Image Primitives and Correspondence

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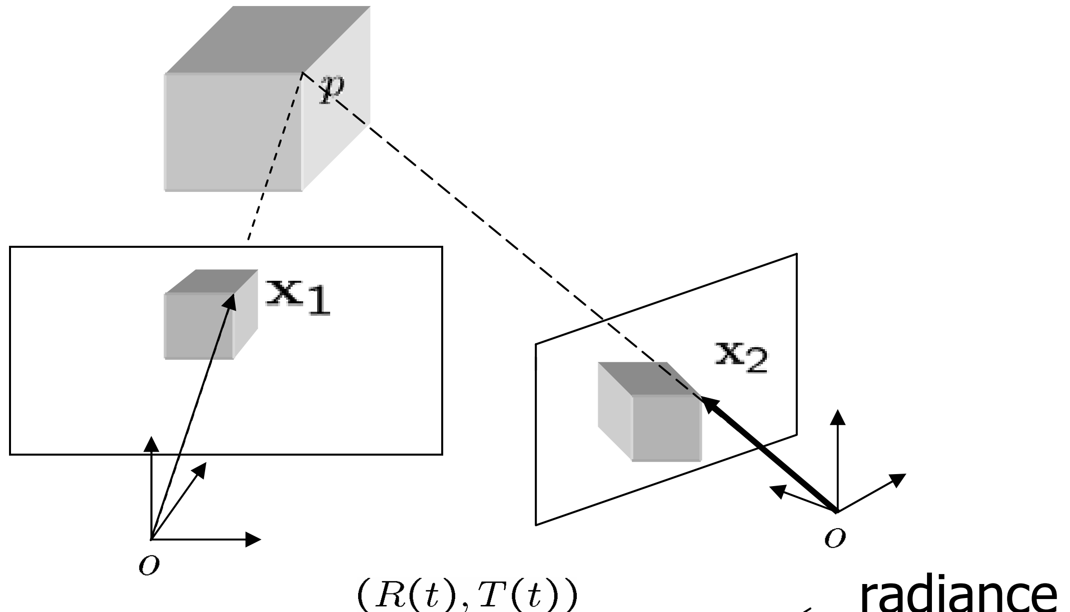
Image Primitives and Correspondence

Given an image point in left image, what is the (corresponding) point in the right image, which is the projection of the same 3-D point

Image Primitives and Correspondence

Difficulties – ambiguities, large changes of appearance, due to change
Of viewpoint, non-uniquess

Matching - Correspondence



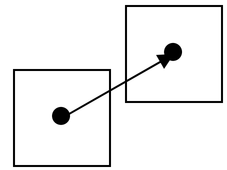
Lambertian assumption $$I_1(\mathbf{x}_1) = \mathcal{R}(p) = I_2(\mathbf{x}_2)$$

Rigid body motion $$\mathbf{x}_2 = h(\mathbf{x}_1) = \frac{1}{\lambda_2(\mathbf{X})}(R\lambda_1(\mathbf{X})\mathbf{x}_1 + T)$$

Correspondence $$I_1(\mathbf{x}_1) = I_2(h(\mathbf{x}_1))$$

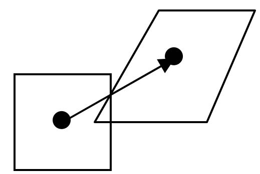
Local Deformation Models

- Translational model



$$h(\mathbf{x}) = \mathbf{x} + d \qquad I_1(\mathbf{x}_1) = I_2(h(\mathbf{x}_1))$$

- Affine model



$$h(\mathbf{x}) = A\mathbf{x} + d \qquad I_1(\mathbf{x}_1) = I_2(h(\mathbf{x}_1))$$

- Transformation of the intensity values taking into account occlusions and noise

$$I_1(\mathbf{x}_1) = f_o(\mathbf{X}, g) I_2(h(\mathbf{x}_1) + n(h(\mathbf{x}_1))$$

Feature Tracking and Optical Flow

- Translational model

$$I_1(\mathbf{x}_1) = I_2(\mathbf{x}_1 + \Delta\mathbf{x})$$

- Small baseline

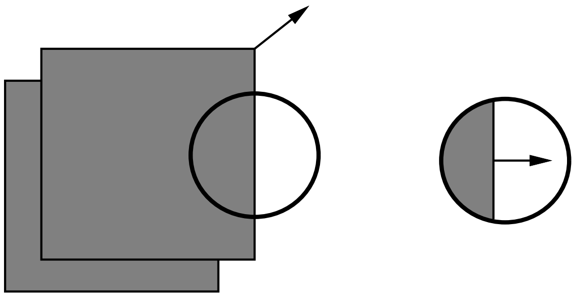
$$I(\mathbf{x}(t), t) = I(\mathbf{x}(t) + \mathbf{u}dt, t + dt)$$

