{2} \begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} E_{uu}(0,0) & E_{uv}(0,0) \\ E_{uv}(0,0) & E_{vv}(0,0) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix}$$

Local quadratic approximation of $E(u,v)$ in the neighborhood of (0,0) is given by the *second-order Taylor expansion*:

Adopted from
S. Lazebnik,
Gang Hua (CS 558)

Corner Detection: Mathematics

$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u,y+v) - I(x,y)\right]^2$$

Second-order Taylor expansion of $E(u,v)$ about (0,0):

$$E(u,v) \approx E(0,0) + \begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} E_u(0,0) \\ E_v(0,0) \end{bmatrix} + \frac{1}{2} \begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} E_{uu}(0,0) & E_{uv}(0,0) \\ E_{uv}(0,0) & E_{vv}(0,0) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$E_u(u,v) = \sum_{x,y} 2w(x,y)\left[I(x+u,y+v) - I(x,y)\right] I_x(x+u,y+v)$$

$$E_{uu}(u,v) = \sum_{x,y} 2w(x,y) I_x(x+u,y+v) I_x(x+u,y+v) + \sum_{x,y} 2w(x,y)\left[I(x+u,y+v) - I(x,y)\right] I_{xx}(x+u,y+v)$$

$$E_{uv}(u,v) = \sum_{x,y} 2w(x,y) I_y(x+u,y+v) I_x(x+u,y+v) + \sum_{x,y} 2w(x,y)\left[I(x+u,y+v) - I(x,y)\right] I_{xy}(x+u,y+v)$$

Adopted from
S. Lazebnik,
Gang Hua (CS 558)

Corner Detection: Mathematics

$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2$$

Second-order Taylor expansion of $E(u,v)$ about (0,0):

$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} \sum_{x,y} w(x,y) I_x^2(x,y) & \sum_{x,y} w(x,y) I_x(x,y) I_y(x,y) \\ \sum_{x,y} w(x,y) I_x(x,y) I_y(x,y) & \sum_{x,y} w(x,y) I_y^2(x,y) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$E(0,0) = 0$$

$$E_u(0,0) = 0$$

$$E_v(0,0) = 0$$

$$E_{uu}(0,0) = \sum_{x,y} 2w(x,y) I_x(x,y) I_x(x,y)$$

$$E_{vv}(0,0) = \sum_{x,y} 2w(x,y) I_y(x,y) I_y(x,y)$$

$$E_{uv}(0,0) = \sum_{x,y} 2w(x,y) I_x(x,y) I_y(x,y)$$

Adopted from
S. Lazebnik,
Gang Hua (CS 558)

Harris detector: Steps

- Compute Gaussian derivatives at each pixel
- Compute second moment matrix M in a Gaussian window around each pixel
- Compute corner response function R
- Threshold R
- Find local maxima of response function (nonmaximum suppression)

C.Harris and M.Stephens. "A Combined Corner and Edge Detector."
Proceedings of the 4th Alvey Vision Conference: pages 147—151, 1988.

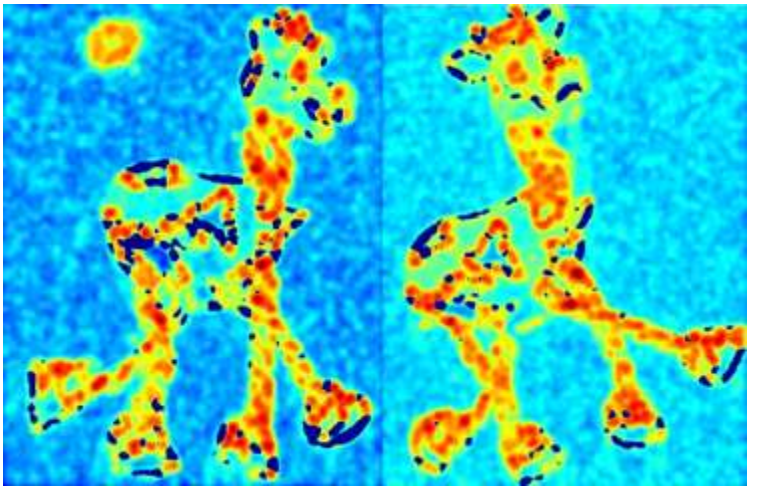
Adopted from
S. Lazebnik,
Gang Hua (CS 558)

