

Lecture-7

Feature-based Registration

Steps in Feature-based Registration

- Find features
- Establish correspondence (correlation, point correspondence)
- Fit transformation
- Apply transformation (warp)

Features

- Any pixels
- Corner points
- Interest points
- Features obtained using Gabor/Wavelet filters
- Straight lines
- Line intersections

Transformations

- Affine
- Projective
- Psuedo-perspective
- Rational polynomial

Good Features to Track

- Corner like features
- Moravec's Interest Operator

Corner like features

$$C = \begin{bmatrix} \square & \square & f_x^2 & \square \\ \square & \square & \varrho & \square \\ \square & \square & f_x f_y & \square \\ \square & \square & \varrho & \square \end{bmatrix} \quad \begin{bmatrix} \square & f_x f_y \\ \square & \varrho \\ \square & f_y^2 \\ \square & \varrho \end{bmatrix}$$



$$C = \begin{bmatrix} \square & \varrho_1 & 0 & \square \\ \square & \square & \square & \square \\ \square & 0 & \square & \square \\ \square & \square & \square & \square \end{bmatrix} \quad \begin{bmatrix} 0 & \square \\ \varrho_2 & \square \\ \square & \square \end{bmatrix}$$

Corners

- For perfectly uniform region $\lambda_1 = \lambda_2 = 0$

- If Q contains an ideal step edge, then

$$\lambda_2 = 0, \lambda_1 > 0$$

- if Q contains a corner of black square on white background

$$\lambda_1 \geq \lambda_2 > 0$$

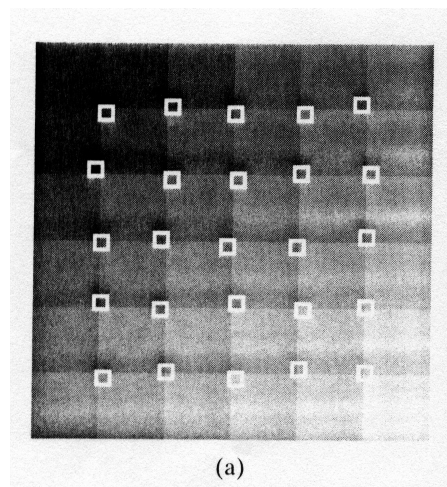
Algorithm Corners

- Compute the image gradient over entire image f.
- For each image point p:
 - form the matrix C over $(2N+1) \times (2N+1)$ neighborhood Q of p;
 - compute the smallest eigenvalue of C;
 - if eigenvalue is above some threshold, save the coordinates of p into a list L.

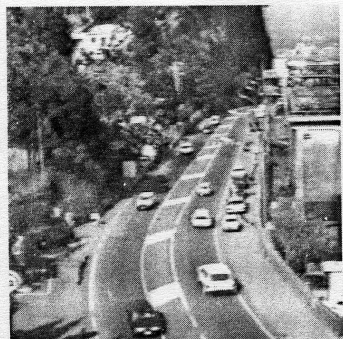
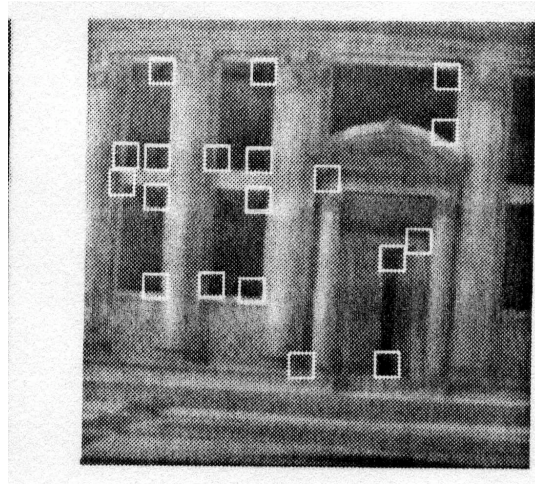
Algorithm Corners

- Sort L in decreasing order of eigenvalues.
- Scanning the sorted list top to bottom: for each current point, p , delete all other points on the list which belong to the neighborhood of p .