- RHS approximation by the first two terms of Taylor series

$$\nabla I(\mathbf{x}(t), t)^T \mathbf{u} + I_t(\mathbf{x}(t), t) = 0$$

- Brightness constancy constraint

Aperture Problem



- Normal flow

$$\mathbf{u}_n \doteq \frac{\nabla I^T \mathbf{u}}{\|\nabla I\|} \cdot \frac{\nabla I}{\|\nabla I\|} = -\frac{I_t}{\|\nabla I\|} \cdot \frac{\nabla I}{\|\nabla I\|}$$

Given brightness constancy constraint at single point – all we can recover is normal flow

Optical Flow

- Integrate around over image patch

$$E_b(\mathbf{u}) = \sum_{W(x,y)} [\nabla I^T(x,y,t)\mathbf{u}(x,y) + I_t(x,y,t)]^2$$

- Solve

$$\begin{aligned} \nabla E_b(\mathbf{u}) &= 2 \sum_{W(x,y)} \nabla I (\nabla I^T \mathbf{u} + I_t) \\ &= 2 \sum_{W(x,y)} \left(\begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \mathbf{u} + \begin{bmatrix} I_x I_t \\ I_y I_t \end{bmatrix} \right) \end{aligned}$$

$$\begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} \mathbf{u} + \begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix} = 0$$

$$G\mathbf{u} + \mathbf{b} = 0$$

Optical Flow, Feature Tracking

$$\mathbf{u} = -G^{-1}\mathbf{b}$$

$$G = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}$$

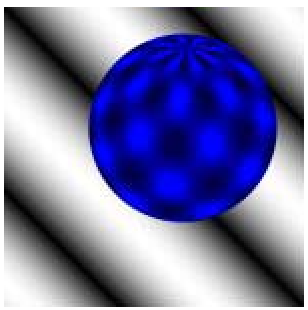
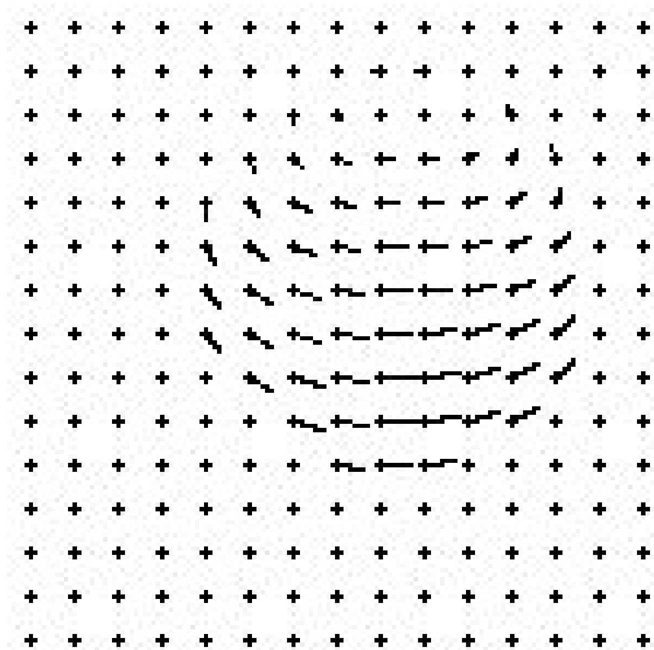
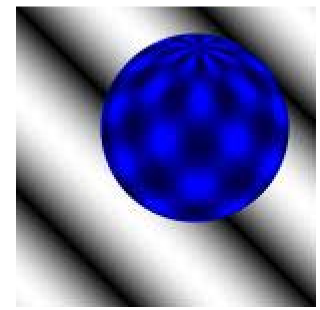
Conceptually:

rank(G) = 0 blank wall problem
rank(G) = 1 aperture problem
rank(G) = 2 enough texture – good feature candidates