Harris Detector: Steps

Adopted from S. Lazebnik, Gang Hua (CS 558)

Harris Detector: Steps

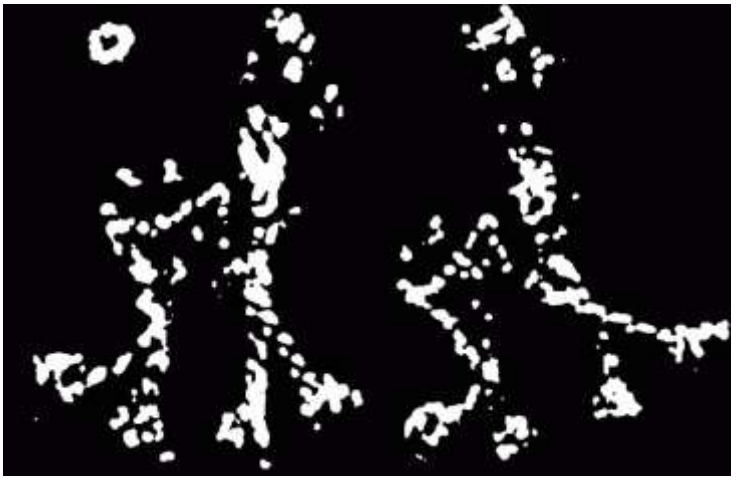
Compute corner response *R*



Adopted from S. Lazebnik, Gang Hua (CS 558)

Harris Detector: Steps

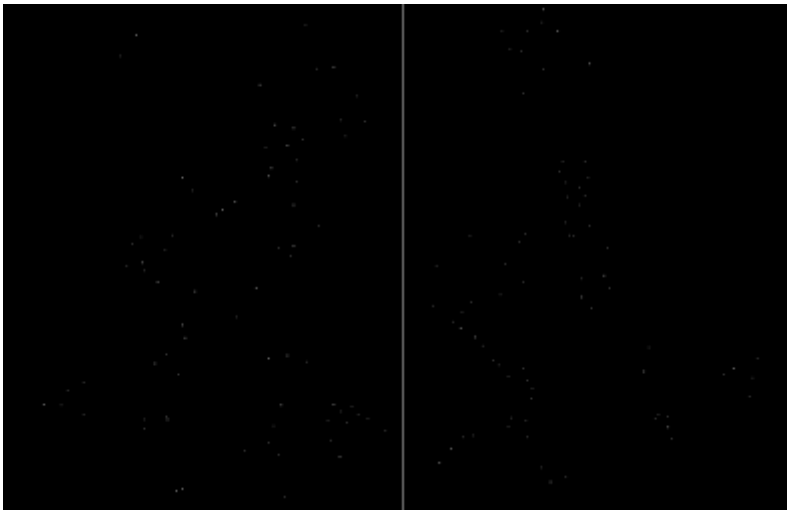
Find points with large corner response: R>threshold



Adopted from S. Lazebnik, Gang Hua (CS 558)

Harris Detector: Steps

Take only the points of local maxima of R



Adopted from S. Lazebnik, Gang Hua (CS 558)

Harris Detector: Steps

Adopted from S. Lazebnik, Gang Hua (CS 558)

Invariance and covariance

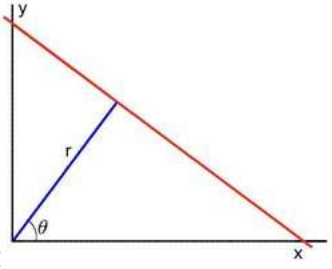
- We want corner locations to be invariant to photometric transformations and covariant to geometric transformations
  - Invariance: image is transformed and corner locations do not change
  - Covariance: if we have two transformed versions of the same image, features should be detected in corresponding locations