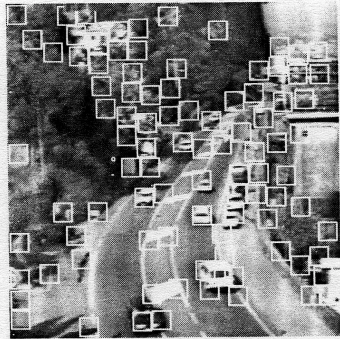
Results



Results



(a)



(b)

Moravec's Interest Operator

Algorithm

- Compute four directional variances in horizontal, vertical, diagonal and anti-diagonal directions for each 4 by 4 window.
- If the minimum of four directional variances is a local maximum in a 12 by 12 overlapping neighborhood, then that window (point) is interesting.

$P_{0,0}$	$P_{0,1}$	$P_{0,2}$	$P_{0,3}$
$P_{1,0}$	$P_{1,1}$	$P_{1,2}$	$P_{1,3}$
$P_{2,0}$	$P_{2,1}$	$P_{2,2}$	$P_{2,3}$
$P_{3,0}$	$P_{3,1}$	$P_{3,2}$	$P_{3,3}$

(a)

$P_{0,0}$	$P_{0,1}$	$P_{0,2}$	$P_{0,3}$
$P_{1,0}$	$P_{1,1}$	$P_{1,2}$	$P_{1,3}$
$P_{2,0}$	$P_{2,1}$	$P_{2,2}$	$P_{2,3}$
$P_{0,0}$	$P_{0,1}$	$P_{0,2}$	$P_{0,3}$

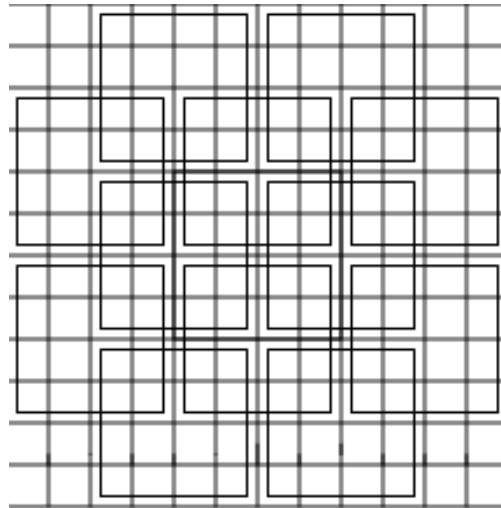
(b)

$P_{0,0}$	$P_{0,1}$	$P_{0,2}$	$P_{0,3}$
$P_{1,0}$	$P_{1,1}$	$P_{1,2}$	$P_{1,3}$
$P_{2,0}$	$P_{2,1}$	$P_{2,2}$	$P_{2,3}$
$P_{3,0}$	$P_{3,1}$	$P_{3,2}$	$P_{3,3}$

(c)

$P_{0,0}$	$P_{0,1}$	$P_{0,2}$	$P_{0,3}$
$P_{1,0}$	$P_{1,1}$	$P_{1,2}$	$P_{1,3}$
$P_{2,0}$	$P_{2,1}$	$P_{2,2}$	$P_{2,3}$
$P_{3,0}$	$P_{3,1}$	$P_{3,2}$	$P_{3,3}$