In reality: choice of threshold is involved

Optical Flow

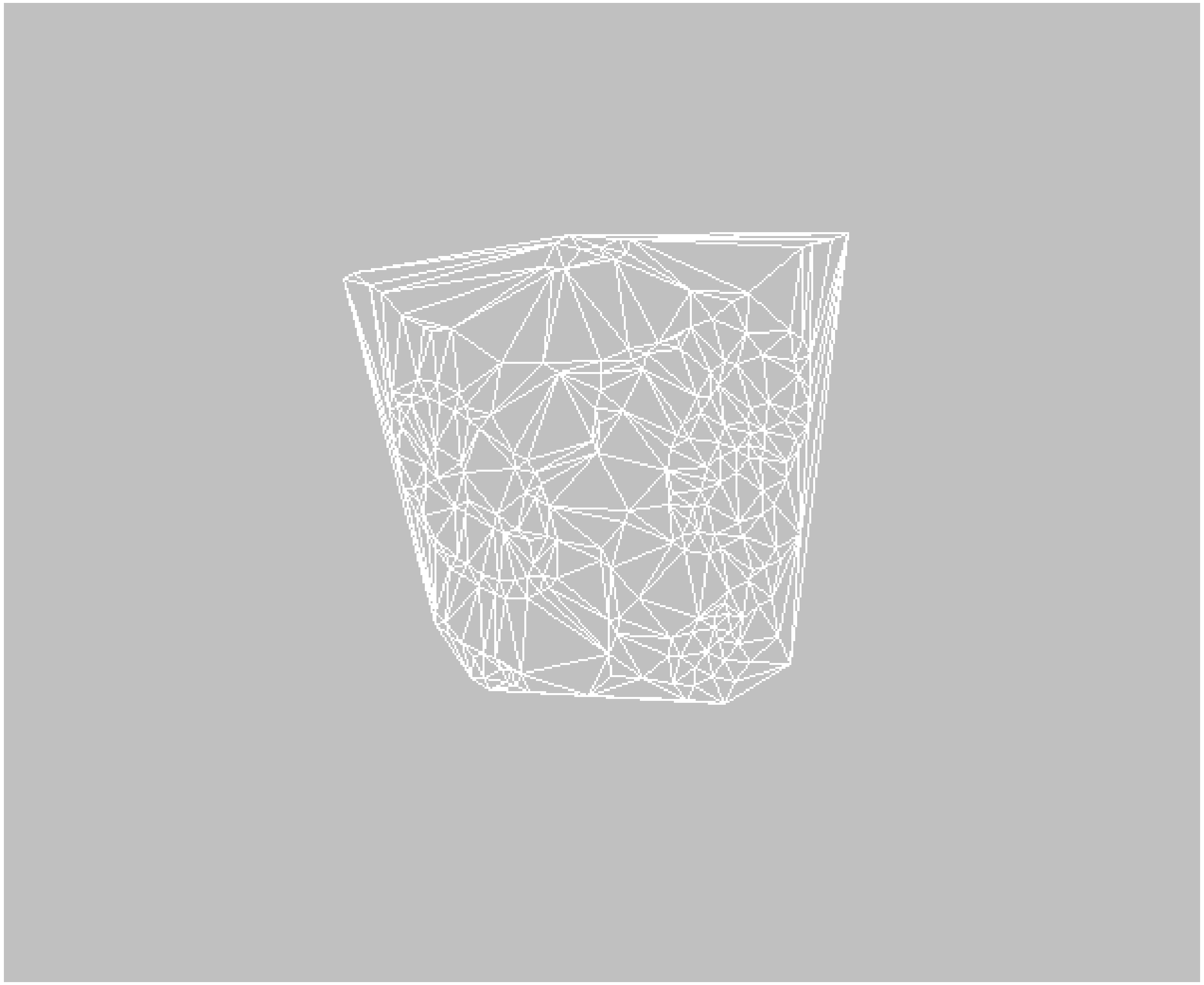
- Previous method - assumption locally constant flow

- Alternative regularization techniques (locally smooth flow fields, integration along contours)
- Qualitative properties of the motion fields

Feature Tracking

3D Reconstruction - Preview



Point Feature Extraction

$$G = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}$$

- Compute eigenvalues of G
- If smalest eigenvalue σ of G is bigger than τ - mark pixel as candidate feature point

- Alternatively feature quality function (Harris Corner Detector)

$$C(G) = \mathrm{det}(G) + k \cdot \mathrm{trace}^2(G)$$

Harris Corner Detector - Example

Wide baseline matching

Point features detected by Harris Corner detector

Region based Similarity Metric

- Sum of squared differences

$$SSD(h) = \sum_{\tilde{\mathbf{x}} \in W(\mathbf{x})} \|I_1(\tilde{\mathbf{x}}) - I_2(h(\tilde{\mathbf{x}})\|^2$$