Adopted from S. Lazebnik, Gang Hua (CS 558)

Line Detection – Hough Lines [1]

- A line in an image can be expressed as two variables:
  - **Cartesian coordinate system:** m,b
  - **Polar coordinate system:** r, θ

    ➔ **avoids problems with vert. lines**



y=**m**x+**b** ➔

$$y = \left(-\frac{\cos\theta}{\sin\theta}\right)x + \left(\frac{r}{\sin\theta}\right)$$

- For each point (x_1, y_1) we can write:

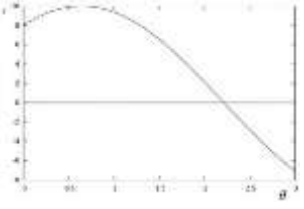
$$r = x_1 \cos\theta + y_1 \sin\theta$$

- Each pair (r,θ) represents a line that passes through (x_1, y_1)

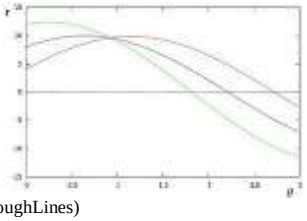
See also OpenCV documentation (cv::HoughLines)

Line Detection – Hough Lines [2]

- Thus a given point gives a sinusoid



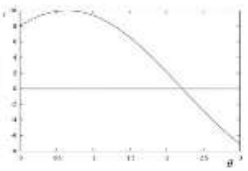
- Repeating for all points on the image



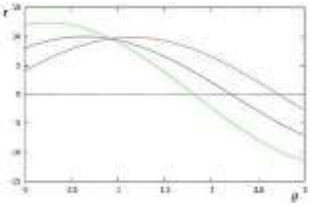
See also OpenCV documentation (cv::HoughLines)

Line Detection – Hough Lines [3]

- Thus a given point gives a sinusoid



- Repeating for all points on the image

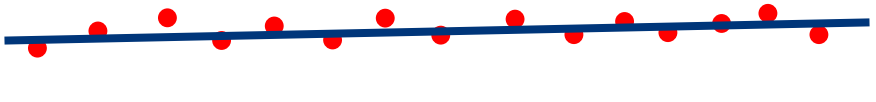


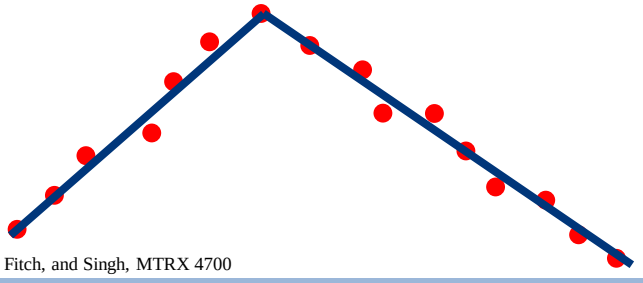
- NOTE that an intersection of sinusoids represents (**a point**) represents **a line** in which pixel points lay.

➔ Thus, a line can be *detected* by finding the number of Intersections between curves

See also OpenCV documentation (cv::HoughLines)