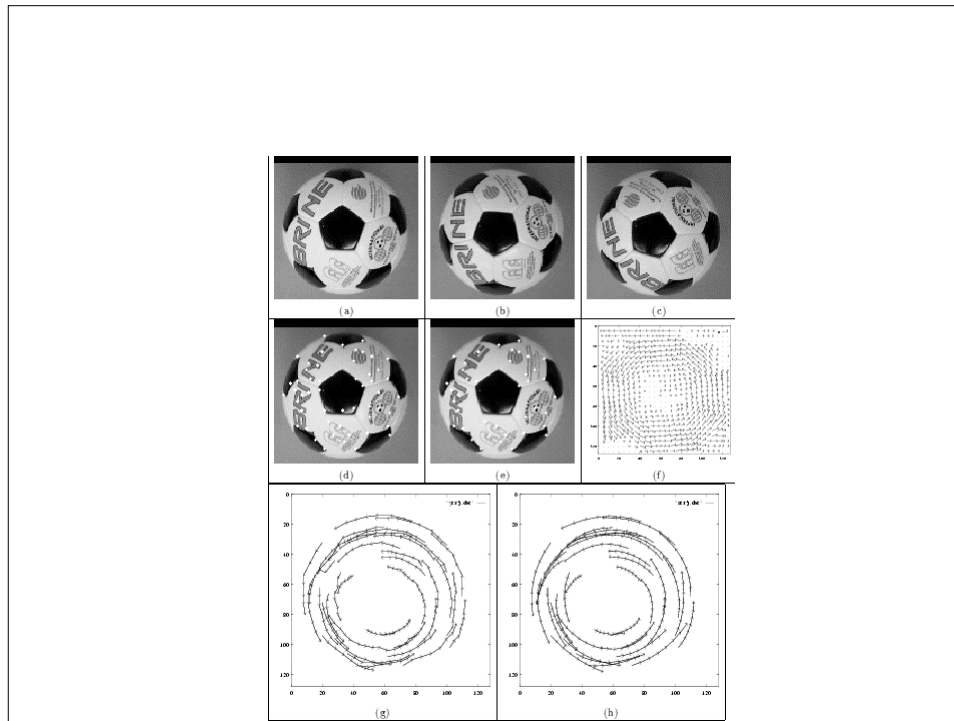
(d)



$$\begin{aligned}
 V_h &= \sum_{j=0}^3 \sum_{i=0}^2 (P(x+i, y+j) - P(x+i+1, y+j))^2 \\
 V_v &= \sum_{j=0}^2 \sum_{i=0}^3 (P(x+i, y+j) - P(x+i, y+j+1))^2 \\
 V_d &= \sum_{j=0}^2 \sum_{i=0}^2 (P(x+i, y+j) - P(x+i+1, y+j+1))^2 \\
 V_a &= \sum_{j=0}^2 \sum_{i=1}^3 (P(x+i, y+j) - P(x+i-1, y+j+1))^2
 \end{aligned}$$

$$V(x, y) = \min(V_h(x, y), V_v(x, y), V_d(x, y), V_a(x, y))$$

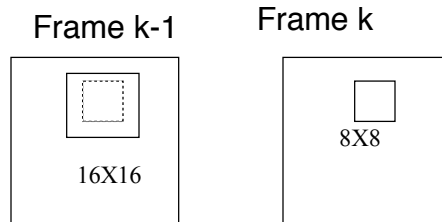
$$I(x, y) = \begin{cases} 1 & \text{if } V(x, y) \text{ local max} \\ 0 & \text{otherwise} \end{cases}$$



Correlation

- Similarity/Dissimilarity Measures
 - Sum of Squares Difference (SSD)
 - Normalized Correlation
 - Mutual Correlation
 - Mutual information $H(X;Y)=H(X)-H(X|Y)$
- Use
 - Gray levels
 - Laplacian of Gaussian
 - Gradient magnitude

Block Matching



Block Matching

- For each 8X8 block, centered around pixel (x,y) in frame k , B_k
 - Obtain 16X16 block in frame $k-1$, centered around (x,y) , B_{k-1}
 - Compute Sum of Squares Differences (SSD) between 8X8 block, B_k , and all possible 8X8 blocks in B_{k-1}
 - The 8X8 block in B_{k-1} centered around (x',y') , which gives the least SSD is the match
 - The displacement vector (optical flow) is given by $u=x-x'$; $v=y-y'$