- Normalize cross-correlation

$$NCC(h) = \frac{\sum_{W(\mathbf{x})}(I_1(\tilde{\mathbf{x}})-\bar{I}_1)(I_2(h(\tilde{\mathbf{x}}))-\bar{I}_2))}{\sqrt{\sum_{W(\mathbf{x})}(I_1(\tilde{\mathbf{x}})-\bar{I}_1)^2 \sum_{W(\mathbf{x})}(I_2(h(\tilde{\mathbf{x}}))-\bar{I}_2)^2)}}$$

- Sum of absolute differences

$$SAD(h) = \sum_{\tilde{\mathbf{x}} \in W(\mathbf{x})} |I_1(\tilde{\mathbf{x}}) - I_2(h(\tilde{\mathbf{x}}))|$$

NCC score for two widely separated views

NCC score

Edge Detection

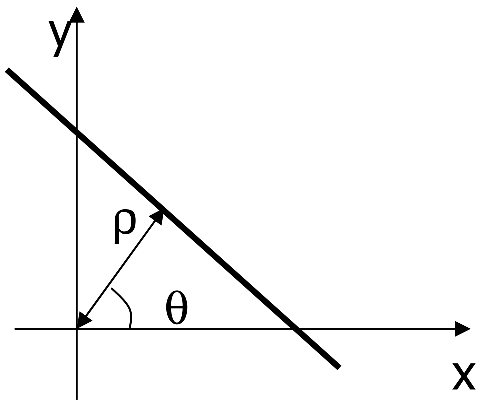
original image

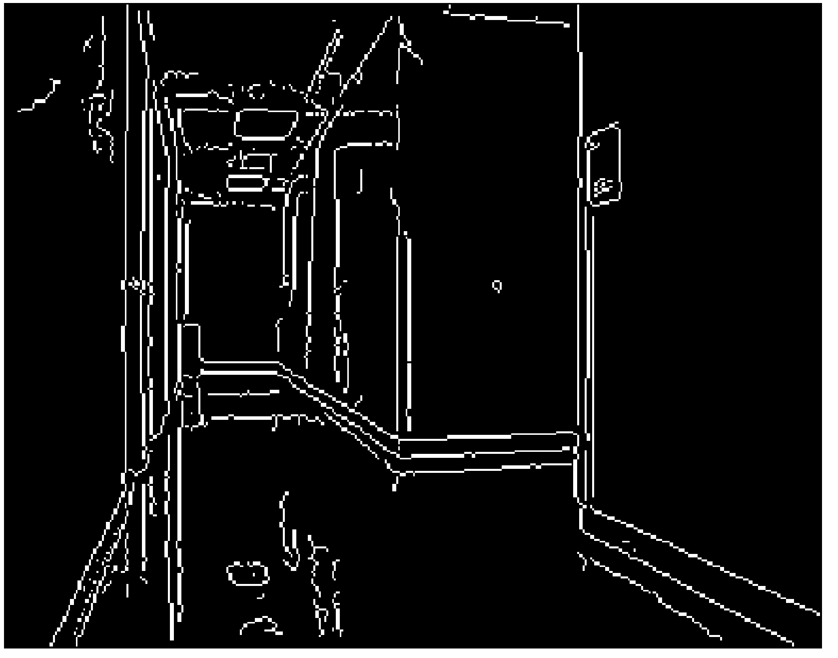
gradient magnitude

Canny edge detector

- Compute image derivatives
- if gradient magnitude > τ and the value is a local maximum along gradient direction – pixel is an edge candidate

Line fitting





Non-max suppressed gradient magnitude

- Edge detection, non-maximum suppression
  (traditionally Hough Transform – issues of resolution, threshold selection and search for peaks in Hough space)
- Connected components on edge pixels with similar orientation
  - group pixels with common orientation

Line Fitting

$$A = \begin{bmatrix} \sum x_i^2 & \sum x_i y_i \\ \sum x_i y_i & \sum y_i^2 \end{bmatrix}$$

second moment matrix associated with each connected component
v_1 - eigenvector of A

$$v_1 = [\cos(\theta), \sin(\theta)]^T$$

$$\theta = \arctan(v_1(2)/v_1(1))$$
$$\rho = \bar{x}\sin(\theta) - \bar{y}\cos(\theta)$$

- Line fitting lines determined from eigenvalues and eigenvectors of A
- Candidate line segments - associated line quality