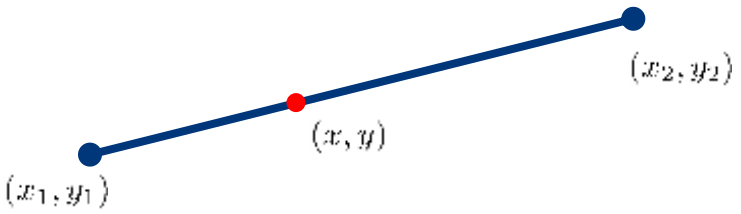
Line Extraction and Segmentation





Adopted from Williams, Fitch, and Singh, MTRX 4700

Line Formula



$$\frac{y - y_1}{x - x_1} = \frac{y_2 - y_1}{x_2 - x_1}$$

$$\mathbf{y} = m\mathbf{x} + b$$

Adopted from Williams, Fitch, and Singh, MTRX 4700

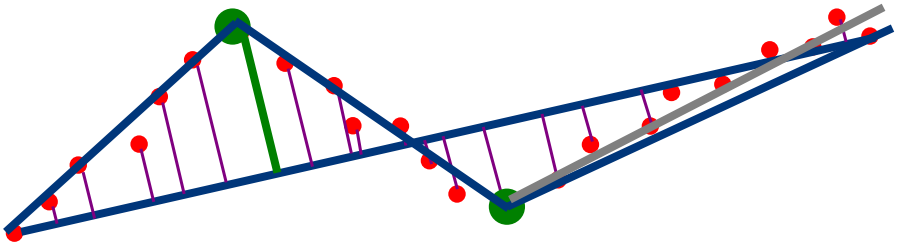
Line Estimation

Least squares minimization of the line:

- Line Equation: $\mathbf{y} - m\mathbf{x} - b = 0$
- Error in Fit: $\sum_i (y_i - mx_i - b)^2$
- Solution: $\begin{pmatrix} \overline{xy} \\ \bar{y} \end{pmatrix} = \begin{pmatrix} \overline{x^2} & \bar{x} \\ \bar{x} & 1 \end{pmatrix} \begin{pmatrix} m \\ b \end{pmatrix}$

Adopted from Williams, Fitch, and Singh, MTRX 4700

Line Splitting / Segmentation



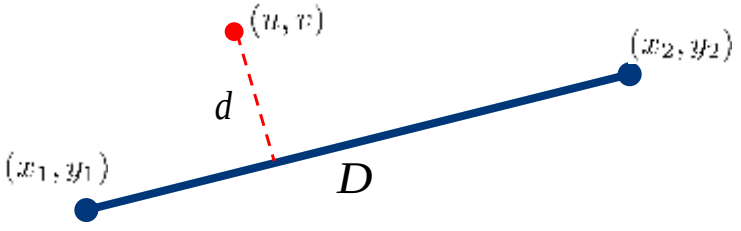
- What about corners?

➔Split into multiple lines (via expectation maximization)

1. Expect (assume) a number of lines N (say 3)
2. Find "breakpoints" by finding nearest neighbours upto a threshold or simply at random (RANSAC)
3. How to know N? (Also RANSAC)

Adopted from Williams, Fitch, and Singh, MTRX 4700

⊥ of a Point from a Line Segment



$$r = u(y_1 - y_2) + v(x_2 - x_1) + y_2x_1 - y_1x_2$$

$$d = \frac{r}{D}$$

Adopted from Williams, Fitch, and Singh, MTRX 4700

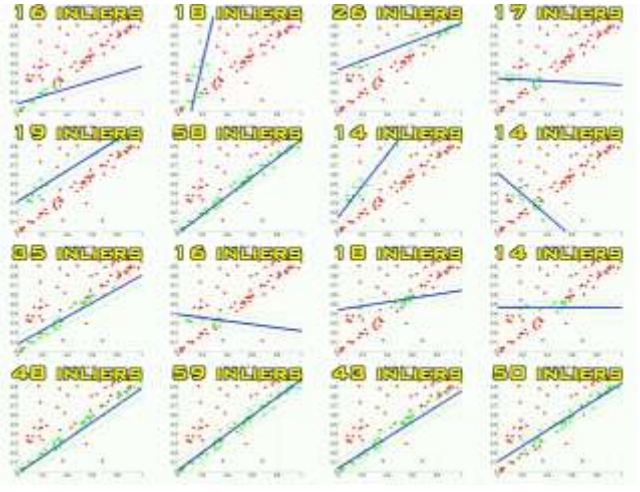
RANdom SAmple Consensus

1. Repeatedly select a small (minimal) subset of correspondences
2. Estimate a solution (in this case a the line)
3. Count the number of "inliers", $|e|<\Theta$ (for LMS, estimate med($|e|$)
4. Pick the *best* subset of inliers
5. Find a complete least-squares solution

- Related to least median squares
- See also: MAPSAC (Maximum *A Posteriori* SAmple Consensus)

From Szeliski, *Computer Vision: Algorithms and Applications*

Cool Robotics Share (this week)