Sum of Squares Differences (SSD)

$$(u(x, y), v(x, y)) = \arg \min_{u, v = \{0, \dots, 3\}} \sum_{i=0}^{\overline{07}} \sum_{j=0}^{\overline{07}} (f_k(x+i, y+j) - f_{k'}(x+i+u, y+j+v))^2$$

Minimum Absolute Difference (MAD)

$$(u(x, y), v(x, y)) = \arg \min_{u, v = \{0, \dots, 3\}} \sum_{i=0}^{\overline{07}} \sum_{j=0}^{\overline{07}} |f_k(x+i, y+j) - f_{k'}(x+i+u, y+j+v)|$$

Maximum Matching Pixel Count (MPC)

$$T(x, y; u, v) = \begin{cases} 1 & \text{if } |f_k(x, y) - f_{k'}(x + u, y + v)| \leq t \\ 0 & \text{Otherwise} \end{cases}$$

$$(u(x, y), v(x, y)) = \arg \max_{u, v = \{-3, \dots, 3\}} \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} T(x + i, y + j; u, v)$$

Cross Correlation

$$(u, v) = \arg \max_{u, v = \{-3, \dots, 3\}} \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} (f_k(x + i, y + j)) \cdot (f_{k'}(x + i + u, y + j + v))$$

Normalized Correlation

$$(u, v) = \arg \max_{u, v = \{3, \dots, 3\}} \frac{\sum_{i=0}^{M-1} \sum_{j=0}^{M-1} (f_k(x+i, y+j)) \cdot (f_{k'}(x+i+u, y+j+v))}{\sqrt{\sum_{i=0}^{M-1} \sum_{j=0}^{M-1} f_k(x+i, y+j) \cdot f_k(x+i, y+j) \cdot \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} f_{k'}(x+i+u, y+j+v) \cdot f_{k'}(x+i+u, y+j+v)}}$$

Mutual Correlation

$$(u, v) = \arg \max_{u, v = \{3, \dots, 3\}} \frac{1}{64 \sigma_1 \sigma_2} \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} (f_k(x+i, y+j) - \mu_1) \cdot (f_{k'}(x+i+u, y+j+v) - \mu_2)$$

Sigma and mu are standard deviation and mean of patch-1 and patch-2 respectively

Issues with Correlation

- Patch Size
- Search Area
- How many peaks

Spatiotemporal Models

- First order Taylor series

$$f(x, y, t) = f(x + dx, y + dy, t + dt)$$

$$f(x, y, t) = f(x, y, t) + \frac{\partial f}{\partial x} dx + \frac{\partial f}{\partial y} dy + \frac{\partial f}{\partial t} dt$$

$$\begin{bmatrix} \mathbf{1} & \mathbf{X}^T \mathbf{f}_x \mathbf{f}_x^T \mathbf{X} \end{bmatrix} \mathbf{a} = \begin{bmatrix} \mathbf{1} & \mathbf{X}^T \mathbf{f}_x \end{bmatrix} f_t$$

$$(u(x, y), v(x, y)) = \arg \min_{u, v \in \mathbb{Z}, 3} \sum_{i=-1}^1 \sum_{j=-1}^1 (f_i(x+i, y+j) - f_{i,j}(x+i, y+j+v))$$