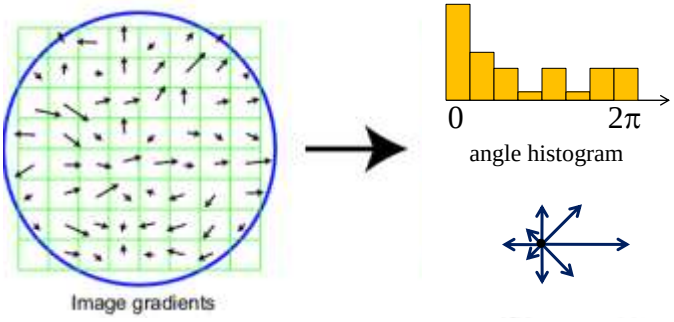


D. Wedge, *The RANSAC Song*

Scale Invariant Feature Transform

Basic idea:

- Take 16x16 square window around detected feature
- Compute edge orientation (angle of the gradient - 90°) for each pixel
- Throw out weak edges (threshold gradient magnitude)
- Create histogram of surviving edge orientations

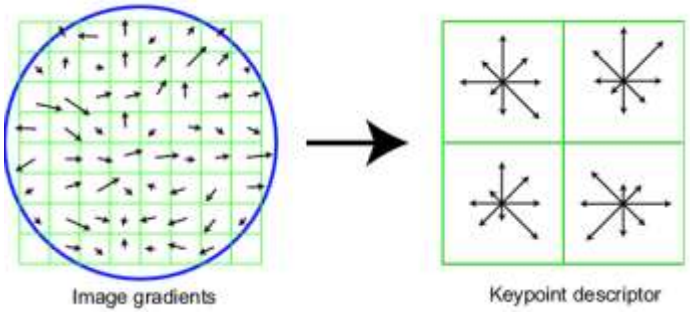


Adapted from slide by David Lowe

SIFT descriptor

Full version

- Divide the 16x16 window into a 4x4 grid of cells (2x2 case shown below)
- Compute an orientation histogram for each cell
- 16 cells * 8 orientations = 128 dimensional descriptor



Adapted from slide by David Lowe

Properties of SIFT

- Extraordinarily robust matching technique
  - Can handle changes in viewpoint
    - Up to about 60 degree out of plane rotation
  - Can handle significant changes in illumination
    - Sometimes even day vs. night (below)
  - Fast and efficient—can run in real time
  - Lots of code available
    - http://people.csail.mit.edu/albert/ladypack/wiki/index.php/Known_implementations_of_SIFT


From David Lowe and Szeliski, *Computer Vision: Algorithms and Applications*

Feature matching

- Given a feature in I_1, how to find the best match in I_2?
  1. Define distance function that compares two descriptors
  2. Test all the features in I_2, find the one with min distance

From Szeliski, *Computer Vision: Algorithms and Applications*

Feature distance

- How to define the difference between two features f_1, f_2?
  - Simple approach is SSD(f_1, f_2)
    - sum of square differences between entries of the two descriptors
    - can give good scores to very ambiguous (bad) matches

I_1 I_2

From Szeliski, *Computer Vision: Algorithms and Applications*

Feature distance

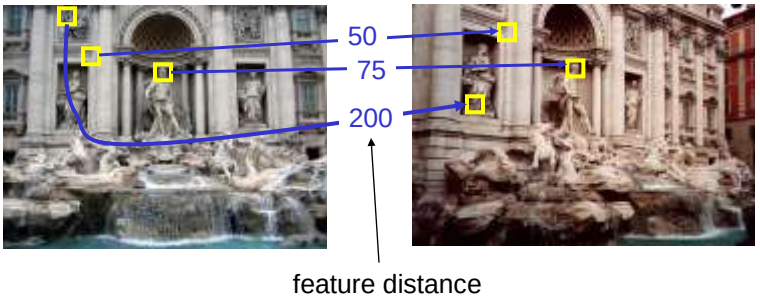
- How to define the difference between two features f_1, f_2?
  - Better approach: ratio distance = SSD(f_1, f_2) / SSD(f_1, f_2')
    - f_2 is best SSD match to f_1 in I_2
    - f_2' is 2nd best SSD match to f_1 in I_2
    - gives small values for ambiguous matches

I_1 I_2

From Szeliski, *Computer Vision: Algorithms and Applications*

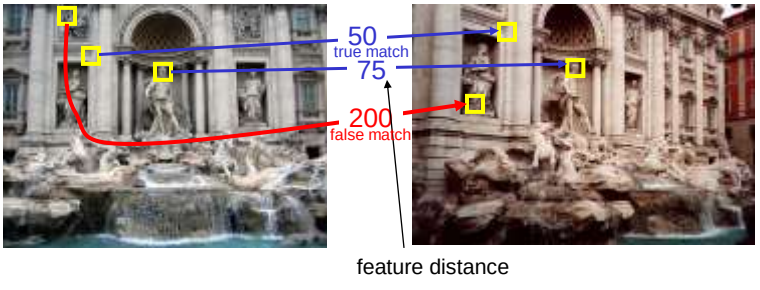
Evaluating the results

- How can we measure the performance of a feature matcher?



From Szeliski, *Computer Vision: Algorithms and Applications*

True/false positives

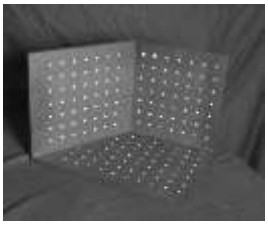


- The distance threshold affects performance
  - True positives = # of detected matches that are correct
    - Suppose we want to maximize these—how to choose threshold?
  - False positives = # of detected matches that are incorrect
    - Suppose we want to minimize these—how to choose threshold?

From Szeliski, *Computer Vision: Algorithms and Applications*

Camera calibration

- Determine camera parameters from known 3D points or calibration object(s)
- internal or intrinsic parameters such as focal length, optical center, aspect ratio:
  what kind of camera?
- external or extrinsic (pose) parameters:
  where is the camera?
- How can we do this?



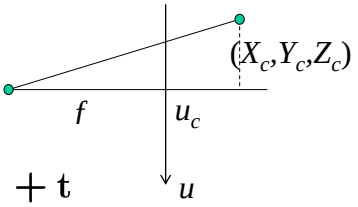
From Szeliski, *Computer Vision: Algorithms and Applications*

Camera calibration – approaches

- Possible approaches:
  - linear regression (least squares)
  - non-linear optimization
  - vanishing points
  - multiple planar patterns
  - panoramas (rotational motion)

From Szeliski, *Computer Vision: Algorithms and Applications*

Image formation equations



$$\begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix} = \begin{bmatrix} \mathbf{R} \end{bmatrix}_{3\times 3} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} + \mathbf{t}$$

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \sim \begin{bmatrix} U \\ V \\ W \end{bmatrix} = \begin{bmatrix} f & 0 & u_c \\ 0 & f & v_c \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix}$$

From Szeliski, *Computer Vision: Algorithms and Applications*

Calibration matrix

- Is this form of K good enough?
- non-square pixels (digital video)
- skew
- radial distortion

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \sim \begin{bmatrix} f & 0 & u_c \\ 0 & f & v_c \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix} = \mathbf{K}\ \mathbf{X}_c$$

$$\begin{bmatrix} fa & s & u_c \\ 0 & f & v_c \\ 0 & 0 & 1 \end{bmatrix} = \mathbf{K}$$

From Szeliski, *Computer Vision: Algorithms and Applications*

Levenberg-Marquardt

- Iterative non-linear least squares [Press'92]
  - Linearize measurement equations

$$\begin{aligned}\hat{u}_i &= f(\mathbf{m}, \mathbf{x}_i) + \frac{\partial f}{\partial \mathbf{m}} \Delta \mathbf{m} \\ \hat{v}_i &= g(\mathbf{m}, \mathbf{x}_i) + \frac{\partial g}{\partial \mathbf{m}} \Delta \mathbf{m}\end{aligned}$$

  - Substitute into log-likelihood equation: quadratic cost function in Dm

$$\sum_i \sigma_i^{-2} (\hat{u}_i - u_i + \frac{\partial f}{\partial \mathbf{m}} \Delta \mathbf{m})^2 + \cdots$$

From Szeliski, *Computer Vision: Algorithms and Applications*

Levenberg-Marquardt

- What if it doesn't converge?
  - Multiply diagonal by (1 + l), increase l until it does
  - Halve the step size Dm (my favorite)
  - Use line search
  - Other ideas?
- Uncertainty analysis: covariance S = A-1
- Is maximum likelihood the best idea?
- How to start in vicinity of global minimum?