Correlation

Bilinear and Pseudo-Perspective

$$(\mathbf{K} \mathbf{K}^T) \mathbf{q} = \mathbf{K} \mathbf{f}_t$$

$$\mathbf{K}^T = [f_x(xy, x, y, 1), f_y(xy, x, y, 1)] \quad \mathbf{bilinear}$$

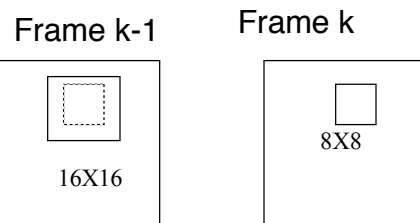
$$\mathbf{K}^T = [f_x(x, y, 1) \quad f_y(x, y, 1) \quad c_1 \quad c_2]$$

$$c_1 = x^2 f_x + xy f_y$$

$$c_2 = xy f_x + y^2 f_y$$

Pseudo perspective

Correlation Vs Spatiotemporal



Correlation Complexity

- $m \times m$ multiplications and additions
- $2 \times m \times m$ additions and 2 divisions for two means
- $2 \times m \times m$ multiplications and additions for variances

$$(u, v) = \operatorname{argmax}_{u, v = \overline{0}, \dots, \overline{3}} \frac{1}{64 \overline{0} \overline{0} \overline{2}} \prod_{i=0}^{\overline{0} \overline{0}} \prod_{j=0}^{\overline{0} \overline{0}} (f_k(x+i, y+j) \overline{0} \overline{0}) \cdot (f_k(x+i+u, y+j+v) \overline{0} \overline{0})$$

Spatiotemporal Complexity

- $3 \times m \times m$ subtractions for spatiotemporal derivatives
- $(36+6) \times m \times m$ additions for generating linear system
- $6 \times 6 \times 6$ multiplications and additions for solving 6 by 6 linear system

$$\left[\prod X^T \mathbf{f}_X \mathbf{f}_X^T X \right] \overline{0} a = \prod \prod X^T \mathbf{f}_X f_t$$

Feature-based Matching

Feature-based Matching

- The input is formed by f_1 and f_2 , two frames of an image sequence.
- Let Q_1 , Q_2 and Q' be three $N \times N$ image regions.
- Let “ d ” be the unknown displacement vector between f_1 and f_2 of a feature point “ p ”, on which Q_1 is centered.

Algorithm

- Set $d=0$, center Q1 on p_1 .
- Estimate the displacement “ d_0 ” of “ p ”, center of “Q1”, using Lucas and Kanade method. Let $d=d+d_0$.
- Let Q’ bet the patch obtained by warping Q1 according to “ d_0 ”. Compute Sum of Square (SSD) difference between new patch Q’ and corresponding patch Q2 in frame f_2 .
- If SSD more than threshold, set $Q_1=Q'$ and go to step 1, otherwise exit.

Lucas & Kanade (Least Squares)

- Optical flow eq

$$f_x u + f_y v = \Delta f_t$$

- Consider 3 by 3 window

$$f_{x1} u + f_{y1} v = \Delta f_{t1}$$

\vdots

$$f_{x9} u + f_{y9} v = \Delta f_{t9}$$

$$\mathbf{A} \mathbf{u} = \mathbf{f}_t$$

Shi-Tomasi-Kanade(STK) Tracker

$$I(\tilde{x}, t + \tilde{t}) = I(x, t)$$

$$\tilde{x} = Ax + d$$

$$\tilde{t} = \frac{1}{W} [I(Ax + d, t + \tilde{t}) - I(x, t)]$$

After the first order Taylor expansion at $A=I$ and $d=0$, we can get a linear 6_6 system:

$$Tz = f$$

$$z = [A_{11} \quad A_{12} \quad A_{21} \quad A_{22} \quad d_1 \quad d_2]$$

$$f = I_t \frac{1}{W} [xI_x \quad yI_x \quad xI_y \quad yI_y \quad I_x \quad I_y]$$

Shi-Tomasi-Kanade(STK) Tracker

- **Advantages:**
 - Easy to implement .
 - Works very well with a small transformation.
- **Drawbacks:**
 - Fail to track in presence of a large rotation.
- **Reason:**
 - The rotation component implied in affine model is non-linear.

Useful Links

<http://twtelecom.dl.sourceforge.net/sourceforge/opencvlibrary/OpenCVReferenceManual.pdf>

<http://vision.stanford.edu/~birch/klt/>