From Szeliski, *Computer Vision: Algorithms and Applications*

Camera matrix calibration

- Advantages:
  - very simple to formulate and solve
  - can recover K [R | t] from M using QR decomposition [Golub & VanLoan 96]
- Disadvantages:
  - doesn't compute internal parameters
  - more unknowns than true degrees of freedom
  - need a separate camera matrix for each new view

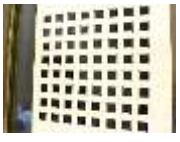
From Szeliski, *Computer Vision: Algorithms and Applications*

Multi-plane calibration

- Use several images of planar target held at unknown orientations [Zhang 99]
  - Compute plane homographies

$$\begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} \sim \mathbf{K} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} \sim \mathbf{HX}$$

  - Solve for K-TK-1 from Hk's
    - 1plane if only f unknown
    - 2 planes if (f,uc,vc) unknown
    - 3+ planes for full K
  - Code available from Zhang and OpenCV



From Szeliski, *Computer Vision: Algorithms and Applications*

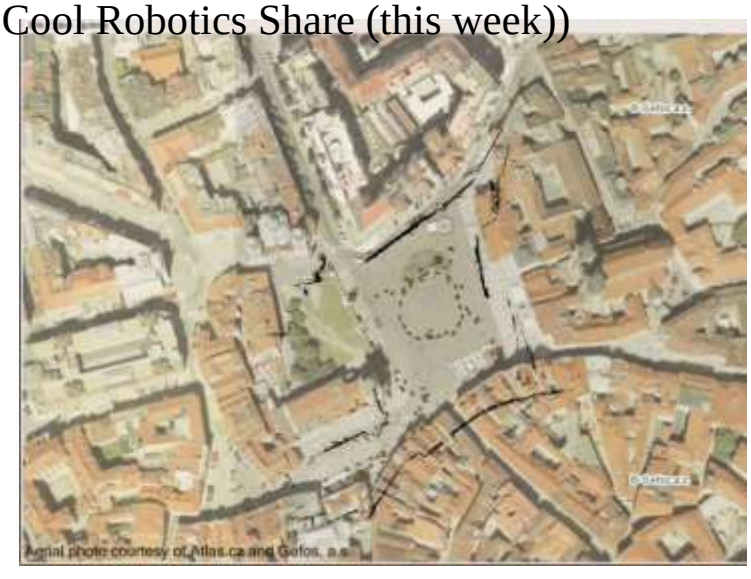
Rotational motion

- Use pure rotation (large scene) to estimate f
  - estimate f from pairwise homographies
  - re-estimate f from 360º "gap"
  - optimize over all {K,Rj} parameters
    [Stein 95; Hartley '97; Shum & Szeliski '00; Kang & Weiss '99]

- Most accurate way to get f, short of surveying distant points

From Szeliski, *Computer Vision: Algorithms and Applications*

SFM: Structure from Motion
(& Cool Robotics Share (this week))



Structure [from] Motion

- Given a set of feature tracks,
  estimate the 3D structure and 3D (camera) motion.

- Assumption: orthographic projection

- Tracks: (u_{fp}, v_{fp}), f: frame, p: point
- Subtract out **mean** 2D position…

  $\mathbf{i}_f$: rotation, $\mathbf{s}_p$: position

$$u_{fp} = i_f^T s_p, v_{fp} = j_f^T s_p$$

From Szeliski, *Computer Vision: Algorithms and Applications*

Structure from motion

- How many points do we need to match?
- 2 frames:
  - (R,t): 5 dof + 3n point locations ≤
  - 4n point measurements ⇒
  - n ≥ 5

$$\hat{u}_{ij} = f(\mathbf{K}, \mathbf{R}_j, \mathbf{t}_j, \mathbf{x}_i)$$
$$\hat{v}_{ij} = g(\mathbf{K}, \mathbf{R}_j, \mathbf{t}_j, \mathbf{x}_i)$$

- k frames:
  - 6(k–1)-1 + 3n ≤ 2kn
- always want to use many more

From Szeliski, *Computer Vision: Algorithms and Applications*

Measurement equations

- Measurement equations

$$u_{fp} = \boldsymbol{i}_f^T \boldsymbol{s}_p \qquad \boldsymbol{i}_f\text{: rotation, } \boldsymbol{s}_p\text{: position}$$
$$v_{fp} = \boldsymbol{j}_f^T \boldsymbol{s}_p$$

- Stack them up…

$$\boldsymbol{W} = \boldsymbol{R}\,\boldsymbol{S}$$
$$\boldsymbol{R} = (\boldsymbol{i}_1,\ldots,\boldsymbol{i}_F,\boldsymbol{j}_1,\ldots,\boldsymbol{j}_F)^T$$
$$\boldsymbol{S} = (\boldsymbol{s}_1,\ldots,\boldsymbol{s}_P)$$

From Szeliski, *Computer Vision: Algorithms and Applications*

Factorization

$$\boldsymbol{W} = \boldsymbol{R}_{2F\times 3}\,\boldsymbol{S}_{3\times P}$$

SVD

$$\boldsymbol{W} = \boldsymbol{U}\,\boldsymbol{\Lambda}\,\boldsymbol{V} \quad \boldsymbol{\Lambda}\text{ must be rank 3}$$
$$\boldsymbol{W}' = (\boldsymbol{U}\,\boldsymbol{\Lambda}^{1/2})(\boldsymbol{\Lambda}^{1/2}\,\boldsymbol{V}) \qquad = \boldsymbol{U}'\,\boldsymbol{V}'$$

Make $\boldsymbol{R}$ orthogonal

$$\boldsymbol{R} = \boldsymbol{Q}\boldsymbol{U}', \quad \boldsymbol{S} = \boldsymbol{Q}^{-1}\boldsymbol{V}'$$
$$\boldsymbol{i}_f^T\boldsymbol{Q}^T\boldsymbol{Q}\boldsymbol{i}_f = 1 \ \ldots$$

From Szeliski, *Computer Vision: Algorithms and Applications*

Results

- Look at paper figures…

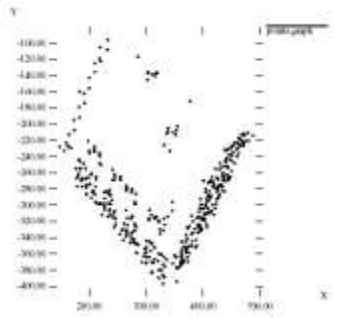


Figure 4.5: A view of the computed shape from approximately above the building (compare with figure 4.6).

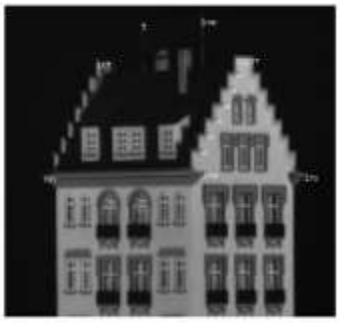


Figure 4.7: For a quantitative evaluation, distances between the features shown in the picture were measured on the actual model, and compared with the computed results. The comparison is shown in figure 4.8.

From Szeliski, *Computer Vision: Algorithms and Applications*

Cool Robotics Share (replay from last, last week)

Fast and Accurate Knife-Edge Maneuvers for Autonomous Aircraft

Andrew Barry
Anirudha Majumdar
Tim Jenks
Russ Tedrake

Robot Locomotion Group
MIT/CSAIL

Huai-Ti Lin
Ivo Ros
Andrew Biewener

Concord Field Station
Harvard University